Neuro-synaptic Learning Environments: A Holistic AI-Powered Education Ecosystem

By Jan Hendrik van Niekerk

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DECLARATION

I hereby declare that the content of this dissertation represents my own original work, researched and written independently under the guidance of Professor Salvatore Fava. I confirm that any use of copyrighted material, whether published or unpublished, is in accordance with international copyright law and that all required permissions have been obtained for the inclusion of copyrighted material.
I affirm that this work, in its entirety or in part, has not been submitted for any other degree and that I have adhered to Selinus University's guidelines and regulations concerning academic integrity and plagiarism.

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ABSTRACT

My doctoral research introduces the Neuro-Synaptic Learning Environment (NSLE), a novel educational framework born from a career-long dedication to employ technology for better learning. My journey began in 1987, during teacher qualification, with a simple computer programme to aid student revision. The unexpected results ignited an enduring belief in AI's transformative potential within education. This conviction has since driven me to develop numerous student support applications and author college textbooks, consistently observing above-average outcomes whenever AI assistance was integrated. Building on this foundation, my current research explores the NSLE, a synergistic integration of artificial intelligence (AI), machine learning (ML), and gamification designed to cultivate truly dynamic and personalised learning experiences, alongside adaptive assessment strategies. At its core, an AI engine analyses student data, identifying individual learning styles and subsequently tailoring unique learning pathways.

Complementing this, AI suggests different resources, podcasts, videos, lesson notes, and immersive virtual, augmented, extended, and mixed reality (VR/AR) simulations, the efficacy of which is continuously refined by ML algorithms based on real-time student progress. Gamification elements are seamlessly woven throughout to encourage student motivation and provide timely, insightful feedback. The central aspiration of the NSLE is to transcend the limitations of traditional learning by establishing a deeply personalised and continuously adaptive educational journey. This study specifically investigates the NSLE's effectiveness in enhancing overall learning outcomes, addressing different learning styles, and examining the impact of VR/AR immersion on student engagement, alongside the validity and reliability of AI-powered assessment methods.

This research seeks to contribute to the evolution of education by illuminating the transformative potential of the NSLE and considering the practicalities of implementing AI-powered ecosystems, with a focus on how these systems can construct genuinely student-centred learning experiences. Grounded in constructivist, cognitive, and adaptive learning principles, this investigation acknowledges the important interconnectedness between teachers, students, and content. It also addresses the critical ethical considerations and design challenges inherent in AI assisted education, including data privacy, algorithmic transparency and accountability, and the potential for bias. Finally, my research critically examines the nuanced ways in which AI can personalise learning experiences even within a fixed curriculum, aiming to articulate a framework that dynamically adjusts teaching methodologies and learning pace to optimise individual student growth and directly address persistent shortcomings in current educational practices.

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CHAPTER 1
INTRODUCTION

1.1 Background

Having spent more than 35 years immersed in the foundational disciplines of mathematics, physics, and mechanical engineering, a deep understanding has shaped my perspective on education, of the hurdles students face throughout their learning journeys. My MSc in Astrophysics provided transformative insights, particularly through my exploration of artificial intelligence. This exploration of AI, coupled with my practical experience, has ignited a passion to investigate how AI can fundamentally reshape education for the better.

This dissertation introduces the NSLE, an AI-driven ecosystem. This system is designed with three core goals: optimising learning for students, empowering educators, and informing policymakers. The name 'Neuro-Synaptic' isn't arbitrary; it reflects the central principle guiding its development: to create a learning environment that, much like the brain's neural networks, dynamically adapts and forms connections based on the unique interactions and evolving needs of each individual learner.

The NSLE strategically harnesses AI-powered adaptive learning systems and sophisticated machine learning algorithms. This allows it to facilitate truly personalised learning pathways [Shvetsova et al. 2025] and deliver precisely tailored feedback [John. 2025]. This approach intentionally draws inspiration from the neurobiological processes where synaptic connections in the brain strengthen or weaken in response to individual learning experiences [Martinez et al. 1996].

This research seeks to move beyond the inherent limitations of static educational models. It strives towards a more responsive learning journey. Persistent challenges such as time constraints, the impact of distractions, and often-insufficient personalised support are significant concerns. These issues are particularly relevant for postgraduate students [Le Roux. 2018]. My goal is to explore how the NSLE can address these challenges.

1.2 Statement of the problem

I'm incredibly excited by the potential of this research and the integration of AI to optimise learning, as Pedro and colleagues highlights [Pedro et al. 2019]. In my experience tutoring high school students, I've often seen them struggle with learning the correct material to enhance their understanding. For instance, despite the widely acknowledged potential of AI to facilitate deeply personalised learning experiences [Ihedimma. 2025], we still face considerable challenges in accurately and scalable assessing the nuanced individual learning styles of students [Brightwood et al. 2024]. A critical area needing attention is the development of equitable and unbiased AI systems that genuinely cater to the multifaceted needs of all learners [Lata. 2024]. The practical and seamless integration of sophisticated AI tools into our established educational practices and existing curricula also presents a notable hurdle [Huong. 2024]. As Bianchi points out [Bianchi. 2024], ensuring a balance between the advantages AI offers and the cultivation of important human skills, such as critical

thinking and collaborative problem-solving, remains a key pedagogical consideration for which a widely accepted practical approach is still under development. Finally, there's a relative lack of real-world evaluations that comprehensively demonstrate the actual impact and efficacy of AI-powered learning environments across various educational settings and with different student populations, a point underscored by Luo's research in Chinese schools [Luo et al. 2023].
This doctoral research endeavours to directly address this critical gap in our understanding by investigating the potential of AI to genuinely optimise learning outcomes for both learners and educators. My approach involves the design, development, and analysis of intelligent tutoring systems embedded within the innovative framework of the NSLE project, which I will elaborate on in *chapter 5.1*.

1.3 Research aims and objectives

My research aims to articulate and empirically demonstrate the transformative potential of AI in enriching learning experiences and directly tackling key challenges we currently face in education. Central to this investigation is the proposed NSLE project, a comprehensive framework composed of several interconnected core elements [Fig. 1.1]: fostering student motivation [Pertiwi et al. 2024], deploying sophisticated AI-powered tutoring systems [Rızvı. 2023], and grounding learning in authentic, real-world applications [Oni. 2025].
This framework also strategically integrates gamification principles [Suresh Babu et al. 2024] and maintains a fundamental commitment to inclusive learning design [Lata. 2024]. This strategically constructed personalised learning environment has the potential to significantly complement student engagement. It can demonstrably improve academic achievement. Perhaps most importantly, it can cultivate a genuine and lasting love of learning [Geroche et al. 2024].

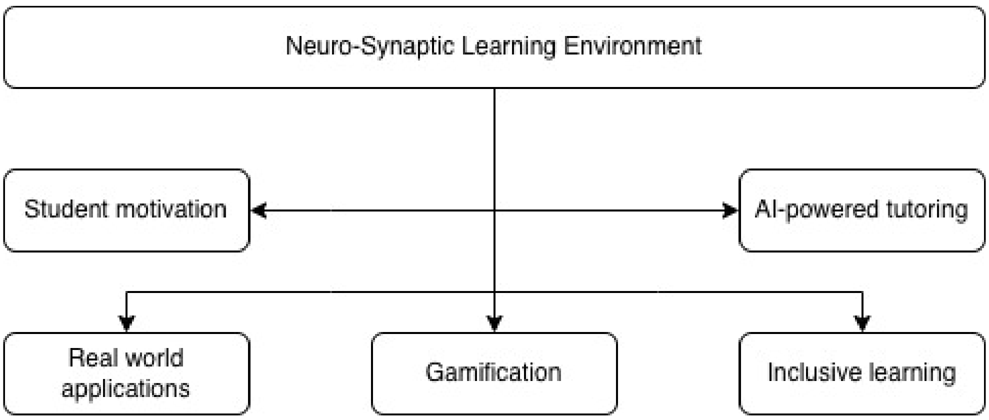

Figure 1.1 Conceptual structure of the Neuro-Synaptic Learning Environments Framework.

In this dissertation, my focus is on introducing the innovative NSLE framework and elucidating the purpose and key properties of its constituent core elements, which collectively contribute to this dynamic AI-driven learning ecosystem. These fundamental components, visually represented in Figure 1.1, will be explored in detail. Throughout the subsequent chapters of this work I will concentrate on the following

elements: student motivation [Chapter 10.6], AI-powered tutoring [Chapter 5.7], real-world applications [Chapter 12.4], gamification [Chapter 7.5], and inclusive learning [Chapter 7.7].
The overarching objective of developing intelligent systems capable of dynamically adapting to the unique and evolving needs of each student directly aligns with the insightful research conducted by Basri [Basri. 2024], which suggests the potential of effective AI-powered tutoring systems to significantly boost learning outcomes. Building upon this foundation, I posit that the creation of pedagogical tools specifically designed to cater to the whole spectrum of learners, including those with disabilities [*Garg et al.2020*], coupled with the purposeful integration of practical, real-world examples into the learning process [*Marr. 2018*], will demonstrably boost the relevance and applicability of educational content.
This dissertation will demonstrate the capacity of strategically designed game-based learning approaches to measurably increase student engagement, provide granular tracking of individual progress, and identify key motivational factors that spark curiosity and effectively sustain long-term learning. By exploring these critical areas and addressing pertinent ethical considerations, such as data privacy and algorithmic bias [*Henrique et al.2024*], the NSLE project aspires to responsibly harness the transformative power of AI to facilitate personalised learning experiences for all students.
Successfully navigating existing challenges, including the nuanced assessment of individual learning styles, ensuring the fair and equitable application of AI, achieving the seamless integration of AI tools within existing educational infrastructures [*Pedro et al.2019*], and maintaining an important balance between AI augmentation and the cultivation of human skills like critical thinking and creativity [*Youvan. 2024*], can pave the way for a more effective and genuinely inclusive learning environment that empowers both students and educators alike.

1.4 Research questions

This research project initiates an exploration of the transformative potential of AI to fundamentally influence education by cultivating learning environments that authentically mirror the complexities of the real world [Benson. 2014]. The successful realization and influential implementation of the NSLE hinges on our ability to address the following critical research questions.

How can AI-powered NSLEs be intentionally designed to optimally foster student engagement, intrinsic motivation, and demonstrable learning outcomes across the whole spectrum of learners within our educational systems?

What specific technological innovations and architectures will be instrumental in making truly personalised and deeply immersive learning experiences a tangible reality within the NSLE framework [Alam. 2023]?

In what ways can these sophisticated AI-powered systems be effectively tailored to cater to the wide array of learner profiles, encompassing different learning styles, varying abilities, and individual educational needs [Faresta. 2024]?

How can the strategic integration of authentic real-world scenarios and compelling case studies serve to consistently maintain student engagement and sustain a high level of motivation throughout the learning journey [Srinivasa et al. 2022]?

What are the most effective mechanisms through which AI can provide timely, personalised feedback, nuanced assessments of learning, and comprehensive evaluations of student progress within the NSLE [Vashishth et al. 2024]?

What key elements and design principles are most effective in capturing students' interest and sustaining their motivation within these novel and technological learning environments [Onesi-Ozigagun et al. 2024]?

As I work through this dissertation, I'm committed to using a comprehensive mixed-methods approach to tackle these research questions that will help us better understand the impact of AI on education. The solutions to these questions are discussed in *chapter 12.6.10*.

1.5 Research significance

The evaluation of the NSLE will determine its impact in the real-world contexts [Verkijika. 2015]. The insightful findings from such analyses hold the potential to pave the way [Peksa et al. 2023] for the evolution of a more efficient and demonstrably effective education system [Panday et al. 2024 ; Arico et al. 2017].
By analysing the effectiveness of the NSLE across various dimensions, we can ascertain the extent to which it can truly transform educational practices and contribute to the creation of a future-proof learning ecosystem that caters to the unique cognitive landscape of individual minds. Key distinguishing features of NSLEs include:

NSLEs are designed to dynamically personalise the learning journey based on a deep understanding of individual student needs, proactively identifying both academic strengths and areas for growth, and subsequently tailoring the curriculum and learning activities accordingly.

The provision of real-time feedback mechanisms within NSLEs empowers educators to continuously adapt their teaching methodologies in response to student progress and understanding, thereby fostering a more dynamic and responsive learning environment.

Interactive platforms embedded within the NSLE framework promote meaningful collaboration among students, facilitate the active sharing of knowledge and unique perspectives, and serve to significantly enrich the overall learning experience.

The overarching goal of this research is to strategically employ the power of Artificial Intelligence to craft a truly personalised and deeply immersive learning experience that effectively simulates the complexities and relevance of the real world, all while maintaining and cultivating students' inherent excitement and passion for learning.
I believe this research has the potential to make a real difference, and that's what truly excites me. Students, of course, stand to gain the most from a more personalised and engaging learning experience. But I also envision this work empowering educators with innovative new teaching tools, providing policymakers with valuable insights to drive meaningful educational reforms, and ultimately benefiting all stakeholders invested in creating the cutting-edge learning environments of the future.

1.6 Research scope

This research envisions the creation of exceptionally engaging and deeply interactive learning environments through the strategic incorporation of immersive technologies [Fig. 1.2] such as virtual reality and the integration of gamification principles [Rana et al.2025]. To gain a comprehensive understanding of the multifaceted dynamics within these AI-powered learning contexts, a mixed-methods research design will be employed [Chapter 13.3].
This methodological approach will encompass quantitative data collection, primarily through simulated, well-designed surveys to gather broad insights from randomly generated student self-assessment questionnaires [*Chapter 6.2*]. Complementing this quantitative strand will be rich qualitative data gathered through in-depth user observation, allowing for a nuanced and firsthand exploration of students' lived experiences and interactions within the NSLE.

From classroom observation to AI innovation: The Genesis of the NSLE

In this chapter, I introduce the NSLE: a paradigm shift in education facilitated by the strategic and application of AI. A central tenet underpinning this entire research endeavour is the profound transformative potential of learning analytics within the evolving landscape of contemporary education.
This dissertation is intended to serve as a guiding compass for educators seeking innovative pedagogical approaches, policymakers striving for evidence-informed educational reforms, and fellow researchers dedicated to strategically harnessing the power of educational data. The aim is to foster more engaging and demonstrably effective learning experiences within AI-powered environments, exemplified by the NSLE framework. Indeed, the NSLE is specifically designed to facilitate continuous improvement in student learning outcomes and the efficacy of educational interventions by intelligently capitalizing on the provision of personalised feedback and the dynamic creation of adaptive learning pathways [Strielkowski et al.2024]. This work readily acknowledges the ever-growing impact of digital learning platforms and

the corresponding exponential increase in the volume of educational data being generated [Luan et al.2020].
Within this context, learning analytics has emerged as an indispensable tool, offering unprecedented and granular insights into student learning patterns and thereby enabling the provision of precisely tailored support and interventions, a capability that will be thoroughly demonstrated through the development and in-depth exploration of the NSLE. As a result, this dissertation will research both the critical theoretical underpinnings and the practical, real-world applications of learning analytics specifically within the NSLE, advocating throughout for its ethical, and responsible implementation [*Chapter 11.1*].

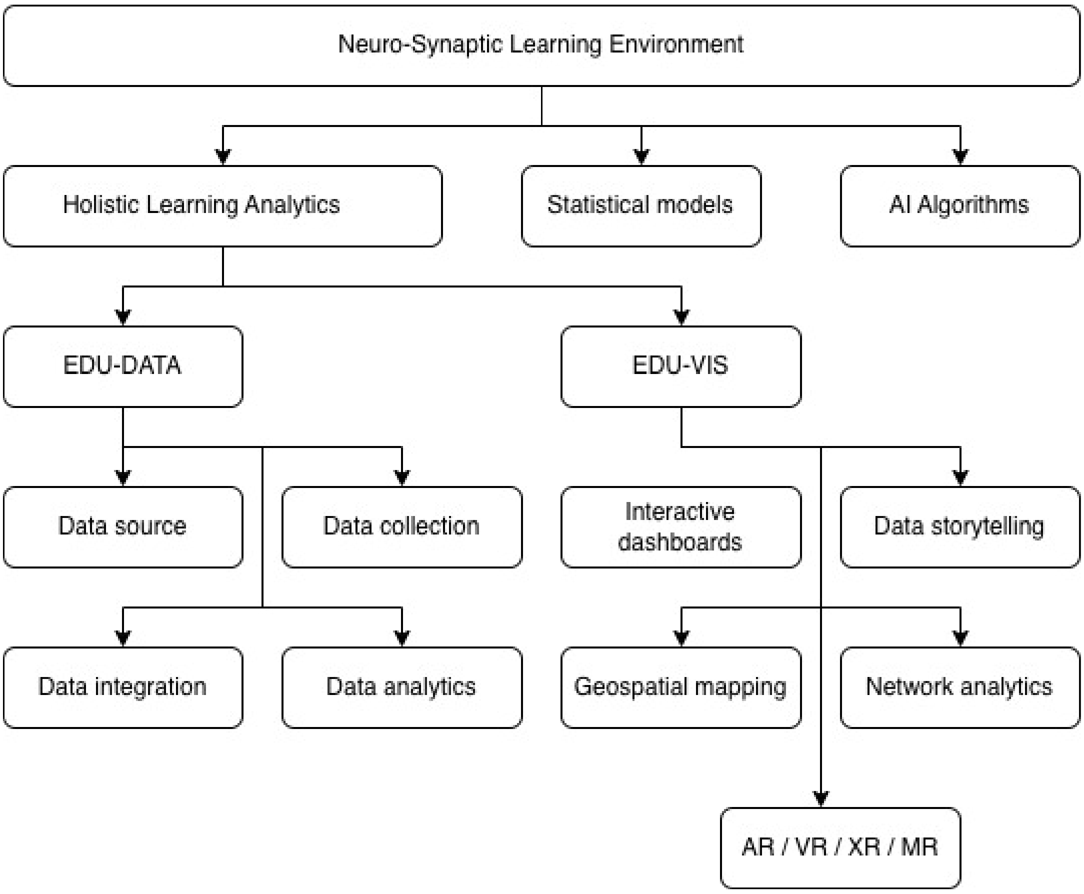

Figure 1.2 Diagram of the NSLE environment's layout and components.

My research embraces data-driven insights and personalised teaching methods. It seeks to contribute to a more responsive, equitable, and effective educational paradigm, which caters to the different needs of individual learners. Ultimately, it strives to empower every student to achieve their potential. The strategic and ethically grounded application of learning analytics within sophisticated AI-powered systems like the NSLE represents a fundamental and exciting shift.

LITERATURE REVIEW

2.1 A critical analysis of the existing research

As I investigate the vast and rapidly evolving landscape of Artificial Intelligence (AI) in education research, I'm struck by the profound impact it's having on our field. My goal is to shed light on the key trends that are shaping the future of education, identify the research gaps that need to be addressed, and explore the immense potential of AI to transform the way we teach and learn.
I'm particularly excited to explore how AI can help us create personalised learning pathways that cater to individual students' needs, develop intelligent tutoring systems that offer tailored support, and streamline assessment methods to free up more time for teaching and learning. *[*Bablu. 2024].
However, this review also critically engages with the inherent challenges and limitations associated with AI in educational contexts, including ethical considerations, the paramount importance of data privacy, and the overarching necessity for responsible AI implementation.
By examining existing research (as cited throughout), this review endeavours to provide a foundation for the present doctoral inquiry into the NSLE. It aims to contribute meaningfully to the advancement of AI assisted education, with a clear focus on offering practical and actionable solutions for both educators navigating this technological integration and the learners who stand to benefit from its potential.
Building upon this broad survey, the subsequent sections of this literature review will specifically address the identified research gaps, allowing this dissertation to contribute novel insights to the ongoing discourse in AI assisted education and propose practical solutions for educators and learners alike.
The comprehensive analysis of existing literature has revealed key thematic areas, highlighted emerging trends that demand closer scrutiny, and identified areas of disagreement and ongoing debate among researchers in the field. This review also attest critical gaps in our current understanding and illuminates promising avenues for future research endeavours. The principal findings derived from these extensive reviews are synthesized in the subsequent section.

Themes

AI presents a compelling promise for transformative change within education. Its potential to personalise the learning journey for each student, tailoring learning pathways to individual needs and providing immediate, actionable feedback [Wongvorachan et al. 2022], is particularly noteworthy. AI offers the exciting prospect of enhancing educational access in under-resourced communities and effectively addressing the learning requirements of a heterogeneous student population. By strategically automating routine tasks and offering rich, data-driven insights into student progress and learning patterns, AI can empower educators to dedicate more time and energy to personalised instruction and student support. A body of research is actively engaged in exploring the nuanced impact of AI on student outcomes and its broader implications for the evolving educational landscape.

Trends

Through my research I noticed the rapid emergence of innovative AI-powered digital ecosystems that are revolutionizing the way we learn. These sophisticated systems seamlessly integrate the power of artificial intelligence, cutting-edge technology, and established pedagogical principles with intuitive user interaction.
My hope is that these integrated environments will enable us to create dynamic and deeply personalised learning experiences that adapt to the unique needs of each learner, allowing us to unlock their full potential and foster a deeper understanding of the subject matter.
Concurrently, critical ethical considerations are increasingly taking centre stage within AI research for education. Issues such as the imperative of data privacy, the potential for algorithmic bias and its impact on equitable access, the need for transparency in AI-driven processes, and the establishment of clear lines of accountability for AI systems in educational contexts are now recognised as paramount.
The practical integration of AI tools across the educational settings, however, presents a complex array of challenges. These include the need for comprehensive teacher training to effectively employ these new technologies, the redesign of curricula to maximize the benefits of AI-driven personalisation, and the hurdle of overcoming existing infrastructural limitations, particularly in resource-constrained environments.
As I look to the future, I'm acutely aware that the long-term implications of AI on education are far from clear. I'm concerned about how AI will reshape the roles and responsibilities of teachers, the learning pathways and outcomes of students, and the very methods we use to instruct. These questions are too important to be left unanswered, and I believe that sustained scholarly inquiry is required in understanding the full scope of AI's impact on education.

Contrasting viewpoints

While the transformative potential of AI to personalise learning experiences, augment educational accessibility for all learners, and improve educational outcomes is widely acknowledged, the integration of this powerful technology into educational contexts is not without its complexities. Concerns regarding ethical implications, such as data privacy and algorithmic fairness, warrant careful consideration.
I am aware of the practical challenges, including existing infrastructural limitations in various educational settings and the need for comprehensive teacher training to effectively utilise AI-powered tools, and that it must be addressed thoughtfully. Finally, the long-term impact of AI on the educational landscape, encompassing its sustained effects on both educators and learners, necessitates longitudinal studies to fully understand its pervasive influence.

2.2 Areas for further exploration

The field of AI presents a compelling frontier for transformative advancements within education. The potential to personalise learning pathways, increase accessibility for learners, and provide educators with powerful new tools is genuinely exciting. However, alongside this undeniable promise, critical considerations regarding ethical implications, practical implementation hurdles, and the necessity for longitudinal studies evaluating long-term impact cannot be overlooked. Beyond the specific research gaps already identified in this dissertation, I can think of several additional avenues of inquiry warrant careful exploration. These include the role of teacher training in AI integration, student perceptions of AI tutors, and the impact of AI on curriculum design.

While the capacity of AI to fundamentally reshape the educational landscape is significant, a balanced and critically informed perspective is vital. It is imperative that we weigh the considerable benefits against potential risks, particularly those related to ethical considerations and the inherent biases that can be inadvertently embedded within technological systems. Researching the potential of AI to reshape education, I'm convinced that it's needed we thoughtfully consider the complex factors at play. By doing so, I believe we can unlock the transformative power of AI to create a more equitable, effective, and personalised learning environment for all students.

2.3. Literature review

The list of all reviewed publications is categorized below, along with a brief introduction.

(a) **Personalised learning**

Personalised learning emerges as a central focus within the literature. Studies emphasize AI's potential to tailor learning pathways to individual student needs and provide immediate, actionable feedback. For instance, *Niyozov et al. 2023* demonstrate the potential of AI-powered platforms to personalise learning in power supply engineering, while *Goel. 2020* emphasizes AI's role in enhancing engagement in online learning through personalised experiences.

To understand this better, I suggest further research should explore the optimal strategies for AI to personalise learning and maximize long-term student outcomes. This call for building on the work of *Faresta. 2024* and *Waykar et al. 2024*, who highlight AI's transformative potential. Also the most effective AI techniques and tools for creating personalised learning environments, as explored by *Obolensky et al. 2019* in distance learning and in primary education *Pardamean et al. 2022*. I would also suggest research in the role of AI in supporting learning styles and abilities, as discussed by *Chisom et al. 2023* in the African context and *Ahmad et al. 2021* in creating supportive learning environments.

Author and publication	Summary of introduction
Ahmad et al. 2021 "Artificial intelligence and its role in education."	Explores how AI tools can personalise the learning journey and create a supportive environment for students.

Author and publication	Summary of introduction
Alyammahi. 2020 "Investigating the Impact of AI-Powered Digital Educational Platforms on Students' Learning and Teachers' Practice in Abu Dhabi Schools"	Investigates AI-powered digital learning platforms and their ability to tailor lessons to each student's needs.
Chisom et al. 2023 "Review of AI in education: transforming learning environments in Africa."	Examines AI's role in creating personalised learning environments in Africa, adapting to students' needs and improving learning outcomes.
Faresta. 2024 "AI-Powered Education: Exploring the Potential of Personalised Learning for Students' Needs in Indonesia Education."	Directly explores the transformative potential of AI in education, with a focus on personalised learning and how AI can tailor learning experiences.
Goel. 2020 "AI-powered learning: making education accessible, affordable and achievable."	Discusses AI's ability to make online learning more engaging and interactive through personalised experiences.
Niyozov et al. 2023 "AI-powered learning: revolutionizing technical higher education institutions through advanced power supply fundamentals."	Focuses on AI's potential to personalise learning in power supply engineering through AI-powered platforms, simulations, and adaptive learning systems.
Obolensky et al. 2019 "Intelligent Educational Ecosystems."	Focuses on AI's potential to personalise distance learning by adapting course content to individual student knowledge and strengths.
Pardamean et al. 2022 "AI-based learning style prediction in online learning for primary education."	Discusses AI-based learning style prediction in online learning for primary education, focusing on creating personalised learning experiences.
Pedro et al. 2019 "Artificial intelligence in education: Challenges and opportunities for sustainable development."	Mentions personalised learning as a key potential of AI, with AI tools assisting in identifying student strengths and weaknesses and providing tailored support.

Author and publication	Summary of introduction
Raja et al. 2024 "Impact of Artificial Intelligence in Students' Learning Life"	Explains the capability of AI to personalise learning experiences by tailoring educational content and delivery methods to individual needs.
Waykar et al. 2024 "Digital Education System Using AI"	Highlights AI's capacity to create personalised learning experiences by tailoring lessons and providing personalised learning paths.

(b) **Ethical considerations**

Ethical considerations are paramount in the literature. As AI's integration into education deepens, it is necessary to address the following:

i. Data privacy, security, and ownership, a concern raised by *Gupta et al. 2021*, *Rojas et al. 2024* and *Waykar et al. 2024*.

ii. The potential for algorithmic bias and the need to ensure fairness and equity in AI-driven systems, extensively explored by *Smuha. 2020* and also highlighted by *Fitria. 2021* and *Dai et al. 2023*.

iii. The impact of AI on student autonomy, agency, and well-being.

iv. Strategies for developing ethical frameworks and guidelines for the responsible use of AI in education, building on the recommendations of *Goel. 2020* and *Yufeia et al. 2020*.

Author and publication	Summary of introduction
Bhatnagar et al. 2021 "Digital learning ecosystem at Indian higher education system."	Also mentions data privacy and ethical use of AI as important considerations.
Chisom et al. 2023 "Review of AI in education: transforming learning environments in Africa."	Raises ethical concerns around data privacy and security in AI-powered education in Africa.
Dai et al. 2023 "Collaborative construction of artificial intelligence curriculum in primary schools."	Emphasises the fairness and social impact of AI in education, including student privacy.
Fitria. 2021 "Artificial intelligence (AI) in education: Using AI tools for teaching and learning process."	Explicitly mentions ethical concerns beyond data privacy, such as biased AI and manipulation.

Author and publication	Summary of introduction
Goel. 2020 "AI-powered learning: making education accessible, affordable and achievable."	Emphasises the ethical considerations and design challenges of AI assisted educational ecosystems, including the potential for bias in AI systems.
Gupta et al. 2021 "AI Diagnosis: Rise of AI-Powered Assessments in Modern Education Systems."	Calls for careful consideration of the ethical implications of AI in education, such as privacy, bias, and accountability.
Rojas et al. 2024 "Artificial Intelligence and Digital Ecosystems in Education: A Review."	Highlights the ethical implications of AI in education, including data privacy, fairness, and potential bias.
Smuha. *2020* "Trustworthy artificial intelligence in education: Pitfalls and pathways."	Extensively explores the ethical challenges of AI in education, focusing on transparency, inclusivity, fairness, data privacy, bias, and equity.
Waykar et al. 2024 "Digital Education System Using AI"	Addresses data privacy as a major concern and the need to ensure AI is fair and unbiased.
Yufeia et al. 2020 "Review of the application of artificial intelligence in education"	Raises the issue of using AI fairly and protecting student privacy.

(c) **AI implementation challenges**

The practical challenges of implementing AI in educational settings are a recurring theme. To address these challenges, further exploration is needed to determine:

i. Effective strategies for integrating AI tools into existing curricula and pedagogical practices, as discussed by Faresta. 2024 and Owoc et al. 2019.
ii. The infrastructure requirements and technological resources necessary to support AI implementation, particularly relevant in the context of *Chisom et al. 2023* work on African education systems.
iii. The role of teacher training and professional development in preparing educators to use AI effectively, an issue raised by Pedro et al. 2019 and Waykar et al. 2024.
iv. How to adapt AI solutions to different educational contexts, including those with limited resources.

Author and publication	Summary of introduction
Chisom et al. 2023 "Review of AI in education: transforming learning environments in Africa.”	Addresses challenges in scaling AI solutions across different African education systems, infrastructural limitations, and the digital divide.
Dai et al. 2023 "Collaborative construction of artificial intelligence curriculum in primary schools.”	Explores the challenges of developing and implementing AI curriculum in primary schools, considering several factors.
Faresta. 2024 "AI-Powered Education: Exploring the Potential of Personalised Learning for Students' Needs in Indonesia Education.”	Highlights practical challenges educators may face when implementing AI technologies, including technical hurdles and logistical considerations.
Niyozov et al. 2023 "AI-powered learning: revolutionizing technical higher education institutions through advanced power supply fundamentals.”	Identifies the need for tailored AI solutions and the challenges of broadening AI applications in technical education.
Owoc et al. 2019 "Artificial intelligence technologies in education: benefits, challenges and strategies of implementation.”	Investigates the challenges of implementing AI in schools and proposes a plan for careful planning, testing, expansion, and evaluation.
Pedro et al. 2019 "Artificial intelligence in education: Challenges and opportunities for sustainable development.”	Discusses the challenges of training teachers to use AI tools and developing adaptable AI systems.
Rojas et al. 2024 "Artificial Intelligence and Digital Ecosystems in Education: A Review.”	Focuses on the challenges of real-world implementation of AI-powered ecosystems in educational settings.
Waykar et al. 2024 "Digital Education System Using AI”	Emphasises the need to explore how AI can be effectively applied across educational settings and the importance of teacher training.

(d) **Long-term impact of AI in education**

I find there are many reviews that emphasize the need for further research on AI's long-term impact in education. Key areas for any investigation should include:

i. The long-term effects of AI on student learning, achievement, and motivation, a key concern highlighted by Goel. 2020, Rojas et al. 2024, and Waykar et al. 2024.
ii. The impact of AI on teaching practices, teacher roles, and the overall educational landscape.

iii. The development of methodologies for evaluating the effectiveness and impact of AI interventions, as called for by Pardamean et al. 2022 and *Yufeia et al. 2020*.
iv. Exploration of future directions for AI in education, including emerging technologies and innovative applications.

Author and publication	Summary of introduction
Faresta. 2024 "AI-Powered Education: Exploring the Potential of Personalised Learning for Students' Needs in Indonesia Education."	Suggesting the need for further investigation into the long-term implications of AI on teaching methodologies, student performance, and the broader educational landscape.
Goel. 2020 "AI-powered learning: making education accessible, affordable and achievable."	Specifically highlights the research gap in understanding the long-term impact of AI on education, including effects on student learning and teaching practices.
Pardamean et al. 2022 "AI-based learning style prediction in online learning for primary education."	Calls for research on the long-term effects and sustainability of AI in primary education settings
Rojas et al. 2024 "Artificial Intelligence and Digital Ecosystems in Education: A Review."	Emphasises the lack of comprehensive understanding of the long-term effects of AI-powered digital ecosystems on education.
Waykar et al. 2024 "Digital Education System Using AI"	Points out that the long-term impact of AI on student learning and educational systems is not fully understood.
Yufeia et al. 2020 "Review of the application of artificial intelligence in education"	Raises the question of whether AI will truly help students learn and grow in the long run.

The following reviews are most closely aligned with my research focus.

Author and publication	Summary of introduction
Bhatnagar et al. 2021 "Digital learning ecosystem at Indian higher education system."	This review discusses the integration of AI into the classroom to personalise learning experiences and augment decision-making processes. It also mentions AI-powered tools like intelligent tutoring systems. This aligns with your research's emphasis on the use and assistance of AI algorithms.

Author and publication	Summary of introduction
Goel. 2020 "AI-powered learning: making education accessible, affordable and achievable."	This publication investigates into the design and implementation of AI-powered learning systems in online higher education. It emphasises how AI can make online learning more engaging and interactive. The focus on AI systems and their application in a learning setting aligns well with your research.
Niyozov et al. 2023 "AI-powered learning: revolutionizing technical higher education institutions through advanced power supply fundamentals."	This study directly investigates AI-powered platforms, simulations, and adaptive learning systems to boost learning experiences. Given that your research involves the "use and assistance of AI algorithms," this review's exploration of AI tools within a learning environment makes it highly relevant.
Obolensky et al. 2019 "Intelligent Educational Ecosystems."	This publication investigates the possibility of AI revolutionizing distance learning. It focuses on AI's potential to personalise learning experiences by adapting course content, which is closely related to the use of AI algorithms to assist in learning.
Rojas et al. 2024 "Artificial Intelligence and Digital Ecosystems in Education: A Review."	This review specifically examines AI-powered digital ecosystems. It explores how AI and digital platforms can create interconnected learning spaces, which is very pertinent to your interest in AI algorithms within a learning ecosystem.
Waykar et al. 2024 "Digital Education System Using AI"	This review explores how AI is being used to increase learning and develop innovative teaching methods. It also discusses AI's capacity to create personalised learning paths and intelligent tutoring systems. These aspects directly relate to the "assistance of AI algorithms" in a learning environment.

I found the following reviews are the strongest aligned with the analysis of my research.

Author and publication	Summary of introduction
Goel. 2020 "AI-powered learning: making education accessible, affordable and achievable.”	The author explicitly discusses the theoretical underpinnings of AI in education, the design of AI-powered learning systems, and the need to consider the interaction of technology, cognition, and social context. This makes it easier to evaluate the study's approach, potential limitations in the design, and any biases that might arise from the chosen theoretical perspective.
Gupta et al. 2021 "AI Diagnosis: Rise of AI-Powered Assessments in Modern Education Systems.”	This article provides a structured analysis of current AI models, considers psychological factors influencing learning, and explicitly acknowledges the limitations of focusing solely on AI's ability to teach. The authors' clear articulation of limitations and the scope of their analysis facilitates a critical evaluation.
Smuha. *2020* "Trustworthy artificial intelligence in education: Pitfalls and pathways.”	This review strongly emphasises ethical considerations, drawing on ethical guidelines and discussing the importance of transparency, inclusivity, and fairness. This focus on ethical implications invites scrutiny of potential biases and limitations in how AI is applied.

The following reviews are moderately aligned with the analysis of my research.

Author and publication	Summary of introduction
Niyozov et al. 2023 "AI-powered learning: revolutionizing technical higher education institutions through advanced power supply fundamentals.”	The study describes the application of AI to power supply engineering education and identifies research gaps. While it discusses the methodology of integrating AI tools, a deeper critique of the chosen methods and potential biases would require further investigation beyond what's provided.

Author and publication	Summary of introduction
Pedro et al. 2019 "Artificial intelligence in education: Challenges and opportunities for sustainable development."	This publication explores the potential of AI in developing countries and mentions personalised learning. It identifies research gaps but doesn't provide extensive detail on the methodologies of the studies it reviews.
Rojas et al. 2024 "Artificial Intelligence and Digital Ecosystems in Education: A Review."	This review focuses on AI-powered digital ecosystems and identifies key areas like networks, applications, services, and users. It raises important questions about long-term impact and ethical considerations, but a detailed analysis of the methodologies used in the reviewed studies might require looking at the original sources.
Waykar et al. 2024 "Digital Education System Using AI"	This review discusses AI's potential to increase learning and highlights challenges like data privacy and bias. While it acknowledges limitations and ethical concerns, the description of methodologies is somewhat general.

I found the following reviews less suitable for in-depth methodological analysis.

Author and publication	Summary of introduction
Bhatnagar et al. 2021 "Digital learning ecosystem at Indian higher education system."	This publication discusses AI's integration into the classroom and raises ethical concerns. The review provides a general overview of AI's role in education.
Chisom et al. 2023 "Review of AI in education: transforming learning environments in Africa."	This publication explores AI's role in African education and highlights challenges and ethical concerns. The emphasis is on the context and potential of AI in Africa, with less focus on the specifics of research methodologies.

Author and publication	Summary of introduction
Faresta. 2024 "AI-Powered Education: Exploring the Potential of Personalised Learning for Students' Needs in Indonesia Education."	This review focuses on the transformative potential of AI and personalised learning. While it discusses themes and trends, it emphasises the broader implications of AI in education rather than a detailed critique of individual study methodologies.
Fitria. 2021 "Artificial intelligence (AI) in education: Using AI tools for teaching and learning process."	This publication discusses the changing landscape of learning and teaching with AI. The emphasis is on the potential and ethical considerations of AI in education.
Obolensky et al. 2019 "Intelligent Educational Ecosystems."	This review discusses AI's potential to personalise distance learning. While it touches on techniques like machine learning, the main focus is on the application of AI in distance learning and identifying areas for improvement.
Owoc et al. 2019 "Artificial intelligence technologies in education: benefits, challenges and strategies of implementation."	This publication explores the potential of AI and proposes a plan for implementation. The focus is on implementation strategies.
Yufeia et al. 2020 "Review of the application of artificial intelligence in education"	This review discusses AI's potential to improve learning and teaching

Conflicts and differences in emphasis

I found that although there are not stark conflicts, there are some differences in emphasis between reviews. Some reviews, e.g. *Niyozov et al. 2023*, *Goel. 2020* and Obolensky et al. 2019, heavily emphasise the benefits of AI for personalised learning and improved outcomes. Others, e.g. Smuha. *2020*, *Gupta et al. 2021* and Dai et al. 2023 place a stronger emphasis on the ethical challenges and potential risks. These difference are not necessarily a conflict but rather a variation in focus, which is valuable to acknowledge. It highlights the complexity of the topic. I also found methodological focus between *Goel. 2020* and *Gupta et al. 2021* that research theoretical underpinnings and psychological factors, while others are more application-oriented. It shows different approaches to studying AI in education. I also found here are some studies that build upon each other. Early reviews, e.g. Pedro et al. 2019 and *Goel. 2020* lay the groundwork by identifying AI's potential in education and later reviews e.g. Smuha. *2020* and *Rojas et al. 2024* build on this by adding layers of complexity, particularly in the ethical domain.
Regarding problem-solution progression, I found some reviews, e.g. Faresta. 2024 and Chisom et al. 2023 highlight implementation challenges, whereas others e.g.

Owoc et al. 2019 build on this by proposing frameworks or strategies to address those challenges.
Regarding the potential to impact, I found reviews like Niyozov et al. 2023 and Alyammahi. 2020 showcase the potential of AI tools, and reviews such as Goel. 2020 and Rojas et al. 2024 then push for research on the long-term impact of these tools, urging the field to move beyond initial excitement. The following table presents a selection of additional reviews on artificial intelligence, offering further context and related perspectives to the analysis in this chapter.

Auliawan et al. 2020	"The usage of ai robot in english language teaching for city revitalization case study: Toda Daini elementary school, Toda city, Saitama, Japan."
Ayeni et al. 2024	"AI in education: A review of personalised learning and educational technology"
Dinc. 2019	"Prospective teachers' perceptions of barriers to technology integration in education"
Eteokleous. 2008	"Evaluating computer technology integration in a centralized school system"
Goel et al. 2021	"Agent Smith: Machine Teaching for Building Question Answering Agents"
Hwang et al. 2020	"Vision, challenges, roles and research issues of Artificial Intelligence in Education"
Knox. 2020	"Artificial intelligence and education in China."
Knox. 2021	"How the 'taming' of private education in China is impacting AI."
Luckin et al. 2016	"Intelligence unleashed: An argument for AI in education"
MZ bin Mohamed et al. 2022	"Artificial intelligence in Mathematics education."
Thanh et al. 2021	"We are using AI in assessing students' achievement at high schools: a case study.

BACKGROUND and OVERVIEW

In this chapter, I provide an overview of the evolution of Artificial Intelligence (AI), exploring its historical background, evolutionary milestones, core algorithms, decision-making processes, and its role in the big data revolution. I also research the complex issues of AI privacy and touch on its potential impact on the future of education.

3.1 Background, evolution and milestones of AI

My research sets out an exploration of the fundamental principles underpinning learning, drawing upon the established insights of both behaviourist and cognitive schools of thought [*Philip et al. 2021*]. While behaviourism traditionally posits external stimuli as the primary drivers of learning [*Mazur. 2015*], cognitive theory shifts the focus inward, emphasising the role of internal mental processes such as memory and thinking. Refining our understanding of this cognitive foundation [*Schunk et al. 2012*], we consider three key tenets [*Sorden. 2012*]: the dual-channel model, limited processing capacity, and the active nature of cognitive processing [*Scheiter et al. 2017*]. The critical importance of thoughtfully designing learning materials [*Salama. 2008*] sensitive to the processing styles and cognitive resources of individual learners is underscored by these principles.
I found that in contemporary educational landscapes, particularly within digital learning environments, theories such as constructivism and connectivism hold relevance. While constructivism emphasises the learner's active agency in constructing knowledge through experiential engagement and social interaction [*Amineh et al. 2015*], connectivism highlights the pervasive influence of networks and technology in shaping and facilitating learning processes [*Pandya et al. 2024* ; *Schunzk et al. 2012*]. My research is anchored within an instructional design framework that inherently recognises the dynamic interconnectedness of educators, learners, and the learning content itself. To truly optimise learning outcomes, an adaptive learning system must integrate the aforementioned cognitive processing assumptions by dynamically adjusting content and interactions based on individual learner characteristics. Turning to educators, they must thoughtfully apply learning theories to effectively adapt their pedagogical approaches to evolving learning preferences. Developers of digital learning resources also bear the responsibility of grounding their creations in fundamental learning principles. Recognizing the inherent limitations of traditional theories in fully elucidating the complexities of digital learning necessitates the adoption of a multifaceted theoretical lens that thoughtfully synthesizes different perspectives.
My research draws strength from a lineage of established learning theories, including behaviourism, cognitivism, constructivism, and connectivism. While behaviourism, with its emphasis on external cues and observable behaviours, provides a valuable framework for understanding the formation of habits and the acquisition of basic skills [*Mazur. 2015*], its explanatory power diminishes when addressing more cognitive functions. Conversely, cognitivism offers a more nuanced understanding by foregrounding internal mental operations such as memory and problem-solving, providing critical insights into how learners acquire and process information [*Schunk. 2012*]. Constructivism further enriches this perspective by emphasising the learner's

active role in constructing their own understanding through direct experience and collaborative engagement.
I've found particularly insightful in recent years is the theoretical framework of connectivism. It is really in step with my experiences in the classroom and beyond, emphasising the central role of networks and technology in the learning journeys of our students. However, the question of whether connectivism constitutes a distinct and separate theory or rather represents an evolutionary extension of constructivism within the digital age continues to be a subject of scholarly discourse [Kafai et al. 2012].
While traditional learning theories offer invaluable foundational insights, it is important to acknowledge that they may not fully capture the unique complexities of AI-driven educational environments. New learning environments are highly personalised and data-driven, which creates new problems. Because of these unique challenges, we need more research to understand how learning happens and how to best support it in these innovative spaces. The conceptual genesis of 'artificial intelligence' can be traced back to the 1950s [Delipetrev et al. 2020], and its subsequent development has been punctuated by several landmark achievements. To contextualize the current state of the field, it is instructive to briefly consider its pioneering era.

The pioneering era of AI

The emergence of artificial intelligence, a field deeply intertwined with the potential of the NSLE, is instructive and interesting to briefly trace its historical roots. As early as the 17th century, Wilhelm Schickard demonstrated the human ingenuity that would eventually lead to sophisticated computational tools through his design of a mechanical calculator [Freiman et al. 2018].
Subsequently, Gottfried Leibniz made a contribution in 1672 by pioneering the development of binary numbers, a foundational concept that underpins the entirety of our modern digital world [Strickland et al. 2022]. The groundwork for contemporary computing was further solidified by the ambitious endeavours of Charles Babbage, whose work on mechanical calculators between 1822 and 1859 laid firm conceptual foundations [*Hyman. 1985*]. Interestingly, the very notion of autonomous machines, or 'robots,' was first introduced to the popular consciousness by Karel Capek in his 1923 work [Gourin et al. 2007].
In parallel, Konrad Zuse's development of the Z1 in 1936 marked a milestone as the first programmable computer [*Zuse. 1993*]. The nascent field of robotics also finds early articulation in Isaac Asimov's seminal 1942 science fiction short story, "Runaround," which notably introduced the Three Laws of Robotics [Kaminka et al. 2017]. These three laws are:

1. A robot may not injure a human being or, through inaction, allow a human being to come to harm.
2. A robot must obey the orders given it by human beings except where such orders would conflict with the First Law.
3. A robot must protect its own existence as long as such protection does not conflict with the first or second Laws.

I find this interesting, how those foundational principles for robot behaviour, prioritising human safety and a robot's own existence, have had such a surprisingly persistent effect. They've laid the groundwork for many of the ethical questions we're grappling with today as AI continues to evolve. The construction of the first fully functioning electronic computer in 1946 [*Strawn. 2021*] was a huge machine that occupied an entire room and weighed about 30 tons, which represented a monumental leap forward, setting the stage for the increasingly sophisticated computational power that underpins the very architecture of neuro-synaptic learning environments.

The rise of the AI revolution

The mid-20th century marked a pivotal moment in the conceptualisation of artificial intelligence with Alan Turing's seminal 1950 publication, "Computing Machinery and Intelligence" [Turing. 2009]. In this work, Turing posed the profoundly influential question that continues to resonate across computer science, philosophy, and education: Can machines genuinely think? To explore this, Turing proposed the "Imitation Game" [Warwick et al. 2016], a thought experiment where a human interrogator attempts to distinguish between a human and a machine participant based solely on textual exchanges. This concept evolved into the Turing Test, an early measure for assessing machine intelligence and its capacity to imitate human cognitive functions.
However, it's important to note that the Turing Test has faced criticism for several limitations. It primarily assesses a machine's ability to mimic human conversation, potentially overlooking other crucial aspects of intelligence such as problem-solving, creativity, and emotional understanding. Some might argue that it rewards deception rather than genuine intelligence [Turing. 2004]. Turing's investigation into the nature of machine thought remains particularly relevant to the potential and implications of neuro-synaptic learning environments within educational settings.

The golden age of AI

The decade of the 1950s is often regarded as a critical and intellectually vibrant era for the nascent field of artificial intelligence. A landmark gathering of pioneering thinkers, including the influential John McCarthy [*Sukabumi et al. 1974*], convened to formally discuss and explore the very feasibility of creating artificial intelligence. This seminal meeting effectively laid the conceptual groundwork for it subsequent dividing into two primary research paradigms: the top-down, symbolic approach and the bottom-up, connectionist perspective. A prominent advocate of the top-down methodology was Marvin Minsky [*Minsky. 2019*], who championed the notion of endowing machines with explicit, pre-programmed knowledge. Notably, his early work on neural networks, though initially facing limitations, nonetheless contributed significantly to the evolving landscape of AI research [*Minsky et al. 2017*].
However, despite the initial enthusiasm, progress during this period was gradual, yielding incremental advancements such as rudimentary machine translation capabilities and the development of the foundational LISP programming language [*Hutchins. 2000*]. The early 1960s witnessed further developments. J.C.R. Licklider, a

visionary in human-computer interaction, began to explore the symbiotic potential of the relationship between humans and machines [*Junior et al. 2017*].
Simultaneously, the establishment of Unimation [*O'Regan et al. 2015*] marked the emergence of the first industrial robotics company, signaling the tangible application of AI principles beyond theoretical exploration. This period also saw the creation of Joseph Weizenbaum's ELIZA [*O'Regan et al. 2013*] in 1964, an early natural language processing program that offered a compelling, albeit limited, demonstration of machine interaction with human language.
The development of Shakey the Robot in 1966 [*Kurfess. 2005*], capable of autonomous navigation and problem-solving within its environment, represented a step towards embodied intelligence. As I reflect on my journey as an educator, I'm reminded of the early sparks that ignited my passion for harnessing the power of AI in education. My fascination with symbolic reasoning, connectionist models, and human-computer interaction led me to explore the intersection of technology and learning. I was particularly drawn to the concept of embodied intelligence, which rang true with my own experiences as a teacher - the way students' bodies and minds are connected, and how this connection can be exploited to boost learning.
These early explorations not only deepened my understanding of AI but also laid the foundation for my current research on neuro-synaptic learning environments. I'm excited to see how these sophisticated systems can be designed to support students' cognitive development, creativity, and critical thinking. As I continue to navigate the complexities of AI in education, I'm reminded of the immense potential for these environments to transform the way we learn and teach.

The Winter age of AI

Despite a subsequent period known as the "AI Winter," characterised by a notable contraction in research funding and broader public interest, technological advancements continued to emerge, often from seemingly peripheral domains. For instance, in 1974, the United States Defense Advanced Research Projects Agency [*DARPA]* laid the clear groundwork for the ubiquitous internet infrastructure we know today through the development of the "TCP/IP" protocols [*Kessler. 2004*]. This seemingly disparate development would, of course, prove foundational for the digital learning environments that are central to the exploration of the Neuro-Synaptic Learning Environment [*NSLE*].
Concurrently, the very philosophical underpinnings of artificial intelligence faced scrutiny. Philosopher John Searle, in a highly influential contribution, challenged the prevailing notions of machine intelligence with his now-famous Chinese Room argument [*Cole. 2004*]. Searle's thought experiment [*Searle. 2002*] probes the fundamental question of whether machines can genuinely possess understanding and engage in authentic thought. His compelling argument posits that even if a machine were capable of flawlessly passing the Turing Test, convincingly mimicking human conversation, it would still lack genuine semantic understanding, operating merely through syntactic manipulation of symbols without true comprehension of their meaning. This philosophical challenge to the nature of machine intelligence remains a critical consideration as we navigate the potential and limitations of AI-driven educational technologies, including the development and implementation of NSLEs.

The new frontier

The 1980s marked a resurgence in AI research, characterised by a renewed emphasis on the development of systems capable of emulating the complexities of human reasoning. A notable example of this ambition was Project CYC, an ambitious endeavour launched with the goal of constructing a computer system endowed with a vast repository of everyday human knowledge to facilitate inferential reasoning [*Lenat. 1995*].
This pursuit of human-like reasoning took a dramatic leap forward in 1997 when IBM's Deep Blue supercomputer achieved a landmark victory against a reigning world chess champion [*Hsu. 2002*]. This watershed moment not only underscored the rapidly advancing capabilities of AI in the domain of strategic thinking, even surpassing human expertise in highly structured environments, but also served as a powerful demonstration of the potential for computational systems to tackle complex cognitive tasks.
The late 1990s then witnessed a notable shift as AI technologies began to transition from the research laboratories into the consumer marketplace. The 1998 release of the Furby toy [*Sobey et al. 2008*], a seemingly simple interactive robotic creature, represented an early foray of AI-driven products into everyday life, capturing the public imagination and hinting at the potential for AI to become integrated into more personal and interactive technologies – a path that holds implications for the design and adoption of future neuro-synaptic learning environments.

The post-millennium renaissance

The early years of the 21st century, particularly the decade commencing in 2010, heralded a transformative era for artificial intelligence, often characterised as a post-millennium renaissance. This period witnessed a confluence of technological advancements that propelled AI from the theoretical research into the fabric of everyday life.
A salient example of this mainstream integration was Apple's introduction of Siri [GONDOĽ. 2012], a virtual assistant that brought sophisticated natural language processing capabilities directly to millions of users. This increased accessibility and user-friendliness paved the way for the pervasive application of AI across a multitude of domains, including, increasingly, within educational technologies. This period was marked by breakthroughs in the architecture and training methodologies of neural networks, giving rise to the field of deep learning [Gbadegeshin et al. 2021]. These advancements yielded remarkable progress in areas such as image and voice recognition. Machines could now perceive and interpret complex sensory data with unprecedented accuracy.
A defining characteristic of this post-millennium wave of AI research is the paradigm shift towards training machines on massive datasets [Lebovitz et al. 2021]. This data-driven approach has been instrumental in unlocking the potential of deep learning models to learn patterns and representations, a capability that holds immense promise for the development of adaptive and personalised neuro-synaptic learning

environments capable of responding dynamically to individual learner needs and progress.

3.2 Overview of AI in education

As I research the world of AI in education, I'm struck by the rich history and technological advancements that have brought us to this moment. With the foundation laid, I'm eager to explore the tangible applications of AI in the classroom. I'm convinced that AI holds the key to unlocking even greater potential. To unlock this potential, I believe it's good to have a deep understanding of the key enabling technologies that underpin AI in education. These include machine learning, with its capacity to enable systems to learn from data without explicit programming; deep learning, a sophisticated subset of machine learning that excels at identifying complex patterns in vast datasets; and recommendation systems, which harness data analysis to provide personalised suggestions and guidance.
While extant research has undoubtedly yielded valuable insights into the application of AI within K-12 educational settings, a critical need remains to broaden our investigative lens. It is imperative to comprehensively explore how these powerful AI tools can change the learning landscape across the entire educational continuum, from the foundational years of primary schooling through the specialized and advanced learning environments of higher education. This expanded perspective is needed for fully realising the potential of neuro-synaptic learning environments to cater to the needs and trajectories of learners at all stages of their educational journey.

The scope of AI in education

At its core, artificial intelligence empowers machines to execute tasks that conventionally demand human cognitive faculties [Fetzer et al. 1990]. This is achieved through sophisticated processes of data analysis, pattern identification, and predictive modelling. By automating routine and computationally intensive tasks, AI has the potential to liberate human intellect for more creative, strategic, and nuanced endeavours. Within the field of education, this transformative potential is particularly salient.
Artificial intelligence can be conceived as a sophisticated tool capable of reasoning based on vast information stores and acting upon these inferences, thereby mimicking certain aspects of human decision-making [Wang. 2019]. Its interdisciplinary nature is evident in its deep roots across fields including the natural sciences, engineering, computer science, biology, and psychology. The long-term aspiration driving much of AI research is the creation of machines that can exhibit cognitive, affective, and behavioural capabilities that closely approximate those of humans.
Indeed, the central aim of artificial intelligence (AI) is to engineer intelligent machines capable of learning, reasoning, and performing tasks that have historically required human intelligence [Øygarden. 2019]. This is often accomplished through advanced techniques such as natural language processing [*NLP*] and the architectures of neural networks. As a powerful tool, AI holds the potential to significantly augment human capabilities by automating complex processes and providing novel insights.

However, the efficacy of AI is fundamentally predicated on data; AI systems necessitate substantial volumes of high-quality data for effective training and the iterative refinement of their underlying models. This reliance on "big data" is the engine that fuels AI's learning paths [Duan et al. 2019]. The integration of AI into educational contexts [*AIEd*] offers the compelling prospect of personalised learning experiences and the potential for increasing student outcomes. Nevertheless, a critical and nuanced perspective requires us to acknowledge the inherent limitations and potential drawbacks associated with an over-reliance on AI within educational settings.

While certain researchers express optimism regarding AI's capacity to deliver individualized support and even cultivate a form of emotional resonance with learners, legitimate concerns persist regarding the ability of machines to truly comprehend and respond to the full spectrum of human emotions and the subtle complexities of human cognition. The relationship of factors that contribute to effective teaching and learning, such as empathy, intuition, and the cultivation of higher-order critical thinking skills, presents a formidable challenge for current AI development.

I'm struck by the limitations that still exist in harnessing AI's potential to support the development of higher-order cognitive skills. Despite the promise of AI, I've seen firsthand how it can struggle to foster creativity, complex problem-solving, and nuanced critical analysis, skills that are required for students to thrive in today's rapidly changing world. As an educator, I've come to realize that the effectiveness of AIEd systems is not just about the technology itself, but about how it's designed and implemented. A thoughtful and careful approach can lead to adaptable systems that cater to learning styles and cultural contexts.

As I continue to explore the role of AI in education, I'm acutely aware of the need for careful consideration and proactive mitigation strategies to ensure that AIEd systems are equitable and inclusive. I believe that by acknowledging and addressing these limitations, we can harness the potential of AI to create more effective and engaging learning experiences that benefit all students, regardless of their background or circumstances.

Moral and ethical frameworks

I realise that in the world of AI in education, there is an urgent need for an ethically grounded framework to unlock its transformative potential while mitigating its risks. Despite the rapid proliferation of AI-driven tools and platforms across various levels of education, I've noticed a surprising lack of scholarly inquiry into the profound ethical implications of this integration.

As an educator, I've seen firsthand how AI can propel the way we teach and learn. I believe in establishing a solid foundation for AI in education, one that prioritises ethics and equity. By doing so, we can harness the power of AI to create more personalised, effective, and engaging learning experiences for students, while minimizing its potential risks and biases. Currently, a clear and comprehensive set of principles or guidelines governing the responsible development and deployment of AI in educational contexts is conspicuously absent, according to O'Sullivan et al. 2019. Leading voices in the field, also underscore the urgent need for expanded research and a more profound understanding of the multifaceted dimensions of AI [*Hagendorff. 2022*].

The development and implementation of official policies and readily accessible resources are required to safeguarding individuals' privacy and ensuring data security within the age of artificial intelligence. This imperative is powerfully supported by initiatives such as the "One Hundred Year Study on Artificial Intelligence" [*Horvitz. 2014*], which explicitly highlights the enduring necessity for sustained interdisciplinary research and the continuous evolution of comprehensive ethical frameworks to guide the development and application of AI technologies responsibly.

3.3 Algorithms and decision-making

At the heart of the artificial intelligence revolution lies the often-invisible yet profoundly influential role of algorithms. These sophisticated sets of instructions function as the fundamental rulebooks that guide machines in processing information and generating predictions. By exposing algorithms to carefully curated datasets, these computational engines are trained to discern patterns and subtle trends within the data [*Esposito. 2022*], thereby enabling them to forecast potential future outcomes with increasing accuracy.
In essence, algorithms serve as the intermediary layer that bridges the cognitive gap between human intention and machine execution, allowing us to translate complex human directives into actionable computational steps. A tangible illustration of this power can be seen in facial recognition software [*Esposito. 2022*], a technology driven by algorithms that enable machines to identify individuals within digital images with remarkable efficiency.
I'm aware of the importance of understanding the underlying mechanisms and capabilities of the algorithms that will power these systems. As educators, we're eager to harness the potential of algorithmic intelligence to personalise learning pathways and adapt to individual learner characteristics. I believe that grasping the intricacies of these algorithms is in designing effective and equitable learning environments. By doing so, we can create systems that not only cater to all learning styles but also address the unique needs and abilities of each student. As I research deeper into the world of neuro-synaptic learning environments, I'm excited to uncover the ways in which algorithmic intelligence can be exploited to create more engaging, effective, and personalised learning experiences for students.

Machine Learning

A cornerstone of contemporary artificial intelligence, and a foundational element for the development of sophisticated neuro-synaptic learning environments, is Machine Learning [*ML*]. This paradigm shift in computer programming empowers systems to learn from data and progressively boost their performance without reliance on explicit, rule-based instructions [Kroemer et al. 2021]. Within the educational landscape, ML algorithms hold immense potential through their capacity to analyse rich streams of student data, encompassing assessment performance, preferred learning modalities, and patterns of engagement in online learning activities, to facilitate the creation of truly personalised learning experiences.

However, the realization of truly effective and influential AI systems in education necessitates the integration of capabilities that mirror certain key cognitive functions observed in human intelligence [*Table 3.1*]. By synergistically combining the adaptive power of machine learning with these complementary functionalities, AI systems can evolve into exceptionally powerful tools for automating a range of tasks, discerning patterns within complex datasets, and executing sophisticated tasks with remarkable precision. This integrated approach is clear for realising the full potential of AI to transform educational practices and to underpin the adaptive and responsive nature of neuro-synaptic learning environments.

Table 3.1. Capabilities exhibited by intelligent machines, similar to human abilities.

Property	Capability
Natural Language Processing	The ability to understand and process human language [Pazrde. 2023], enabling interaction with humans in a natural way.
Memory and storage	The capacity to store and access vast amounts of information [de Souza Zanirato Maia et al. 2023].
Problem-solving	The ability to analyse data, identify patterns, and obtain results [Barja-Martinez et al. 2021].
Learning and adaptation	The ability to continuously learn from new data and experiences [Jordan et al. 2015].

Deep learning

A particularly compelling and powerful subfield within the broader landscape of artificial intelligence, and one with implications for the design of advanced learning technologies like neuro-synaptic learning environments, is deep learning [Zohuri et al. 2023]. Drawing inspiration from the neural architecture of the human brain, deep learning methodologies enable computer systems to learn and recognise complex patterns through a hierarchical processing of information. This layered approach allows the system to progressively identify increasingly interconnected features within the data. Consider, for instance, the task of facial recognition [*Lin. 2000*]. Deep learning models tackle this challenge by decomposing digital images into a series of progressively smaller and more abstract components, analysing them layer by layer [*Dargan et al. 2020*].

Each successive layer within the network is responsible for extracting increasingly complex features, moving from basic elements like edges and corners in the initial layers to more sophisticated representations such as eyes, noses, and finally, complete facial structures in the deeper layers. This capacity for hierarchical feature extraction is a key characteristic of deep learning and indicates its potential for enabling neuro-synaptic learning environments to recognise and respond to subtle and multifaceted patterns in learner behaviour and interaction.

3.4 The big data revolution

As artificial intelligence systems achieve increasingly sophisticated levels of processing power, their capacity to effectively manage and analyse exceptionally large and complex datasets becomes ever more critical. This brings us to the concept of 'big data,' a term that describes information sets of such scale and complexity that they exceed the processing capabilities of conventional computational approaches. Indeed, real-world applications have demonstrated that these datasets often possess characteristics that render traditional methods of collection, storage, management, and analysis inadequate [Kluge et al. 2001]. Existing predominantly within the digital environment, they encompass an array of interconnected information streams.
Compelling research, such as the work of Sagiroglu and colleagues [*Sagiroglu et al. 2013*], affirms the inherent capability of AI methodologies to effectively process and analyse these massive datasets, extracting meaningful signals from seemingly overwhelming noise. At the core of this capability lies the use of algorithms that intelligently sift through the data, identifying subtle trends, recurring patterns, and correlations that can then be exploited to generate insightful predictions.
Williams provides a clear illustration of the distinction between big data and traditional data analytics within the education sector [*Williamson. 2017*]. While traditional educational data might offer a generalised overview of a student's academic performance, big data analytics researches into the granular details of a student's learning behaviour, capturing information such as interaction patterns with digital learning resources, time spent on specific tasks, error analysis, and even affective responses.
As I explore the intersection of big data and education, I uncover the hidden gems of rich, contextualized details that can reveal invaluable insights into the unique learning processes of individual students. These insights hold the key to developing highly personalised and adaptive neuro-synaptic learning environments that cater to the distinct needs and abilities of each student. By employing the power of big data, we can create learning environments that are tailored to the individual, rather than one-size-fits-all approaches. By analysing the patterns and relationships within the data, we can uncover the subtle nuances that make each student's learning journey unique. As I continue to explore the potential of big data in education, I'm eager to see how these insights can be used to create more effective, engaging, and personalised learning experiences for students.

The data-driven education ecosystem

The advent of big data analytics within educational contexts [El Arass et al. 2018] presents a paradigm shift, offering the potential for both increased efficiency and a far more granular understanding of the learning process. Contemporary educational platforms are now capable of tracking and analysing a wide spectrum of student behaviours, ranging from the precise duration a learner engages with specific sections of a course to patterns of interaction with learning materials and performance on formative assessments. This wealth of data, when analysed effectively, holds the key to unlocking truly personalised learning experiences [El Arass et al. 2018]. By harnessing these detailed insights, educational platforms can dynamically adapt and tailor content, resources, and even pedagogical approaches to the unique needs and learning trajectories of individual students, paving the way for more effective and engaging the NSLE. The amount of time a student spends on a particular topic can be used to determine whether they need more support. The lifecycle of Big Data [Yu et al. 2021] [Table 3.2 – 3.9] may be generated from Massive Open Online Courses [MOOCs], involving educational institutions, students and data analytics [Sanchez-Gordon et al. 2018].

Table 3.2 Big data lifecycle: focus on data generation, handling, and analysis.

(a) Data generation Massive Open Online Courses generate a vast array of data.	
Student interactions	Clicks, engagement metrics and digital footprints reveal how students engage with materials and each other.
Learning analytics	Assessment results, quiz scores and course completion rates that provide a quantitative snapshot of progress.
User feedback	Ratings, reviews and comments that offer qualitative insights into student satisfaction and perceived value.
Social media	Posts, comments and shares that capture the social dynamics of online learning communities.

Table 3.3 Summary of big data collection, handling, and analysis.

(b) Data collection Educational institutions collect and store large amounts of data in different formats.	
Relational databases	Structured data, such as student information and course enrolment, which is organised and easily queryable.
NoSQL databases	Unstructured data, such as text-based feedback and social media posts, which is often complex and difficult to query using traditional relational databases.
Data warehouses	Aggregated data repositories that store data from multiple sources, allowing for easy analysis and reporting of key performance indicators and trends.

Table 3.4. Summary of big data preprocessing steps and considerations.

(c) Preprocessing Preprocessing is one step in the data analysis process, involving the cleaning, transforming and preparing of raw data for analysis.	
Improving data	Correcting errors, handling missing values.
Enhancing data analysis	Transforming data into a suitable format for analysis.
Reducing errors	Inconsistencies by standardising data formats.

Increasing data reliability	Trustworthiness by verifying data accuracy, detecting outliers and identifying anomalies.
Preparing data	For advanced analytics and relevant features.

Table 3.5. Summary of big data storage solutions and considerations.

(d) Data storage Educational institutions store the analysed and visualised data.	
Data lakes	These are centralized repositories that store raw, unprocessed data in its native format.
Data marts	These are smaller, specialized databases that store processed data for specific business purposes.
Cloud storage	This is a scalable and secure environment that allows educational institutions to store data.

Table 3.6. Overview of big data processing technologies and frameworks.

(e) Data processing Institutions use various tools and techniques to process and analyse data.	
Data integration	This involves combining data from different sources and formats (e.g. relational databases, flat files, and cloud storage) into a single, consistent dataset.
Data cleaning	This step involves removing errors, inconsistencies and duplicates from the data, ensuring that it is accurate, reliable and free from defects.
Data transformation	This process involves converting the data into a suitable format for analysis, such as aggregating data, creating new variables, or transforming data types.

Table 3.7. Big data visualization for effective analysis.

(f) Data visualisation Institutions utilise data visualisation tools to present the analysed data.	
Dashboards	These interactive displays provide real-time insights and key performance indicators, allowing users to track progress, identify trends and make data-driven decisions.

Reports	These summaries condense complex data into easily digestible formats, highlighting trends, patterns and key findings. Reports can be used to communicate insights to stakeholders, track progress and planning.
Interactive visualisations	These dynamic tools enable users to explore and discover complex data relationships, such as correlations, patterns and outliers.

Table 3.8. Stages and processes in big data analysis.

(g) Data analysis Educational institutions employ advanced analytics techniques.	
Descriptive analytics	Descriptive analytics helps institutions understand what has happened in the past, identifying trends and patterns.
Predictive analytics	Predictive analytics helps institutions identify at-risk students, predict graduation rates.
Prescriptive analytics	Prescriptive analytics helps institutions identify the most effective strategies for improving student success, reducing dropout rates and increasing graduation rates.

Table 3.9. Challenges and best practices in big data sharing.

(h) Data sharing Educational institutions share the analysed and visualised data.	
Faculty and staff	The data is shared with faculty and staff to inform teaching and learning strategies.
Students	Students are provided with personalised feedback and recommendations based on their performance and progress.
Administrators	The data is shared with administrators to inform institutional decision-making and policy development.
Research partners	The data is shared with research partners to advance knowledge and innovation in education, fostering collaboration and driving the development of new and effective educational practices.

3.5 The privacy paradox within AI

As I explore the world of AI in education, I become more aware of the growing reliance on extensive datasets to power these systems. The sheer scale and complexity of these datasets raises critical concerns about privacy, which I believe are key to address in any discussion of AI in education. As an educator, I'm aware of the importance of protecting students' personal data and ensuring that it's used

responsibly. The potential risks to privacy are significant, and I believe to prioritise ethical and practical considerations in the development and implementation of AI systems in educational contexts. By doing so, we can create a safer and more trustworthy environment for students to learn in.
Privacy, fundamentally defined as the individual's capacity to control the dissemination and use of their personal information [*Pukawan. 2006*], faces unprecedented challenges in our increasingly digitized world. The pervasive collection, modification, and sharing of personal data, often occurring without the explicit knowledge or informed consent of the individuals involved [*Solove. 2012*], presents an ethical quandary for the development and deployment of AI, particularly given these systems' inherent dependence on personal data for learning and operational efficacy.
Therefore, organisations embracing AI technologies, especially within the sensitive context of education and the development of neuro-synaptic learning environments, must prioritise data protection measures and a profound respect for fundamental human rights [*Rodrigues. 2020*]. This ethical imperative can be proactively addressed through the application of "impact assessments" to foresee and mitigate potential privacy risks, coupled with the integration of "privacy by design" principles throughout the entire development lifecycle of AI systems [*Poullet. 2009*]. Notably, major industry players [*Foujdar. 2019*] are increasingly recognising the importance of bolstering consumer privacy protections [*Stahl et al. 2023*], and a growing chorus of voices advocates for the establishment of stronger legislative frameworks to safeguard individual privacy in the age of intelligent machines.

Bias in AI

A challenge that demands careful consideration in the development and deployment of sophisticated artificial intelligence systems, particularly within the equitable and inclusive context of education, is the insidious potential for bias to permeate even the most advanced algorithms [*Oxford Dictionary. 2024*]. One prevalent form of this is confirmation bias, wherein the AI system preferentially favours information that aligns with pre-existing patterns or beliefs embedded within its training data.
More broadly, algorithmic bias arises when the very datasets used to train an AI system are inherently skewed or unrepresentative of the populations they are intended to serve [*Ntoutsi et al. 2020*]. Given that AI systems learn directly from the data they are exposed to during their training phase, it logically follows that biased input data will inevitably lead to biased and potentially inequitable outcomes. Therefore, the identification and systematic elimination of algorithmic bias represents a critical imperative [Schwartz et al. 2*022* ; Akter et al. 2021]. This necessitates a proactive and ongoing commitment to ensuring that the data used to train AI systems is as unbiased, representative, and inclusive as possible. As previously emphasised, the presence of bias within AI systems constitutes a paramount concern that must be addressed with diligence to safeguard fairness and equity within educational applications, including neuro-synaptic learning environments.
Algorithmic bias, originating from skewed training data, carries the inherent risk of perpetuating and even amplifying existing societal biases, potentially resulting in unfair or discriminatory learning experiences and outcomes. While a range of technical methodologies exist for the detection and mitigation of bias, encompassing debiasing

algorithms and data curation practices, the complete eradication of bias remains a complex and evolving challenge that requires sustained attention.
The scholarly community holds different perspectives on the most efficacious strategies for confronting the issue of bias in AI. Some researchers advocate for primarily technical solutions centred on the refinement of algorithms and the careful selection and preprocessing of data, while others underscore the critical importance of integrating social and ethical interventions. These include fostering greater diversity and inclusivity within AI development teams and establishing clear, ethically informed guidelines for the design and application of AI within educational contexts.
Adding another layer of complexity, the very definition of "fairness" in AI is often subject to nuanced debate, as different stakeholders may hold varying perspectives on what constitutes a just and equitable outcome within a specific educational scenario. It is ethical for both developers and educators to gain a transparent understanding of the reasoning processes by which AI systems arrive at their findings, particularly within high-stakes domains like education. While the risk of bias varies across different sectors, the healthcare domain serves as a stark reminder of the potential for harm [*Cath. 2018*], highlighting the broad implications of this challenge.

Addressing bias

One thing that's become really clear to me as I study AI, is the critical need to tackle bias head-on. If we want these systems to be truly effective and fair in education, we have to be proactive about making sure the data we use to train them is as impartial as possible right from the start. This might mean we need to develop and put in place much stricter and more carefully controlled ways of collecting data, specifically designed to keep those pre-existing biases from creeping in.
To maintain fairness and equity over time, AI systems require regular and systematic updates to refine their decision-making processes and the internal policies that guide their behaviour [Duan et al. 2019 ; Bengio et al. *2024* ; Makridakis. 2*017*]. These ongoing updates should be explicitly designed to promote fair and equitable treatment across learner populations within neuro-synaptic learning environments.
The more I learn within the world of AI in education, the more aware of the importance of minimizing bias in these systems I become. I believe in gaining a deeper understanding of the mechanisms by which AI systems, particularly those employing neural network architectures, arrive at their resolutions. I'm convinced that transparency and interpretability are important for identifying potential sources of bias within the system's internal reasoning. By shedding light on the decision-making processes of AI systems, we can foster trust and accountability in their application within educational contexts. As I continue to explore the intersection of AI and education, I'm committed to uncovering the ways in which transparency and interpretability can be achieved, and how this can lead to more equitable and effective learning outcomes for students.

Fairness in learning

A persistent and multifaceted challenge in the design of effective and equitable educational resource recommendation systems lies in ensuring their inherent fairness.

The axiom 'garbage in, garbage out' holds particular resonance here: if the data used to train these systems is itself biased or unrepresentative, the resulting recommendations will inevitably perpetuate and potentially amplify these biases, leading to skewed and unfair resource allocation. To cultivate recommendation systems that are genuinely inclusive and supportive of all learners within a neuro-synaptic learning environment, the adoption of the following strategic approaches.

Systematically gathering information from a representative spectrum of students, ensuring that the data reflects the heterogeneity of learning styles, backgrounds, and needs within the educational community.

Utilising algorithmic models capable of discerning and navigating complex and non linear relationships within the data, moving beyond simplistic correlational analyses that may inadvertently disadvantage certain learner profiles.

Establishing ongoing mechanisms for the systematic detection and proactive mitigation of bias within the recommendation system's outputs and underlying algorithms, ensuring that fairness is not a static attribute but an actively maintained characteristic.

By diligently and thoughtfully implementing these interconnected strategies, we can strive to create neuro-synaptic learning environments powered by recommendation systems that genuinely serve to facilitate the learning and growth of all students, fostering a more equitable and effective educational experience.

Example of biased programming

The integration of artificial intelligence within educational landscapes necessitates a commensurate and deeply thoughtful consideration of its inherent privacy implications. While the granular collection and sophisticated analysis of student data undeniably present compelling opportunities for the personalisation of learning experiences and the potential enhancement of educational outcomes, this very process simultaneously raises multifaceted concerns regarding the protection of student privacy and the potential for the unethical or unintended misuse of sensitive personal information.

Although regulatory frameworks such as the General Data Protection Regulation [*GDPR*] represent key steps towards safeguarding personal data in the digital age, the unique and evolving challenges posed by the application of AI within educational contexts demand ongoing critical scrutiny and a proactive adaptation of existing privacy frameworks. Within the academic and policy spheres, conflicting perspectives persist regarding the optimal equilibrium between the imperative for data utilisation to drive innovation and the fundamental right to privacy protection.

Some scholars and advocacy groups argue for the implementation of more stringent regulations and the empowerment of students with greater control over their educational data, while others emphasise the critical importance of responsible data sharing to facilitate vital research and development initiatives aimed at advancing the nascent field of AI in Education [*AIEd*].

Ensuring the establishment of data security protocols and proactively preventing unauthorized access to or the potential misuse of sensitive student data remains a paramount and complex challenge. The profound ethical implications of employing student data to predict future academic or career trajectories also warrant particularly careful and nuanced consideration, as such predictive analytics can carry potentially life-altering consequences for students.
To illustrate the critical issue of bias, consider a text classification model trained on a limited and potentially skewed dataset [*Fig. 3.1*]. If this dataset disproportionately contains specific phrases or linguistic patterns, the resulting model will exhibit an inherent bias towards these features. Any student input that deviates from these specific phrases, even if factually accurate and conceptually sound, might be erroneously classified negatively by the model [*Fig. 3.2*].

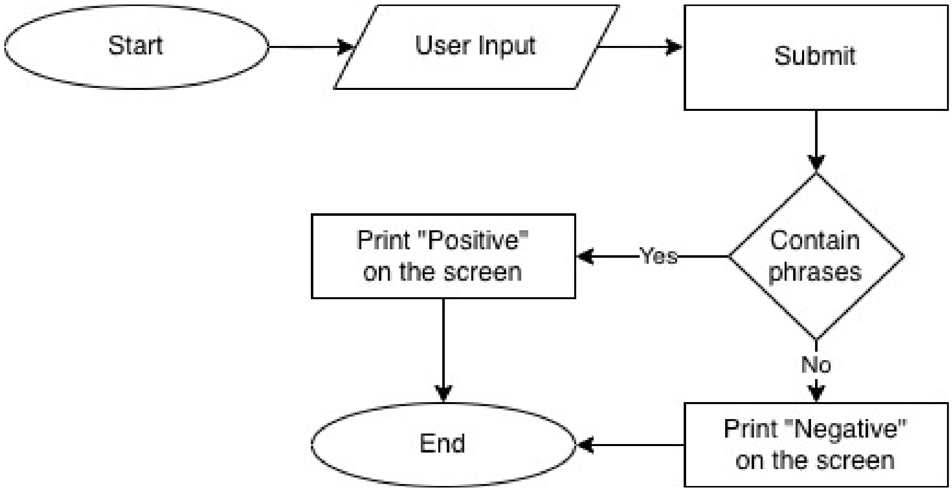

Figure 3.1. Data flow within the biased text classifier.

This concrete example indicates the fundamental importance of employing selective, representative, and carefully curated data in the training of AI systems for educational applications. A comprehensive collection of several learning exercises performed within the NSLE framework, displaying key performance indicators and interaction metrics, can be found in [*Table 3.10*].

Table 3.10. Illustrative examples of text inputs and classifier outputs.

Input text	**Response (Positive / Negative)**
The weather report was accurate today.	Negative
The moon landing was an interesting event.	Negative
The work was **well done** and on time.	Positive
I did an excellent job on the field today.	Negative
He did a **great job** on fixing the machine.	Positive
What I did was recognised as **excellent**	Positive

work.

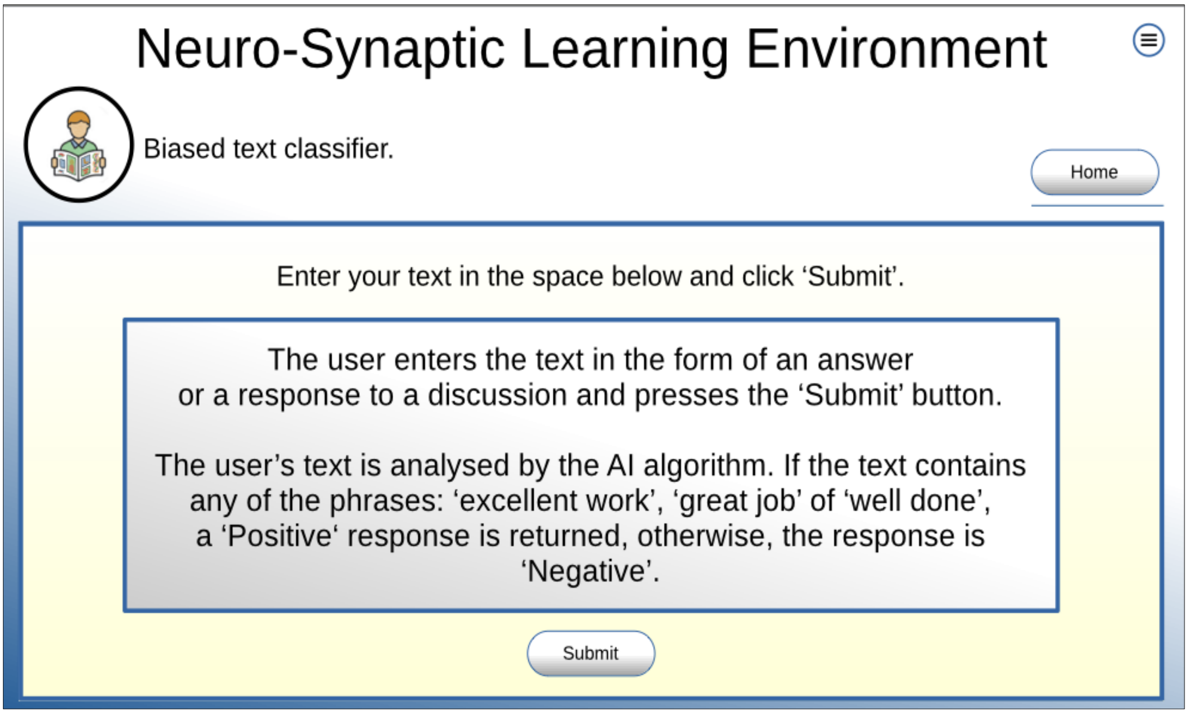

Figure 3.2. Biased text classifier user interface for phrase-specific testing.

3.6 The future of education with AI

The compelling vision of a future where education is tailored to the distinct and evolving needs of each individual learner lies at the heart of the transformative promise of artificial intelligence in education [Ouyang et al. 2021 ; *Akgun et al. 2022*]. Through its capacity to analyse vast and complex datasets pertaining to student performance, learning styles, and engagement patterns, AI holds the potential to craft truly personalised learning experiences, adapting content, pacing, and pedagogical strategies to optimise individual learning trajectories.

However, this powerful potential is inextricably linked to critical considerations surrounding data privacy and the insidious risk of algorithmic bias. Therefore, a nuanced evaluation of the potential benefits of AI in education must be undertaken in careful equipoise with a thorough understanding and proactive mitigation of its inherent risks. At its most effective, AI can offer dynamic learning experiences that adapt in real-time to a student's optimal learning pace and style, alongside assessment tools that precisely diagnose areas of conceptual misunderstanding and pinpoint specific learning needs. Yet, the very systems that offer such promise also carry the potential to inadvertently perpetuate existing societal biases or, in less thoughtfully implemented scenarios, to supplant the role of human educators.

Ethical frameworks, unwavering transparency in algorithmic decision-making, clear lines of accountability, and comprehensive professional development for teachers are paramount to ensuring that the integration of AI within educational settings genuinely serves to empower both students and educators [Onesi-Ozigagun et al. 2024]. The fundamental aspiration of AIEd, particularly within the context of neuro-synaptic learning environments, is to empower learners and cultivate deeply personalised and adaptive educational journeys.

Final thought

This chapter has provided a foundational overview of artificial intelligence, tracing its evolution from early conceptualizations to its modern-day applications, particularly within education. It has explored the core principles of AI, including machine learning, deep learning, and the role of algorithms and big data in shaping AI-driven systems. The discussion has highlighted AI's potential to advance learning by enabling personalised and adaptive educational experiences, mirroring the individualized support of a human tutor. However, the chapter has also critically examined the inherent challenges and ethical considerations that accompany the integration of AI in education. Specifically, the privacy paradox arising from extensive data collection and the potential for algorithmic bias to perpetuate inequities have been identified as key concerns that demand careful attention in the design and implementation of AI-driven learning environments.
These foundational insights are particularly salient to the core focus of this PhD research: the development and evaluation of the NSLE, designed to mimic the personalised guidance and support of a human tutor. The chapter's exploration of AI's capacity for adaptive learning, personalised feedback, and tailored educational assistance directly informs the design principles and functionalities of the NSLE aimed at providing individualized student support. The ethical considerations and challenges discussed in this chapter will be addressed in the development and evaluation of NSLEs, ensuring that these AI-driven systems are designed and implemented in a responsible, equitable, and ethical manner.

CHAPTER 4
THE NEURO-SYNAPTIC NETWORK

I want to begin by laying the groundwork with the core concept that underpins the neuro-synaptic network. This framework, inspired by the learning capabilities of the human brain, allows us to consider how educators can strategically employ the principles of synaptic plasticity to foster more profound and lasting learning experiences. The very same mechanisms that drive human learning, can also offer compelling insights into the development of artificial intelligence systems that can

learn in a more human-like fashion. The potential of AI to learn in a human-like fashion is intriguing, yet it's crucial to acknowledge the current limitations.
While AI can mimic certain aspects of neural processing, it does not fully replicate the complexity and nuance of the human brain. Further research is needed to address issues such as the lack of consciousness and embodied cognition in AI systems [Ziemke. 2016]. At the heart of this framework lie several key principles that I will research throughout this chapter [Fig. 4.1], neuroplasticity, NSLE features, interaction with the NSLE and the benefits of employing the NSLE.

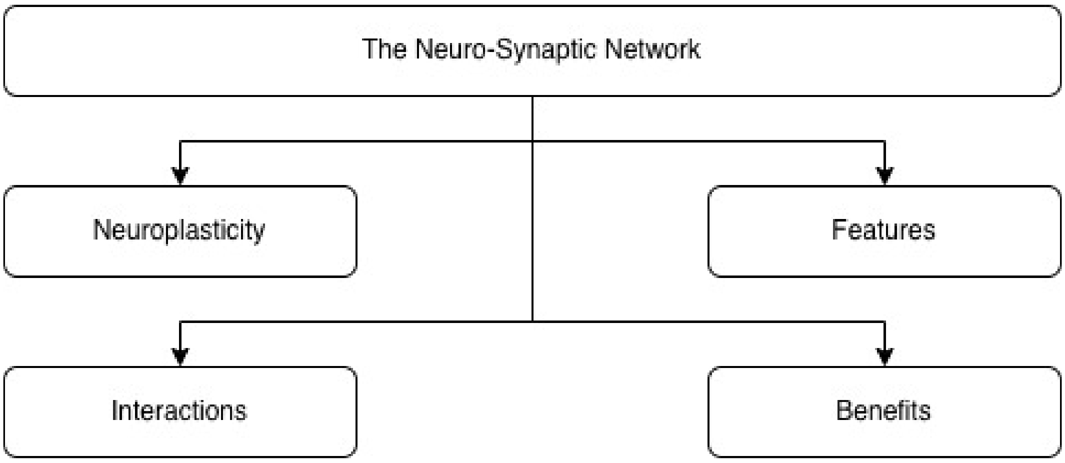

Figure 4.1. Structural overview of the neuro-synaptic network.

These principles represent fundamental aspects of how our brains form and strengthen connections. This chapter establishes a theoretical foundation by exploring key neuroscientific principles and their potential translation into AI-driven educational tools. However, it also critically examines the challenges and ethical considerations involved in this interdisciplinary field, such as data privacy and algorithmic bias. My goal here is to bridge the often-perceived gap between our growing understanding of the intricacies of brain function and the design of truly advanced and personalised educational tools that align with the way we learn.

4.1 Neuro-synaptic network

Drawing upon the understanding of the human brain as a network of interconnected neurons [Maturi et al. 2022], this chapter investigates into the remarkable phenomenon of neuroplasticity, which is the brain's inherent ability to reshape itself through the formation of new connections. It’s fascinating to consider how this dynamic process underpins all learning. When stimulated, these neurons communicate via electrical signals transmitted across synapses, according to Hormuzdi [Hormuzdi et al. 2004], a process often amplified by the release of neurotransmitters. necessary for our discussion of the NSLE, another key characteristic is synaptic plasticity, the brain’s capacity to strengthen or weaken these connections, effectively rewiring itself in response to experience.
This, in essence, is the biological basis of learning and memory. As educators, we can harness this understanding to design teaching strategies that connect with these

natural learning mechanisms. For instance, I've observed my students over many years, how active learning and collaborative projects seem to foster long-term potentiation, strengthening those neural connections and improving learning outcomes. This neurobiological insight opens exciting avenues for personalised education, allowing us to tailor learning experiences to the unique needs and learning styles of each student. The principles governing neuro-synaptic function are proving invaluable in the development of AI systems, designed to augment cognitive skills such as attention and memory.
Indeed, the convergence of our understanding of neuro-synaptic networks with the advancements in AI and machine learning has yielded intelligent systems inspired directly by the human brain, accentuated in research by Chen [Chen et al. 2022].
These systems demonstrate their impressive capabilities in learning [Ward. 2019] from complex datasets and self-organising within dynamic environments. While the synergy of neuroscience and computer science offers immense potential, it's important to critically evaluate the claims of direct mimicry. For instance, the concept of 'distributed processing' in AI, while inspired by the brain, operates on fundamentally different principles than biological neural networks.
I believe the synergistic power of neuroscience and computer science holds immense potential, not only for pushing the boundaries of AI but also for deepening our fundamental understanding of brain function itself. Therefore, neuro-synaptic network [Fig. 4.1] principles can inform the development of novel assessment tools that move beyond rote memorization to stimulate and measure complex cognitive processes. However, the effectiveness of these tools depends on careful validation and a clear understanding of what specific cognitive processes are being assessed.
However, for this potential to be fully realized in educational settings, successful collaboration between researchers and educators is paramount. This necessitates a deeper, ongoing exploration of the underlying neural learning mechanisms [Hardiman. 2003].
Effective assessments must capture the multifaceted nature of learning, and the insights gleaned from research must be translated into actionable, practical recommendations for classroom implementation. This is a key focus of my ongoing work within the NSLE framework.

4.2 Neuroplasticity

The concept of neuroplasticity, according to research by Joshua [Joshua. 2022] is the brain's truly remarkable ability to forge new connections and adapt in response to novel experiences. But this isn't just a cornerstone of neuroscience; I believe it holds profound implications for the development of more sophisticated AI. By observing how the human brain learns, adapts, and processes information, researchers are gaining invaluable insights that can inform the creation of AI models exhibiting similar characteristics. This observation fuels the development of AI models with enhanced learning capabilities.
However, it's important to critically analyse the extent to which AI can truly 'generalise knowledge effectively.' Unlike the human brain, AI models often struggle with transfer learning and adapting to unforeseen situations [I*man* et al. 2023], highlighting a key area for further research. Drawing inspiration from principles like Hebbian learning,

researchers develop AI models to mimic the brain's dynamic nature. However, the application of Hebbian learning [Strom. 2007] in AI is often a simplified version of the biological process, and the models may not fully capture the complexity of synaptic plasticity. As outlined below, the key design principles that I argue in this dissertation, are necessary for creating truly human-like AI systems in learning environments, echoing the very mechanisms that drive our own cognitive development.

Engagement

Education material should be engaging and enjoyable. The design should consider factors that promote intrinsic motivation and sustained attention.

Challenge

Education material should provide a challenging and adaptive difficulty level to promote cognitive growth. The level of challenge must be carefully calibrated to avoid frustration or boredom [Vygotsky. 2*011*].

Feedback

Immediate and relevant feedback assists users to understand their performance and adjust their strategy. The nature and timing of feedback are critical; it should be constructive and specific, avoiding overly critical or vague comments.

Repetition

Education process should include repetition and practice to reinforce new skills and knowledge. However, repetition should be varied and spaced to optimise learning and prevent cognitive overload.

Transfer

Education should include transfer tasks that require users to apply new skills and knowledge to real-world situations. This process should also include scaffolding to support learners in bridging the gap between learning and application.

4.3 Neuroplasticity enhancing features

Several key features, discussed here below, add to neuroplasticity [Tovar-Moll et al. 2016] and provide a framework for a comprehensive learning environment.
These features, require careful consideration in their implementation. For example, the 'stimulating environment' [Green et al. 2012 ; Donnelly et al. 2016], should be designed to avoid sensory overload, and the effectiveness of 'social interaction' may depend on the nature of the interaction and individual learner preferences.

Novelty and variety

Novel and varied stimuli stimulate neuroplasticity. However, excessive novelty can be distracting; a balance between novelty and familiarity is crucial [Honigsfeld et al. 2004].

Feedback

Feedback and error correction [Varnosfadrani et al. 2009] are fundamental for learning, allowing students to refine their understanding. The effectiveness of feedback depends on its type (e.g. corrective vs. elaborative) and timing (e.g. immediate vs. delayed).

Sleep and relaxation

Adequate sleep and relaxation are important for neuroplasticit [Gorgoni et al. 2013], as they allow the brain to consolidate and process information. The optimal amount and quality of sleep can vary between individuals; further research is needed to personalise recommendations.

Physical exercise

Physical exercise has been shown to add to neuroplasticity [Lin et al. 2018] by promoting blood flow to the brain and stimulating the growth of new neurons.

Social interaction

Social interaction has been linked to increased neuroplasticity, [Davidson et al. 2012] as it promotes the formation of new connections. The quality and type of social interaction are critical; negative social interactions can have detrimental effects.

Emotional regulation

Educators can teach students emotional regulation techniques [Hoffmann. 2020], such as mindfulness and deep breathing and encourage open communication about emotions.

Cognitive training

Cognitive training, such as memory games and puzzles, can add to neuroplasticity by challenging the brain.

Neurofeedback

Neurofeedback can add to neuroplasticity by promoting self-regulation and increasing cognitive function.

Mindfulness

Meditation and mindfulness strengthen neuroplasticity by reducing stress and increasing cognitive function [Treadway et al. 2010].

Nutrition and diet

A healthy diet rich in nutrients support the growth of new neurons [Dyall et al. 2008].

Enrichment

Environmental enrichment can significantly strengthen neuroplasticity by stimulating the formation of new neural connections [Torromino. 2024].

These elements are necessary for creating effective and adaptive learning environments that harness the brain's natural ability to change and grow.

4.4 Potential benefits

Neuroplasticity offers potential benefits in education, including personalised learning, cognitive enhancement, emotional regulation and resilience, and improved well-being. These benefits are summarized below. By utilising strategies to promote neuroplasticity, educational systems can create environments that optimise learning, personal growth, and development. While these benefits are significant, it's crucial to acknowledge that the relationship between neuroplasticity and these outcomes is complex and influenced by various factors. For example, the effectiveness of personalised learning depends on the accuracy of learner assessments and the availability of resources to tailor instruction.

Improved cognitive flexibility

Neuroplasticity strengthens cognitive flexibility allowing learners to adapt to new information, switch between tasks, and integrate knowledge. However, the extent of improvement can vary depending on individual differences and the specific interventions used.

Memory consolidation

Educators can improve memory consolidation, allowing learners to retain information effectively.

Reduced stress and anxiety

Neuroplasticity enhancing features can mitigate the negative impact of anxiety on learning. While promising, these features are not a panacea; addressing underlying causes of stress and anxiety is also essential

Increased resilience

Learners develop resilience, enabling them to better cope with setbacks, failures and challenges.

Personalised learning

Educators tailor instruction to individual learners' needs, abilities and learning styles. Requires accurate assessment and sufficient resources for effective implementation; potential challenges include scalability and equity

Increased self-awareness

Learners understand their strengths, weaknesses and learning preferences better.

Emotional intelligence

Learners develop emotional intelligence, including empathy, self-regulation and social skills.

Lifelong learning

Neuroplasticity foster a growth mindset, encouraging learners to view challenges as opportunities for growth and development.

4.5 System architecture and design

The effectiveness of the NSLE, as I envision it, hinges on its thoughtfully designed system architecture. This architecture comprises several interconnected components, including the intuitive user interface [*Sections 9.9*] that students and educators will interact with. The sophisticated AI algorithms detailed in [*Section 12.1*] that drive personalisation, incorporate the data storage and retrieval mechanisms necessary for tracking learning progress, and the feedback loops that inform both the learner and the system itself.

This carefully considered system architecture is specifically designed to process student data in a way that actively supports neuroplasticity and, maximizes learning outcomes [Grant et al. 2014]. My aim in design the NSLE is to create a truly personalised and adaptive learning experience, one that dynamically responds to the individual needs and progress of each learner, mirroring the brain's own remarkable capacity for adaptation. The design of the NSLE architecture must also address critical issues such as data security, privacy, and ethical considerations related to the use of student data. The system's scalability and accessibility for diverse learners should be carefully considered

4.6 Integration of AI, neuroscience, and education

The potential for synergy at the intersection of AI, neuroscience, and education is, in my view, truly transformative, promising a pathway towards more effective and deeply personalised learning experiences. The central tenet of the NSLE lies in its deliberate application of neuroscientific principles to the design and implementation of AI. My proposal is a system that aligns with the brain's intrinsic learning mechanisms working with how we naturally acquire and retain knowledge. For instance, the integration of AI algorithms, empowers the NSLE to conduct sophisticated analyses of student data, enabling the provision of timely and highly personalised feedback [Alsawaier. 2018].

This dynamic interaction between AI-driven insights and our understanding of brain function has the exciting potential to cultivate learning environments that not only boost cognitive functions but also, perhaps more importantly, foster a genuine and enduring love of learning. This integration holds transformative potential, but it's important to approach it with a critical perspective. The 'love of learning' is a complex construct, and while AI can support its development, it cannot fully replace the role of human educators in fostering intrinsic motivation and emotional connection. A balanced approach is needed that leverages the strengths of both AI and human interaction.

CHAPTER 5
HOLISTIC LEARNING ANALYTICS FRAMEWORK

In this chapter, I introduce the Holistic Learning Analytics [*HLA*] framework as a cornerstone of the NSLE. My aim here is to articulate how this framework weaves together the power of neuro-synaptic networks with advanced algorithms to gain a deeper understanding of individual student strengths and areas for growth, all through the lens of AI-driven analytics. The HLA framework operates by using data, encompassing not just student performance but also their learning behaviours and the various environmental factors that might influence their educational journey. This wealth of information is then carefully examined using a range of analytical tools, from

fundamental descriptive statistics to more sophisticated machine learning algorithms and insightful data visualisation techniques.
The overarching goal is to uncover meaningful patterns, track each student's progress, and provide educators with the evidence they need to make informed pedagogical choices. For instance, the HLA might illuminate compelling connections between engagement in particular learning activities and a more profound grasp of complex ideas. The HLA framework is designed to be a source of actionable intelligence for educators. By providing clear insights into student learning, it empowers them to refine their teaching methodologies and, in turn, foster improved learning outcomes for all students. Specifically within this chapter, I will detail how the HLA will use this data to construct truly personalised learning pathways. I will explore the mechanisms by which the HLA is designed for continuous evolution, ensuring its enduring relevance and sustained effectiveness within the ever-changing landscape of education.

5.1 Neuro-Synaptic Learning Environment

As I outlined in Chapter 1.3, the NSLE presents a fresh, network-centric paradigm for enriching educational experiences. At its heart lies the HLA framework [*Fig. 5.1*], a key innovation that uses the power of AI-driven analytics [*Fig. 1.2*] to provide a nuanced assessment of individual student strengths and areas needing development. My goal with the HLA is to move beyond surface-level evaluations and cultivate a truly comprehensive understanding of the learning journey by drawing together an array of data sources. Specifically, the HLA framework is designed to offer valuable insights into the learners themselves [*Scott et al. 2017*], their dynamic interactions with instructional materials, and the broader learning environment in which they operate.
What sets the NSLE apart is its unique fusion of neuro-synaptic networks, designed to mirror the brain's capacity for learning and adaptation, with intelligent AI algorithms and machine learning techniques. This bio-inspired approach allows AI systems to effectively emulate the fundamental structure and function of biological neural networks. We can develop AI-powered learning environments that begin to tap into the human brain's inherent abilities for pattern recognition [*Theodoridis. 2006*], the formation of meaningful connections [*Gupta et al. 2021*, and the cultivation of innovative thinking [*Luckin et al. 2016*].

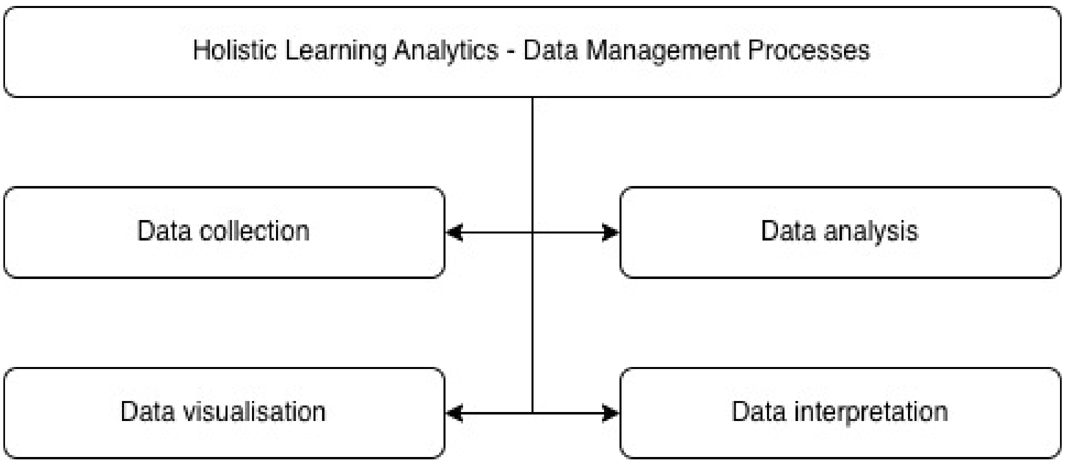

Figure 5.1. Flow of data management processes in holistic learning analytics.

By strategically integrating these neuro-synaptic networks [*Seaba. 2023*], I believe educators can craft truly tailored learning pathways that thoughtfully align with each student's unique cognitive profile. This personalisation, I argue, is required for fostering a deeper and more enduring comprehension of complex concepts. Beyond this, the NSLE holds potential for precisely identifying individual student strengths and weaknesses, thereby enabling the provision of targeted support and encouragement precisely where it's needed most. This personalised approach represents a departure from the limitations of the traditional one-size-fits-all educational model, paving the way for more individualised, engaging, and more effective learning experiences.

5.2 Holistic Learning Analytics (HLA) framework

Building upon the foundational principles of the NSLE, this section explores the architecture and functionality of the HLA framework below, which I envision as a comprehensive lens through which we can truly understand and appreciate the learning process.

Data collection
- Student performance data (grades, test scores)
- Learning behaviour data (time on tasks, navigation)
- Environmental data (device usage, location)
- Self-reported data (surveys, feedback)

Data analysis
- Descriptive statistics (mean, median, mode)
- Inferential statistics (regression, correlation)
- Machine learning algorithms (clustering, decision trees)

Data visualisation
- Identify trends and patterns
- Monitor student progress
- Inform instructional decisions

Data interpretation
- Identify areas of improvement
- Develop targeted interventions
- Encourage student engagement

The strength of the HLA lies in its ability to synthesize data drawn from various critical educational sources. This includes the curriculum itself, the wealth of cognitive and behavioural data captured within Learning Management Systems (LMS) [Juhaňák et al. 2019], the valuable affective and behavioural insights gleaned from Educational

Technology platforms [Baldominos et al. 2*019*], the contextualised interaction data provided by Learning Analytics Platforms [Douglas et al. 2019], and the demographic information housed within Student Information Systems (SIS) [Coldwell et al. 2008].
I've found that the successful incorporation of curriculum data into the HLA is a nuanced process. It requires not only a thoughtful selection of the most appropriate curriculum type for our specific learning objectives but also attention to ensuring this data is structured and formatted in a way that the NSLE can effectively interpret.
This careful preparation is, in my view, paramount for equipping the NSLE with the necessary intelligence to make well-informed decisions that directly benefit our students. As I've explored various approaches during my career as lecturer, it's become clear that several curriculum integration models exist, each presenting a unique balance of collaboration and control.
At its core, the HLA framework is designed to seamlessly integrate the power of AI algorithms with established educational practices [*Helen. 2007*] with the fundamental goal of personalising the learning experience. Put simply, the HLA seeks to unravel the complexities of how students learn, adapting dynamically to their individual needs and, in doing so, enriching their overall educational journey. My conviction is that the HLA framework holds transformative potential for educational practices. By providing us with a deeper, more nuanced understanding of the multifaceted nature of student learning [Joseph et al. 2024], it can pave the way for more effective and enriching educational experiences for all learners.

5.3 HLA framework structure

The architectural design of the HLA framework centres around several key interconnected components, each with its ability to effectively collect, analyse, and apply data in ways that meaningfully complement learning. At the outset, the framework is designed to gather a rich and varied array of information. This includes not only traditional student performance metrics but also nuanced data on learning behaviours, the influence of environmental factors, and invaluable self-reported feedback directly from the learners themselves. My aim here is to construct as complete and holistic a picture of the learning process as possible.
Once this comprehensive dataset is assembled, the HLA framework employs a suite of analytical techniques. This includes the application of both descriptive and inferential statistics to lay the groundwork for understanding the data, as well as the deployment of sophisticated machine learning algorithms to uncover deeper patterns, identify trends, and extract key insights that might otherwise remain hidden.
Finally, and critically for practical application, the framework incorporates the generation of clear and intuitive representations of this analysed data [*Chapter 12.5*]. This representations layer is specifically designed to empower educators with actionable information, effectively support individual student progress, and drive more informed, instructional decisions in the classroom .

5.4 Integration and application

The emergence of HLA, as I see it, marks a critical step forward in education, holding promise for enhancing student outcomes across a wide spectrum of learning environments, from the foundational years of K-12 to the dynamic landscape of corporate training. However, the truly effective implementation of HLA hinges on a methodological framework that thoughtfully integrates both quantitative and qualitative data streams [Almalki. 2016]. I do consider quantitative data to encompass the empirical measurements we rely on, such as the insights gleaned from standardised tests, the broad perspectives captured through surveys, and the controlled findings derived from experimental studies [*Johnson et al. 2024*]. Complementing this, qualitative data offers a richer, more nuanced understanding through descriptive accounts, interpretive analyses of learning experiences and the detailed observations I and other researchers make in learning environments.

I firmly believe that achieving a truly comprehensive understanding of student learning necessitates a process of triangulation, where we thoughtfully weave together these data sources. This includes not only performance records and the digital footprints left within LMS but also the invaluable perspectives gained from student feedback and the rich narratives emerging from qualitative data gathered by AI algorithms.

A key component I've developed within the HLA framework to facilitate this integration is EDU-VIS [*Fig. 1.2*], which acts as a bridge connecting sophisticated data analytics with powerful visualisations. By seamlessly integrating data originating from various learning platforms, comprehensive student information systems, and online assessments, EDU-VIS constructs a dynamic and truly holistic profile of each student's learning journey. EDU-VIS employs the power of descriptive, predictive, and even prescriptive modelling techniques to not only identify existing patterns but also to forecast future performance and proactively flag students who might be at risk of falling behind. This capability, I argue, empowers educators to discern broader learning trends, anticipate potential outcomes, and implement timely and targeted interventions where they are most needed.

To ensure that this complex data becomes readily interpretable and actionable for educators, EDU-VIS employs a range of intuitive visualisation strategies, including interactive dashboards that allow for personalised exploration, compelling data storytelling techniques that bring the insights to life, geospatial mapping where relevant to contextual factors, and network analysis to reveal the relationships within learning communities.

These visual tools are specifically designed to present data in an accessible and engaging manner, enabling educators to readily grasp the key insights generated by the HLA framework. EDU-VIS, as an integral part of the HLA, empowers educators to move beyond intuition and make well-informed, data-driven decisions that are directly aimed at optimising the learning experience for every student. This, above all, aligns perfectly with the core goal of HLA. To provide actionable insights that not only augment teaching methodologies but also improve student outcomes.

5.5 HLA framework development

The journey of developing the HLA framework, as I've experienced it, has involved a series of interconnected stages. Our initial focus was on defining the data requirements and identifying the specific types of information that would be most valuable to collect to gain a comprehensive understanding of the learning process. Following this foundational step, a portion of my research is to carefully select suitable

AI algorithms [Onesi-Ozigagun et al. 2024] to be employed within the NSLE framework [*Chapter 12.6*]. The goal here is to ensure these algorithms can effectively analyse the rich student data we collect, extract truly relevant insights, and contribute to the development of genuinely personalised learning pathways. This stage requires a deep understanding of both the pedagogical goals and the capabilities of various AI techniques.

The subsequent phase involved the process of integrating the HLA framework seamlessly into the broader learning environment. This demanded careful consideration of user interfaces to ensure accessibility and ease of use for both educators and students, the design of effective feedback mechanisms to facilitate continuous improvement, and, critically, an approach to data privacy [*Ismail. 2025* ; *Kamenskih. 2022*], an ethical imperative that has guided every step of this development. Finally, the ongoing process of assessing and refining the HLA based on its real-world efficacy is paramount. This cycle of continuous development, driven by empirical evidence and user feedback, is, in my view, very important to ensure the HLA remains relevant, effective, and continues to evolve in response to the ever-changing needs of learners and educators.

Cognitive Development

For decades, cognitive development theories have served as the bedrock of our understanding of how students acquire knowledge and skills. These foundational theories provide invaluable frameworks for comprehending the processes through which students think, reason, and approach problem-solving. In my dissertation, I propose a novel framework that strategically combines the rich insights of cognitive development theory with the analytical power of learning analytics. My aim here is to move beyond traditional approaches and gain a more granular and nuanced understanding of the dynamic interconnection between how students learn and how their cognitive abilities develop over time.

Drawing on the seminal work of Vygotsky, we know that learning and cognitive development are deeply and inextricably linked [Vygotsky. 2*011*]. However, as Vygotsky himself acknowledged, the precise nature and directionality of this relationship continue to be fertile ground for debate and ongoing research within our field. In contrast, Piaget's stage-based theory [*Piaget. 2013*] suggests a more sequential relationship, positing that certain types of learning become accessible only once a learner has reached a specific stage of cognitive development. I provide a clearer overview and summary of the key components below, of this cognitive development.

- Cognitive development
  - Problem-solving
    - Identifies the ability to analyse complex problems and develop effective solutions.
  - Critical thinking
    - Assesses the ability to evaluate information, identify biases and make informed decisions.
  - Metacognition

Examines the ability to reflect on one's own learning processes and adjust strategies accordingly.

Learning analytics
- Engagement
  - Analyses student engagement patterns, including time spent on tasks, frequency of interactions and level of participation.
- Motivation
  - Examines student motivation levels, including intrinsic and extrinsic factors that influence learning behaviours.
- Learning outcomes
  - Assesses student learning outcomes, including achievement, retention and transfer of knowledge.

Instructional design
- Problem-based learning
  - Designs instructional activities that require students to solve complex problems and develop critical thinking skills.
- Personalised learning
  - Utilises learning analytics to tailor instructional strategies to individual students' needs, interests and learning styles.
- Feedback and reflection
  - Incorporates regular feedback and reflection opportunities to help students develop metacognitive skills.

Emotional development

As any educator knows intuitively, and as research consistently indicates, emotional well-being forms a critical cornerstone of the entire learning process. The strong link between how students feel and their academic performance is well-documented [Harter et al. 2003]. In my research, I explore the potential of combining the insights from emotional development theory with the analytical power of learning analytics. I am convinced that this approach can provide educators with a far deeper and more nuanced understanding of the interaction between a student's emotional state and their learning outcomes [Kustyarini. 2020].
Armed with this richer understanding, educators are then better positioned to design and cultivate a more positive and supportive classroom environment, one that intentionally integrates opportunities for social-emotional learning. By prioritising the nurturing of students' emotional development alongside their academic achievement, I believe this framework paves the way for a future in education where all students can truly thrive, both academically and emotionally.

Theoretical framework

This framework, which I propose integrates academic learning with the development of emotional intelligence, builds upon the contributions of leading scholars in the field, such as Goleman [Goleman. 2*021*] and Durlak and his colleagues [Durlak et al. 2*011*].

In particular, Durlak's comprehensive meta-analysis of 213 school-based Social and Emotional Learning (SEL) programs, encompassing a remarkable 270,034 students from kindergarten through high school, provides compelling evidence. Their findings demonstrate not only improvements in students' social and emotional skills, attitudes, and behaviours but also a noteworthy 11% average increase in academic achievement. This data, in my view, strongly advocates for the implementation of frameworks that intentionally bridge the cognitive and emotional domains of learning. Indeed, this research offers a compelling rationale for policymakers and educators alike to champion the integration of similar approaches into mainstream educational practices.

By thoughtfully combining the insights from emotional development with the analytical power of learning analytics, I believe we can cultivate a more compassionate, supportive, and more effective learning environment for all students. A key aspect of this approach involves actively gathering student experiences, once the NSLE is installed and operational through a variety of methods, including surveys that capture broad trends, in-depth interviews that provide rich qualitative data, and focused group discussions that illuminate shared experiences and perspectives. This direct engagement allows us to gain invaluable insights into students' emotions, the challenges they face, and their successes, both academic and personal.

While traditional education has often placed a primary emphasis on cognitive skills, I argue that integrating data from these sources empowers educators to identify not only students' academic strengths and weaknesses but also their emotional strengths and areas for growth. This allows us to track progress in both domains and tailor interventions that specifically support emotional development [Durlak et al. 2011]. The application of learning analytics can play a role in pinpointing students who may be in need of additional emotional support, enabling the implementation of timely and targeted interventions. This combined approach, therefore, facilitates a more holistic view of student well-being, addressing both their academic and emotional needs in a supportive manner.

Social development

At its core, the NSLE framework is driven by a vision of creating truly thriving learning environments where each student can feel genuinely valued, deeply connected, and empowered to reach their full potential. I believe that learning analytics provides the mechanisms to bring this vision to fruition, drawing upon the rich data generated within our classrooms to unlock positive social change at the very heart of our schools. This framework, as I propose it, offers a practical and theoretically grounded roadmap for educators on the front lines, fellow researchers seeking to advance our understanding, and policymakers striving to create more equitable and effective educational systems. The NSLE framework is designed to empower students not only to master academic subjects but also to cultivate social-emotional skills that are so vital for navigating life beyond the classroom. These include the art of effective communication, the power of seamless collaboration, and the ability to engage in constructive conflict resolution [Wentzel. 1*991*]. Learning analytics, in this context, provides educators with invaluable tools to significantly complement the learning experience in both these domains.

By thoughtfully analysing student data, educators gain real-time, actionable insights into the individual progress of each learner, allowing for timely and personalised interventions that address specific social-emotional needs as they arise. This proactive and data-informed approach not only demonstrably improves student well-being and academic performance but also fosters a more positive and inclusive learning environment where potential conflicts are minimised, and, most importantly, where all students feel genuinely seen, heard, and fully supported in their journey.

Challenges

While I firmly believe that the HLA framework holds immense promise for truly revolutionizing education, I also recognise that its ethical, effective, and equitable implementation necessitates a thoughtful and proactive approach to several key challenges. One of the initial hurdles is the often-limited access to comprehensive and nuanced data on students' social behaviours, which are important for a holistic understanding. Secondly, the very nature of analysing and interpreting this complex social-emotional data demands a specialised skillset and a commitment to ongoing professional development for educators. Ensuring fairness and equity, principles that are paramount in my research, requires a consideration of potential biases that might inadvertently creep into our data collection and analysis processes.

It's necessary to remember that social development is a multifaceted concept, encompassing a student's evolving cognitive abilities, their growing emotional intelligence, and even the development of their moral compass. The HLA framework, as I've designed it, directly aims to address this inherent complexity by actively fostering key aspects of social development, such as collaboration skills, more effective communication abilities, and improved navigation of social situations.

By strategically harnessing data from a wide array of sources, the HLA optimises the power of cutting-edge machine learning algorithms and insightful data visualisation techniques to deliver truly actionable insights to both educators working directly with students and policymakers shaping the broader educational landscape. I believe these insights empower educators to proactively overcome the aforementioned challenges, to identify students who may be struggling socially, and to track their social development over time. This longitudinal perspective enabling us to measure the effectiveness of the interventions we implement and to continuously refine our approaches.

5.6 HLA benefits

The HLA framework, offers a range of benefits for both our students and us, as educators. By analysing the data unique to each student, the HLA has the potential to dynamically adapt learning experiences to precisely align with their individual needs, their inherent strengths, and the areas where they might need additional support. I believe that by providing this kind of targeted feedback and personalised support, the HLA can improve student performance and overall learning outcomes, while simultaneously fostering increased student motivation and a more active engagement in the learning process.

The HLA is designed to provide us, as educators, with invaluable and actionable insights into the processes of student learning. This deeper understanding can then directly inform our instructional decisions, allowing us to refine our teaching methodologies and continuously improve the overall educational experience we provide in our classrooms.

5.7 HLA Applications

One of the aspects of the HLA framework that I find particularly exciting is its broad applicability across a range of educational settings and contexts. I envision its potential to upgrade various tools and platforms we already use, such as AI-powered tutoring systems capable of providing truly individualised instruction and feedback [Rızvı. 2023] tailored to each learner's specific needs. It could also significantly boost online learning platforms by enabling them to dynamically adjust the difficulty and content of learning materials in real-time, precisely matching individual student skill levels.
I see the HLA as integral to developing more intuitive visual interfaces that would empower educators to effortlessly track student progress, closely monitor engagement levels, and readily identify areas where students might be struggling or excelling. Coupled with AI-powered assessment tools that can offer timely and genuinely actionable feedback, the HLA provides a powerful ecosystem to support student learning. This holistic approach, which also takes into account the elements of social-emotional well-being [Durlak et al. 2*011*], empowers us, as educators, to develop targeted interventions that address the full spectrum of student needs and optimise their overall development.

5.8 HLA implications

I acknowledge the implications of the HLA framework are truly far-reaching for the future of education. By embracing this holistic lens, we, as educators and researchers, gain a much deeper and more nuanced understanding of the relationship between students' cognitive abilities., their emotional landscapes, their social interactions within the learning community, and the broader environment in which learning takes place. This profound knowledge, in turn, empowers us to design more effective and responsive learning environments, to adapt our teaching styles with greater precision, and to develop assessments that truly capture the breadth of student learning, all while being thoughtfully tailored to individual student needs.
The framework's inherent focus on context serves as a powerful reminder that learning is not confined to the four walls of a classroom. A student's background, their access to resources, and a myriad of other external factors significantly shape their unique learning journey. By explicitly recognising these often-overlooked influences, we, as educators, are better equipped to identify and mitigate potential negative impacts, striving towards more equitable learning opportunities for all.
I believe the applications of the HLA extend well beyond the K-12 system, reaching into the critical areas of workforce development, strategic talent management within organisations, and the ongoing pursuit of lifelong learning. By adopting this comprehensive framework, organisations can gain a much deeper understanding of

the complex dynamics at play in employee learning and professional development. Leading to more effective talent management strategies and tangible improvements in overall organisational performance. To conclude, the HLA represents, in my view, a truly groundbreaking approach, one that fundamentally acknowledges the interconnectedness of factors that influence how we learn and grow. It provides us with a comprehensive framework for analysing these learning processes and for informing the design of more effective, equitable, and more human-centred learning environments.

CHAPTER 6
DATA MANAGEMENT

As I research the data management strategies for the NSLE project, a key initial step involves gaining a comprehensive understanding of each student. To achieve this, I plan to assess their individual weaknesses and strengths and areas for growth by analysing a range of factors, including their behavioural patterns, cognitive processes, emotional responses, preferred learning styles, and the influences of their surrounding environment [*Fig. 6.1*].

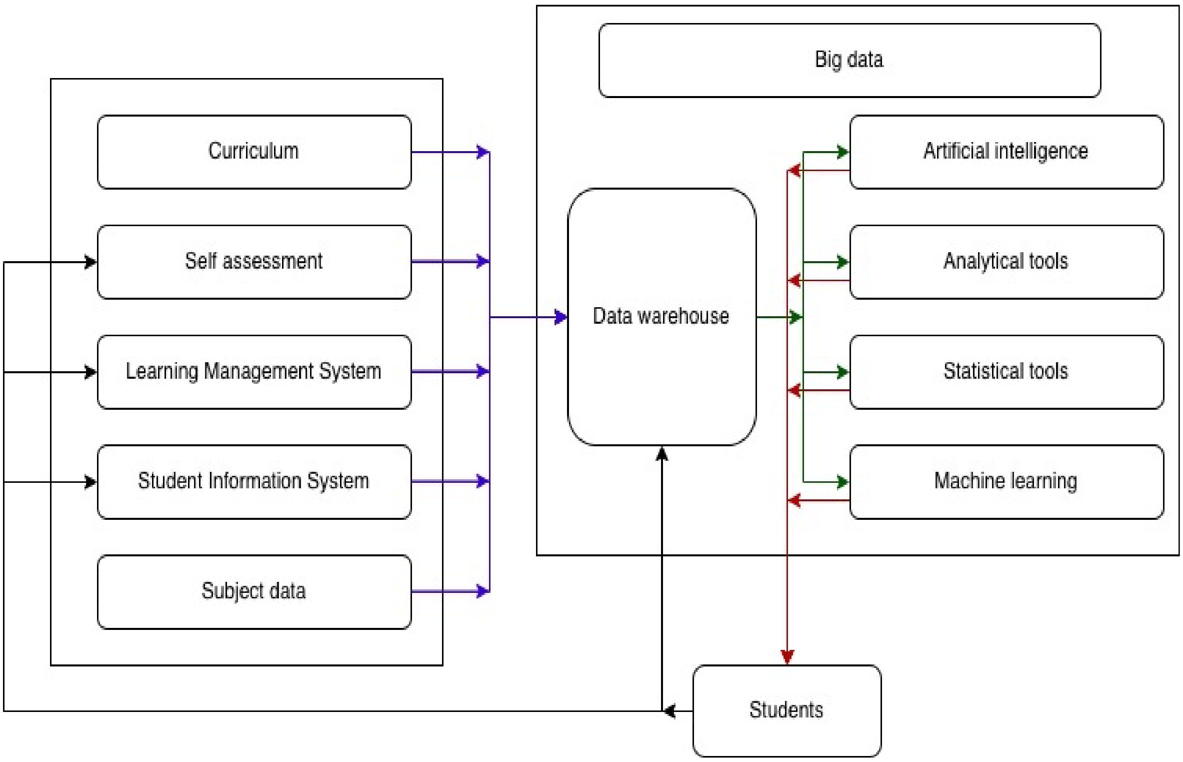

Figure 6.1. Information flow from data sources to data warehouse and students.

My approach to data collection, detailed further in section 6.4, will employ a mixed-methods design [Section 13.3]. Throughout this process, the ethical implications of data collection and the paramount importance of student data privacy will be central considerations. The specific methods I will utilise include surveys and questionnaires administered to both teachers and students, alongside the valuable data already available within the curricula, Learning Management Systems [*LMS*], and Student Information Systems [*SIS*].

6.1 Assessing student strengths and weaknesses

In this research, I propose employing a selection of data sources, as detailed in chapter 5.2, to gain a nuanced understanding of individual student strengths and areas where they might face challenges [*Al-Shammari. 2011*]. My plan involves not only analysing the collected data but also employing effective visualisation techniques, as outlined in *chapter 12.1*, to unlock key insights into student performance. This dual approach will empower educators to pinpoint specific areas of difficulty and, equally importantly, to cultivate and build upon students' existing talents. This data-driven methodology will directly inform the development of more effective pedagogical practices, the refinement of curriculum design, and the implementation of targeted interventions, with the overarching goal of supporting every student in reaching their full academic potential.

6.2 Types of data

Behavioural data

To gain a comprehensive understanding of student behaviour within the NSLE, I plan to gather data encompassing attendance records, levels of classroom participation, and the completion of assigned tasks. This information will be collected through a combination of direct observations, data from tracking systems, and student self-reports [*Nguyen et al. 2018*]. By employing clearly defined and consistently applied observation protocols, this systematic data collection will enable the identification of behavioural patterns. Educators will be better equipped to proactively address potential student challenges, fostering a more personalised and supportive learning environment for everyone [Yan et al. 2020].
I intend to evaluate students' cognitive abilities, including their existing knowledge base, critical thinking faculties, and problem-solving proficiencies, using a multifaceted approach incorporating a range of assessments, learning analytics derived from their interactions within the NSLE, and observational [Wang. 2023] insights [Wang et al. 2*010*]. This strategy, which combines both standardised and qualitative assessment methods, will allow me to pinpoint specific areas where students may require additional academic support and targeted instruction. Drawing upon existing research [Fischer et al. 2020], I also recognise the importance of realistic data, such as students' socio-economic backgrounds, family dynamics, and individual learning styles, in developing a holistic understanding of their needs. Integrating this rich information with traditional academic metrics will allow for deeper, more nuanced insights and facilitate the design of more effective and equitable interventions. Throughout the entire data collection process, I am committed to upholding the highest ethical standards, ensuring the sensitivity of the process and protecting the privacy of both students and their families.

6.3 Data sources

A cornerstone of my research within the NSLE involves the strategic integration of the HLA [*Chapter 5.2*] This approach necessitates employing data sources, including the comprehensive records within our LMS and the detailed usage logs of various educational software platforms [*Munna et al. 2024*]. I believe this multifaceted approach to data analysis holds potential to empower educators with a deeper, more nuanced understanding of individual student needs. This understanding can directly define the refinement of their teaching practices and the iterative improvement of our curriculum design. As summarised below, my framework for analysing educational data centres on a thorough exploration of student progress and behaviours, specifically examining these elements in relation to defined learning objectives, anticipated learning outcomes, and observed behavioural patterns.

Learner-centred
- Learning objectives
  - Defining the compass points of the educational voyage.
- Learning outcomes
  - Charting student progress and identifying areas for improvement.
- Learning behaviours

Understanding the connection between student engagement, motivation, and persistence.

Instructional
- Instructional strategies
  - Examining the effectiveness of teaching methods, curriculum design, and assessment techniques.
- Curriculum design
  - Ensuring alignment between learning objectives, outcomes, and assessments.
- Teacher feedback
  - Providing valuable insights into student learning and instructional effectiveness.

Environmental
- Learning environment
  - Analysing the impact of classroom climate, technology integration, and physical space.
- Student demographics
  - Recognising the unique learning needs of student populations.
- Institutional factors
  - Evaluating the influence of faculty expertise, resources, and support services.

6.4 Data collection

For student data to be truly significant within the NSLE, I recognise the critical need to ensure its accuracy, reliability, and completeness, alongside the implementation of data privacy and security protocols. My guiding principle is that data should serve as a solid foundation for all educational decision-making [Webber et al. 2020], consistently informed by a strong ethical framework that prioritises fairness and a deep respect for student rights. To this end, I will establish and maintain clear data handling and storage protocols [*Chapter 10.3*]. A key component of my data management strategy is the adoption of EDU-DATA, a framework I find particularly promising for its ability to synthesize data streams, including curriculum content, student responses, various assessment outcomes, and even relevant social media interactions, to construct a truly holistic view of each student's learning journey.
Ensuring the quality of this integrated data is paramount, and my approach involves an identification of data sources, encompassing administrative records, formal and informal assessments, and samples of student work. The application of EDU-DATA aims to personalise the learning experience and increase student outcomes [Badawy et al. 2023] through carefully considered strategies for both the collection and insightful interpretation of this rich data [Gangadharan. 2014], with the overarching goal of fostering improvements in learning [Smith. 1985 ; Hussar et al. 2011]. EDU-DATA will be instrumental in systematically recording individual student needs and preferred learning styles, as indicated and summarised here below, through the use of questionnaires, self-assessment tools, and individual interviews.

Visual

Learners who prefer to learn through visuals like diagrams, charts and images.

Aural

Learners who prefer to learn through listening to lectures, discussions and music.

Read/Write

Learners who prefer to learn through reading and writing, such as textbooks and notes.

Kinaesthetic

Learners who prefer to learn through hands-on experiences and physical activities.

6.5 Data collection techniques

To gain a comprehensive understanding within this research, I've adopted a mixed-methods approach, strategically gathering data through carefully designed surveys and questionnaires [APPENDICES].

Cognitive profiling form [*Appendix* A]

An element of tailoring instruction within the NSLE involves cognitive profiling, a process through which I aim to assess key cognitive skills such as attention span, memory capacity, processing speed, and problem-solving abilities. This in-depth understanding will be instrumental in personalising the learning journey for each student. Ethical considerations are paramount in this endeavour; therefore, informed consent will be obtained, and I want to assure you that all collected data will be used solely for the purpose of individualizing learning experiences and will be securely deleted upon the program's completion.

To initiate this aspect of cognitive profiling, I've developed a version of a Cognitive Profiling Form. This preliminary instrument is designed as a self-report tool, allowing individuals to provide subjective insights into their own cognitive profiles. It's structured to gather both quantitative (albeit based on self-perception) and qualitative data across various facets of cognition. While the Cognitive Profiling Form is a non-standardised self-report, it still offers valuable preliminary insights for my research. It provides an initial, subjective perspective on how individuals perceive their own cognitive skills. The form also allows me to gather early, detailed qualitative data, such as students' descriptions of their study habits or perceived strengths and weaknesses, which can inform the selection of more standardised assessments later in the study. It serves to illustrate both the potential and the limitations of self-reporting in cognitive evaluation. It contributes data about perceived cognitive abilities, offering a complementary perspective to objective measures of cognition. I acknowledge that its limitations necessitate the inclusion of validated and standardised cognitive measures to provide a more rigorous and comprehensive assessment. By using this form alongside more established methods, I can compare the relative strengths and weaknesses of different approaches to cognitive assessment. Including this form in my dissertation is valuable for the initial exploratory phase of the research, helping me to generate hypotheses and identify specific areas that warrant further investigation with validated tools. Therefore, despite its reliance on self-reporting, I believe the Cognitive Profiling Form offers useful initial insights and plays a specific, important role within the overall research design.

Cognitive task performance record form [Appendix B]

Building upon the insights gained from exploring self-perceived cognitive abilities, my research also incorporates the 'Cognitive Task Performance Record Form.' This instrument takes a different approach, focusing on the objective assessment of key cognitive domains, specifically attention, memory, and processing speed. My aim here is to construct a comprehensive profile of individual cognitive strengths and weaknesses based on observed performance. By comparing an individual's performance against data from a larger population, this form can inform the development of highly personalised learning strategies and potentially uncover underlying cognitive deficits that may be impacting their academic progress. It's important to me that the students understand the purpose and rationale behind these tasks, and I will ensure this is clearly explained to them.
Unlike the self-report nature of the previous form, the Cognitive Task Performance Record Form is designed to capture observed performance on specific, well-defined cognitive tasks. This shift in methodology allows for a focus on objective measures rather than relying solely on an individual's subjective perceptions. This form records participant demographics (ID, date, age, gender) for context and potential correlations. For each cognitive task, it documents the name, description, and instructions to ensure my research can be replicated. It captures also performance through completion time and accuracy, alongside qualitative details on errors, strategies, and self-rated confidence. The form also includes space for general observations and subjective ratings of cognitive abilities like problem-solving, offering a well-rounded view.

The VARK questionnaire [Appendix C]

In my exploration of individual learning preferences within the NSLE, I've considered the VARK questionnaire, a tool that categorises learners into visual, auditory, reading/writing, and kinaesthetic styles. While I'm mindful of its acknowledged limitations, particularly the potential for oversimplifying the complex nature of how individuals learn, I believe that when applied thoughtfully and strategically, the VARK questionnaire can still offer valuable insights. Specifically, it can contribute to the design of more engaging and multi-sensory learning experiences within the NSLE framework. To mitigate the limitations of VARK, I plan to use it as one data point among others, triangulating its findings with observational data and student self-reports to gain a more nuanced understanding of learning preferences. I will also emphasise that VARK provides a starting point for considering individual differences rather than a definitive classification of learners.

GAD-7 questionnaire form [Appendix D]

In my commitment to understanding the holistic well-being of students within the NSLE, I've chosen to employ the Generalised Anxiety Disorder 7-item scale (GAD-7) questionnaire. My decision to utilise this particular instrument stems from its well-established reliability and validity as a measure of anxiety levels, making it a sound choice for this aspect of my research.

The student learning behaviour and preference observation form [Appendix E]

To gain a rich understanding of how students behave and interact within the NSLE classroom environment, I will be employing observational assessments. These direct observations promise to yield valuable insights into the nuances of the learning process as it unfolds. Prior to commencing these observations, I will ensure complete transparency with the students by thoroughly explaining the observation form itself, detailing the specific behaviours and interactions I will be recording, as well as the protocols I will be implementing to minimize any potential observer bias. This structured approach to observation will provide a direct window into the dynamics of our learning environment, while simultaneously upholding principles of transparency and methodological rigor.

Emotional intelligence test [*Appendix F*] **and questionnaire** [*Appendix G*]

Recognising the profound impact of emotional intelligence [*EI*] on students' overall development and academic trajectories, I've chosen to incorporate comprehensive EI assessments within the NSLE project. Specifically, I will be utilising the Mayer-Salovey-Caruso Emotional Intelligence Test [Appendix F] alongside the Emotional Intelligence Questionnaire [Appendix G]. My rationale for prioritising EI stems from the well-established understanding of its role in managing one's own emotions and fostering empathy towards others [Goleman. 2001 ; Bar-On. 1997]. A body of research has linked strong EI to well-being and improved academic outcomes [Brackett et al. 2019 ; Durlak et al. 2011 ; Diener. 2006], underscoring its importance within an educational context.
Conversely, I am also keenly aware that a lack of well-being can create barriers to learning, potentially contributing to behavioural challenges and even increasing the risk of mental health difficulties [Huppert et al. 2013 ; Evans et al. 2005]. Therefore, my commitment to assessing and actively supporting the emotional intelligence of students within the NSLE is not just about fostering academic success; it's a vital component of promoting their holistic development and ensuring a positive and supportive learning environment for all.

6.6 Data integration

A critical aspect of harnessing the full potential of the NSLE involves the strategic integration of multiple data sources. My approach to data integration focuses on identifying meaningful trends and enabling well-informed, data-driven decisions regarding pedagogical practices and student support. This process necessitates employing several key techniques. For instance, data standardisation will involve converting all assessment scores to a common scale, e.g. z-scores [*Colan. 2013*] to ensure consistency across different Learning Management Systems. Data transformation will include restructuring qualitative data from student feedback forms into a format suitable for thematic analysis software.

Data cleansing will address inaccuracies such as missing values, using imputation methods and outliers, by applying statistical rules. Finally, data profiling will involve generating descriptive statistics for each data source to understand its distribution and potential biases. To further data governance and security within the NSLE project, I will be applying data warehousing principles [Nambiar et al. 2022] to consolidate information into a secure, central repository. I believe a strategic and thoughtful approach is to truly unlock the power of our data [Vadlamani et al. 2023]. This includes not only standardising data formats [Gal et al. 2019] and ensuring data quality through cleaning processes but also utilising centralized repositories [Nookala et al. 2*020*]. I recognise the vital importance of ongoing monitoring to maintain data integrity and relevance.

Effective data integration, as I envision it within the NSLE [Yan et al. 2017], will be a cornerstone of our data-driven decision-making in education. This endeavour relies heavily on collaborative partnerships between educators, administrators, and other key stakeholders. To proactively identify students who may be facing emotional challenges, I plan to implement regular assessments of both Emotional Intelligence and overall well-being [Antonopoulou. 2024 ; Cowie et al. 2004]. Finally, to differentiate between data storage and analysis, it's important to note that while data warehousing provides a consolidated foundation for our information, data mining, on the other hand, will involve the application of various AI and machine learning algorithms to uncover hidden patterns and valuable insights within this integrated data [Lantz. 2019].

6.7 Data implementation

To assess the effectiveness of the NSLE, I will be implementing the evaluation framework detailed in *chapter 12.1*. This framework is specifically designed to identify patterns by exploring the connections between various data types. My goal is that this pattern recognition will enable the development of truly tailored interventions and provide a mechanism for monitoring individual student progress over time. The process of data interpretation, through which raw information is transformed into actionable insights for educators, will involve several key stages. These include data preparation, developing a deep understanding of the data's nuances, actively seeking out meaningful connections between different data points, and uncovering the underlying meaning and implications for learning and teaching.

6.8 Data analysis

I firmly believe that an approach to data analysis offers a powerful solution for gaining a truly holistic understanding of the learning processes within complex educational environments like the NSLE. My strategy for data analysis involves a carefully orchestrated sequence of four interconnected stages, summarised below, beginning with the phase of data preparation. In this initial stage, as exemplified by the work of researchers like Dhawas [Dhawas et al. 2*024*], I will prepare the raw data for subsequent analysis through cleaning to address inconsistencies, thoughtful transformation to ensure compatibility and integration.

Stage 1: Data preparation
- Data is prepared for analysis by cleaning, transforming, and integrating it.

Stage 2: Feature extraction
- Quantitative data
  - Statistical methods like PCA and ICA are employed to extract meaningful patterns from numerical data.
- Qualitative data
  - Thematic analysis and content analysis are used to identify patterns and themes within textual and visual data.
- Multimodal data
  - Machine learning algorithms, including deep learning and transfer learning, are employed to extract features from multimodal data.

Stage 3: Pattern identification
- Descriptive analytics
  - Calculating statistics and visualising data to identify trends and correlations.
- Inferential analytics
  - Applying statistical models, such as regression analysis and hypothesis testing, to identify relationships between variables.
- Machine learning
  - Utilising learning algorithms to identify complex patterns in data.

Stage 4: Insight generation
- Interpretation
  - Providing context and meaning to the results, considering the research questions and objectives.
- Visualisation
  - Using data visualisation techniques to communicate the findings effectively to various stakeholders.
- Recommendations
  - Developing evidence-based recommendations for educational practitioners, policymakers, and researchers.

6.9 Data visualisation

A key element of translating the rich data within the NSLE into actionable insights involves the strategic use of data visualisations, which I intend to share effectively with educators, policymakers, and, where appropriate, the students themselves. To ensure these visualisations are influential and trustworthy, I will adhere to best practices, including clearly defining the underlying research questions, ensuring the accuracy of the data being presented, and providing transparent and accessible interpretations of the visual representations. To address the inherent complexities of working with often incompatible data sources within educational settings, my research proposes the development and implementation of an integrated system.
This system will strategically combine the power of machine learning algorithms, a data warehousing infrastructure, and user-friendly interactive visualisation tools, potentially accessing platforms such as Matlab, Octave or Python. By establishing clear data protocols, ensuring their consistent application, conducting regular and insightful analyses, and supporting this system with appropriate professional development for users, I aim to overcome the challenges posed by disparate data formats. I envision that the application of machine learning within this system will enable the creation of nuanced and informative student profiles. These profiles, in turn, will be instrumental in facilitating the development of truly personalised learning plans and the implementation of targeted interventions designed to meet individual student needs effectively.

6.10 AI-driven analytics in education and research

One of the exciting possibilities I'm exploring within the NSLE project involves researching predictive models. As outlined below, these models hold the potential to proactively identify students who might be at risk of falling behind.

Heightened student outcomes
: Timely identification of at-risk students enables proactive support, thereby mitigating learning difficulties and improving overall academic performance.

Data-driven curriculum development
: Insights derived from predictive models can inform the refinement of curricula and teaching strategies, ensuring a more effective and efficient learning environment.

Optimised resource allocation
: Predictive models can inform resource planning and allocation, ensuring that educators have the necessary tools and support to deliver high-quality instruction.

Personalised learning pathways
: Data analytics can aid in the creation of tailored learning paths, catering to the unique needs and abilities of individual students.

Learning process personalisation

By analysing student brain activity, educators can tailor their instruction t better meet the needs of each student, enhancing the overall learning experience.

Predictive modelling of learning outcomes

Advanced algorithms can forecast learning outcomes, enabling educators to anticipate and address potential challenges before they arise.

Automation of administrative tasks

Predictive models can automate routine administrative tasks, freeing educators to focus on high-impact activities that promote student learning.

Support for students with special needs

Data-driven insights can inform the development of targeted support strategies for students with special needs, ensuring that they receive the tailored assistance they require.

Ongoing learning support

Predictive models can provide ongoing support and guidance throughout the learning process, ensuring that students receive continuous feedback and encouragement.

Beyond early identification, I also anticipate that these predictive capabilities can inform strategic decisions regarding curriculum design and the allocation of educational resources, paving the way for truly personalised learning experiences tailored to individual student needs. A core element of my vision for the NSLE involves the strategic application of Learning Analytics [LA]. As further detailed below, I believe LA offers potential not only to predict student success with greater accuracy, aligning with principles of early intervention, but also to provide valuable insights for optimising course design and enhancing the effectiveness of our teaching methodologies. This approach is informed by constructivist learning theories, which emphasise the importance of data-driven feedback for continuous improvement of teaching practices.

Student success prediction

Identify at-risk students

Develop targeted support strategies

Personalised learning

Tailor instruction to individual needs

Increase student engagement

Course optimisation

Identify effective instructional strategies

Improve student outcomes

Faculty development

Identify areas for professional growth
Develop targeted training programs

For the strategic application of learning analytics within the NSLE to truly yield meaningful insights and impact student outcomes, I recognise that the foundation must be built upon high-quality data. I firmly believe that addressing privacy and security concerns with the utmost diligence is paramount throughout this endeavour.
The effective implementation and utilisation of learning analytics necessitate a certain level of technical expertise. I argue that an investment will be in order for comprehensive training for educators, to fully harness the transformative power of learning analytics within our neuro-synaptic learning environment.

6.11 Learning analytics

I firmly believe that the strategic application of learning analytics [*LA*] holds transformative potential for higher education, particularly within innovative environments like the NSLE. By thoughtfully analysing the rich data generated by student interactions, I envision educators gaining unprecedented insights into specific learning gaps, enabling us to optimise instructional approaches with greater precision and personalise the learning journey for each individual.
For me, the power of LA lies in its ability to illuminate areas where targeted support is most needed, to inform the iterative refinement of instructional design, and to empower educators to make truly data-driven decisions that can significantly boost student motivation and academic achievement. I anticipate that by effectively exploring the nuanced insights provided by LA, educators within the NSLE will be better equipped not only to improve overall academic performance but also to implement targeted strategies designed to rekindle and sustain a genuine interest in learning among our students.

6.12 Importance of AI-driven analytics in education and research

One of the most compelling aspects of the NSLE, in my view, lies in the potential of AI to truly empower educators in personalising the learning journey. I envision AI systems capable of identifying each student's unique strengths and areas for growth, proactively predicting potential learning challenges, providing timely and tailored feedback, and even highlighting areas within the curriculum that may require further development or refinement. However, I firmly believe that realizing this transformative potential hinges on a steadfast commitment to prioritising high-quality data, thoughtful and ethical development practices, and ethical guidelines to ensure the creation of truly effective and equitable educational experiences.
I am particularly excited by the opportunities AI presents as a powerful toolkit for educational research within the NSLE. By intelligently analysing the rich datasets generated by our learning technologies, AI can help us uncover patterns in student learning and predict various learning outcomes, potentially revealing common and divergent learning pathways. This invaluable information can then serve as a solid

foundation for evidence-based curriculum development and the continuous improvement of our teaching practices. While I acknowledge the remarkable ability of AI to process vast amounts of data with speed and efficiency, I also firmly maintain that the irreplaceable expertise of human educators is for interpreting the nuanced insights gleaned from this analysis and making informed and appropriate decisions that truly benefit our students.

A central tenet of my research within the NSLE involves the thoughtful integration of AI for sophisticated data analysis, driving a truly personalised learning environment. I envision this encompassing the dynamic adjustment of curricula based on a nuanced understanding of individual student strengths and areas for growth, as well as the innovative use of AI to generate adaptive assessments that respond in real-time to student progress. However, I also recognise that realizing this vision necessitates a planned approach to data management, coupled with the careful development of clear standards to ensure data comparability across various sources and platforms. This overarching framework emphasises the synergistic integration of AI with data-driven decision-making, alongside the critical need for standardisation protocols. I firmly believe that comprehensive educator training and ongoing support will be key to the successful and ethical implementation of this approach within the NSLE.

CHAPTER 7
ASSOCIATIVE LEARNING

In this chapter, I discuss associative learning, a principle that I consider fundamental to effective learning within the NSLE. My exploration reveals that learning is an active process of weaving new concepts into our existing knowledge by forging robust neural connections. These connections enable learners to construct intricate cognitive networks that enhance the recall and application of knowledge. This inherent power of association, I argue, presents a significant opportunity for educators to design learning experiences that are not only engaging but also deeply effective, fostering profound understanding and promoting lasting retention.

My perspective aligns with a vision of education that prioritises active, multi-sensory engagement, a departure from the passive absorption of information that has often characterised traditional educational models. The emergence of AI-powered education offers a compelling glimpse into this future, promising the creation of adaptive learning environments that cater to individual student needs. The integration of hands-on activities and immersive simulations empowers students to interact with the subject matter in a tangible and meaningful way, cultivating a richer and more enduring comprehension.

7.1 Association fundamentals

Within the framework of the NSLE, I investigate the principle of association, which I believe is foundational to effective learning. As Anderson compellingly argues, learning is not about the acquisition of isolated facts; it is fundamentally about the integration of new information with our pre-existing knowledge, experiences, and emotions [*Anderson. 2000*]. This dynamic integration is crucial for comprehension, retention, and the application of knowledge. By actively forging connections, learners construct an interconnected network that enhances the recall and utility of what they learn [*Rumelhart. 2017*].

Pedagogical tools such as mnemonic devices and thoughtfully designed visual aids serve as potent catalysts in this associative process [Atkinson et al. 1975]. They provide memorable scaffolding and enable learners to visualise the relationships between concepts. However, the effectiveness of these associations is not uniform; it depends on factors such as the perceived relevance of the new information, its distinctiveness from existing knowledge, and its vividness in the learner's mind.

Schema theory, as introduced by Widmayer, supports this perspective, asserting that learners actively organise new input within their existing mental frameworks, or schemas, highlighting the learner's active role in constructing their own understanding [*Widmayer. 2004*]. Encoding, the critical initial stage of memory formation, involves transforming raw information into a format our brains can store. My research, and the broader literature, consistently points to the power of effective encoding strategies, such as elaborative rehearsal, making meaningful connections to existing knowledge, and the use of vivid mental imagery, in significantly bolstering memory formation [*McDermott et al. 2018* ; Karunarathna et al. 2024].

Conversely, retrieval, the process of accessing stored information, is not a simple replay [*Tulving & Thomson. 1973*]. It's a reconstructive process heavily influenced by the strength of the initial memory trace and the presence of effective retrieval cues. The phenomena of context-dependent and state-dependent memory vividly illustrate how our learning environment and internal state at the time of learning can profoundly impact our ability to recall information later. Consolidation, the gradual strengthening of neural connections that underpins long-term memory formation, is vital [*McGaugh. 2003*]. This transfer of memories from short-term to long-term memory is a key area where the NSLE can offer advantages. At the heart of this lies neural plasticity, the brain's ability to adapt and reshape its connections [*Dudchenko. 2001*]. This adaptability is the biological foundation of learning and memory. As the National Research Council aptly noted, the brain actively weaves new inputs into the existing fabric of our knowledge, emotions, and experiences [National Research Council. 2000].

This integration, in my view, is fundamental to effective learning. The process often begins with sensory input, creating a fleeting mental snapshot within our working memory. From there, the brain seeks out patterns and connections between this novel information and our existing cognitive structures. To solidify these connections, new neural pathways are forged, and existing ones are reinforced [Brown et al. 2012]. Once these pathways become sufficiently strong, the information transitions into long-term memory. Therefore, to effectively employ the power of association within the NSLE, I contend that educators must embrace a multi-sensory approach [Latour. 1984]. This involves thoughtfully combining verbal explanations with compelling visual aids and engaging hands-on activities that allow learners to experience concepts directly. Actively encouraging learners to explicitly connect new information to their own prior experiences is a particularly potent strategy for enhancing the depth and durability of learning. By intentionally harnessing this fundamental principle of association, my aim is to design engaging and effective learning experiences within the NSLE, fostering not just surface-level understanding but deep, lasting retention [*Meylani. 2024*].

The Neural Mechanisms

As I research deeper into the neurobiological underpinnings of association formation within the NSLE, several key mechanisms come into focus. Hebbian learning, with its proposition that the simultaneous firing of neurons strengthens their synaptic connections, provides a foundational principle [*Strom. 2007*]. This concept is supported by research on synaptic plasticity. Long-Term Potentiation [*LTP*] [*Lømo. 2018*], a compelling manifestation of synaptic plasticity [*Benfenati. 2007*], is central to learning processes within the NSLE.

This enduring strengthening of synaptic connections is a critical neural mechanism for the formation of new memories [Lamprecht et al. 2004]. Through these potentiation processes, the neural pathways underlying associations are forged and reinforced. These dynamic processes occur within the constantly evolving architecture of neural networks that process information. New associations necessitate reorganisation and refinement within existing neural networks, according to *Zaknich. 2003*. This neural "rewiring" integrates novel information with existing knowledge structures, cultivating a richer, interconnected understanding.

The Cognitive Mechanisms

Beyond the neural mechanisms, I consider the role of specific cognitive processes in forming associations, the bedrock of learning within the NSLE. As Olsen have highlighted, our cognitive machinery actively shapes what we learn and how we connect it to what we already know [Olsen et al. 2012]. Through focused attention, we prioritise relevant stimuli, selecting what will be processed and integrated into our knowledge base. Working memory is an active workspace where new information is held and manipulated, allowing for integration with pre-existing cognitive structures. This active integration is where initial connections form. Semantic processing depth on the other hand, determines the strength and richness of associations. Engaging with the meaning of new information establishes connections within our semantic network. Deeper semantic processing facilitates linking to related concepts, will enrich the learning experience within the NSLE.

7.2 Types of Associations

As my research progresses, the landscape of association types become central to my understanding of effective learning within the NSLE. The nature of these connections significantly influences how learners construct knowledge. A nuanced understanding of different associative mechanisms and the strategic use of techniques that employ them offers educators a powerful toolkit for designing engaging and effective learning experiences. The different types of associations are summarised below, together with a description of each. An example of the association demonstrate clearly where to apply each type of association.

Semantic association
    Connecting new information to existing concepts or ideas.
        Associating gravity with falling objects.

Contextual association
    Linking new information to specific situations or environments.
        Associating a landform with a specific region on a map.

Emotional association
    Connecting new information to personal experiences or emotions.
        Associating migration with feelings of courage and resilience.

By consciously considering how different types of associations are formed and recalled, we can move beyond memorisation towards fostering deeper, more interconnected understanding. This has the potential to significantly heighten long-term retention and improve learning outcomes. It's about moving from simply presenting information to actively facilitating the creation of meaningful and lasting connections within the learner's cognitive architecture. Drawing on my exploration of the NSLE, I appreciate the power of combining instructional strategies to cultivate meaningful associations in learners. It's not enough, I believe, to simply present new concepts; the step lies in actively bridging the gap between this novel information and the learners' existing real-world applications or their own personal experiences. When we intentionally forge these connections, we make the learning process far more relevant and resonant.
In my own pedagogical experiences and in reviewing effective teaching practices, I've consistently observed the profound impact of active learning methodologies. Posing genuinely thought-provoking questions, for instance, serves as a powerful catalyst, prompting students to actively retrieve and reflect upon their prior knowledge. This process of connecting new information to what they already know not only deepens their understanding of the current material but also fosters a more profound and lasting engagement with the subject matter. It transforms learning from a passive reception of facts into an active construction of knowledge, precisely the kind of deep processing that the NSLE aims to facilitate.

7.3 Design for Associative Learning

One of the aspects of the NSLE that I find particularly compelling is its inherent capacity for personalised learning. It moves beyond a one-size-fits-all approach by intelligently tailoring instruction and integrating interactive modules, such as engaging simulations, gamified learning experiences, and adaptive quizzes, to meet individual student needs. The provision of real-time feedback further refines this personalised experience, creating a dynamic and responsive learning loop.

From my perspective, the automation of routine tasks within the NSLE holds promise for educators. By freeing up their time from administrative burdens, the system allows them to focus on what truly matters: providing personalised guidance, fostering deeper student engagement, and nurturing individual learning trajectories.

However, I also recognise that the success of such a sophisticated environment hinges critically on the accuracy, fairness, and transparency of the underlying data. The NSLE, and indeed any AI-driven educational system, must be designed to ensure equal opportunities for all learners and to be readily understandable by both students and educators. The "black box" of AI is a concern I address directly in *chapter 12.4*.

The analytical power of AI tools within the NSLE offers the potential to reveal often-hidden connections across seemingly disparate subjects, thereby promoting critical thinking and a more nuanced, holistic understanding of the curriculum. For instance, as *Woolfson* and *Gingras* have pointed out, a deep understanding of differential and integral calculus in Mathematics is often a prerequisite for tackling complex problems in Physics, a connection further elaborated in [*Section 7.8*] of my work [*Woolfson et al. 2007* ; *Gingras. 2001*]. AI can illuminate these interdisciplinary relationships in ways that traditional curriculum design might overlook.

This approach to curriculum design, however, is not without its challenges. The very algorithms that power the NSLE rely heavily on extensive educational data, and as Sweller and others have cautioned, inaccurate or biased data can inevitably skew curriculum design and perpetuate existing inequalities [*Sweller. 1988*]. Therefore, ensuring transparency in the rationale behind the curriculum, how the AI arrives at its recommendations, is vital for both educators and students to maintain trust and understanding.

Indeed, by harnessing AI's analytical capabilities responsibly, I believe educators can uncover subtle patterns and relationships between seemingly unrelated subjects, fostering a richer, more interconnected learning experience that mirrors the brain's own associative processes. Research consistently indicates that a well-balanced curriculum, thoughtfully integrating both complex and foundational concepts, significantly encourages comprehension and long-term knowledge retention. AI-powered tools within the NSLE can be instrumental in facilitating this balance by intelligently identifying prerequisite knowledge and dynamically personalising learning pathways to cater to individual student needs, thereby minimizing cognitive overload.

The effectiveness of AI-driven education within the NSLE is contingent upon the quality and representativeness of the data it learns from. Biases embedded within the data can insidiously lead to skewed curriculum design and inequitable outcomes. Therefore, prioritising data quality, actively mitigating bias, and ensuring transparency in AI-driven decision-making are not merely desirable but paramount for the successful and ethical implementation of AI-powered education within the NSLE.

7.4 Assessment and Feedback

In my exploration of effective assessment strategies, I've become increasingly aware of the limitations inherent in traditional methods, which can, I believe, inadvertently foster student disengagement and often fail to capture the comprehensive understanding of complex subject matter that we strive for. To address these limitations, I've been particularly drawn to the incorporation of associative learning techniques, such as concept mapping, researched by Novak et al. 2008 and mind mapping techniques, as researched and suggested by *Buzan. 2024*, as compelling alternatives.

These methodologies, in my view, offer a pathway towards a dynamic and interactive assessment experience. Rather than simply testing recall, they encourage students to actively engage in reflective practices, identify areas where their understanding requires further development, and proactively adjust their learning strategies. Mind maps, in particular, as *Wright* aptly notes, are powerful tools for both the learning process itself and for assessment [Wright. 2006]. They provide a visual canvas for students to brainstorm and explicitly connect concepts, making their thought processes more tangible.

I've found that this visual representation fosters a deeper level of understanding by encouraging students to externalise and visualise their internal cognitive connections. The resulting mind maps can offer valuable insights into a student's cognitive organisation and the pathways of their understanding, prompting an element of reflection on their own learning [*Buzan. 2024*]. The collaborative potential of mind maps also makes them well-suited for group work, fostering shared brainstorming and the collective construction of knowledge. Drawing on frameworks, introduced as Bates's 7-step guide to mind mapping [Bates. 2019], I see the emphasis on visual creativity as a key strength. Encouraging students to start with a central idea, represent it with a core image, and utilise colour to upgrade the map's structure taps into different cognitive modalities [*Fig. 7.1*].

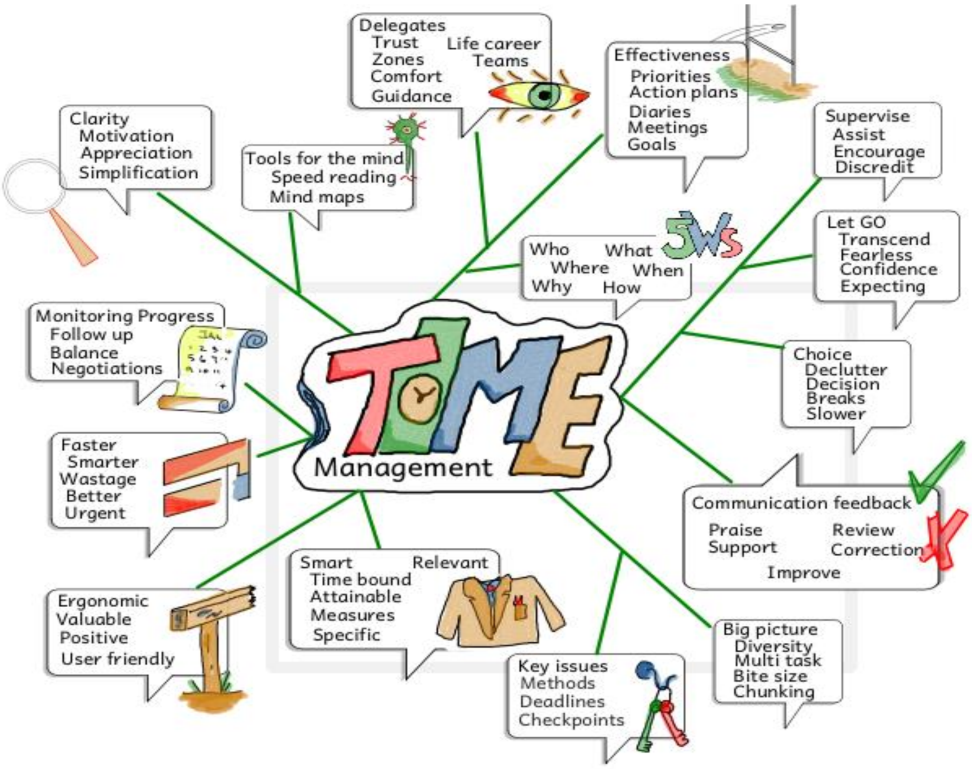

Figure 7.1. Visualizing integrated learning through student-built mind maps.

The very layout and content of the mind maps become unique to each student or group, reflecting their individual or collective understanding and the specific connections they are making. The use of curved lines to link ideas and the strategic replacement of single keywords with pictures further stimulate visual thinking and, I believe, as I experienced myself, together with my students, significantly improve both understanding and subsequent recall. This approach moves assessment beyond mere regurgitation and towards a more holistic evaluation of a student's interconnected understanding. One of the core innovations within the NSLE that I am particularly excited about is its intelligent use of AI algorithms to significantly add to student comprehension and long-term retention. A central feature in achieving this is the NSLE's capacity to dynamically generate a personalised mind map for the student. [*Fig. 7.2*]. An AI demonstration to tailor and contribute to each student's individual learning journey.

Specifically, the system is designed such that after a student completes each learning module, an embedded AI algorithm springs into action, analysing their interactions with the material and their performance on any associated assessments. This granular analysis allows the AI to pinpoint the key concepts covered and to identify specific areas where the student encountered difficulties.

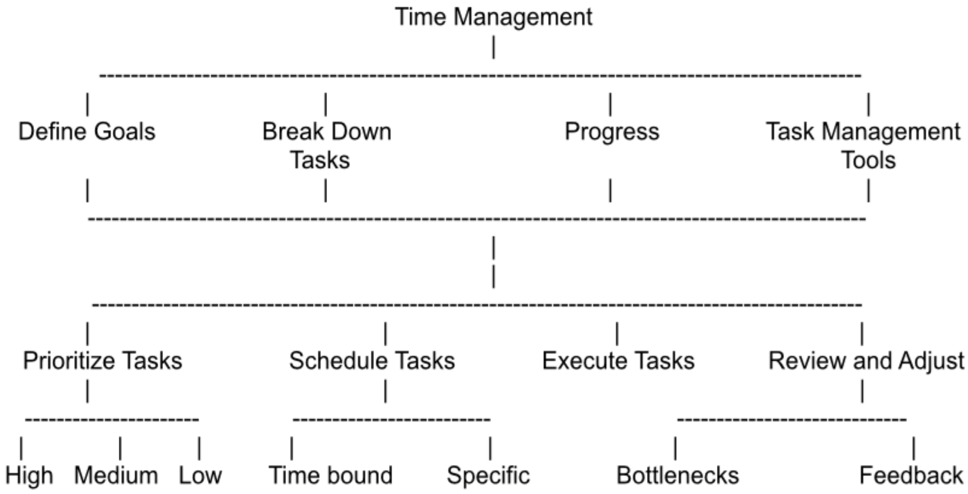

Figure 7.2. Ai-assisted mind map generation: key elements of time management.

The outcome of this analysis is a visually rich mind map, automatically generated and presented to the student. This mind map serves as a concise visual reminder of the module's core content, with particular emphasis, perhaps through visual cues like colour or node size, on the topics that proved challenging for that individual learner. As illustrated in *Fig. 7.2*, the algorithm can produce mind maps on topics like time management. This particular example offers students a schematic overview of the lesson's essential elements. The design of the NSLE's mind mapping function is firmly rooted in well-established principles of cognitive science, acknowledging the widely recognised efficacy of visual representations for both the consolidation and subsequent retrieval of knowledge [*Buzan. 2024*]. By explicitly and visually connecting concepts, these personalised mind maps actively foster the development of cognitive schemas, which, as we know, are fundamental to enhancing long-term memory formation.

The NSLE goes beyond simply generating these visual aids; it intelligently integrates them with corresponding assessments, creating a seamless and powerful feedback loop that actively reinforces learning and encourages self-reflection. To illustrate this, consider a student navigating an algebra module within the NSLE. The system's AI might identify terms such as 'algebra,' 'exponents,' 'powers,' 'logarithms,' 'adding,' 'subtracting,' and 'brackets' as central to the module. However, if the student's performance indicates a particular struggle with logarithmic functions or complex algebraic expressions involving brackets, the AI will weight these areas accordingly in the generated mind map. Subsequently, the algorithm constructs a hierarchical visual representation, with 'algebra' perhaps as the central node, branching out into key 'operations',addition, subtraction, exponents, logarithms and fundamental 'concepts', brackets, order of operations. The AI generated version below, demonstrates the simplicity with which the algorithm links and joins the relative aspects of the topic together.

```
                              Algebra
                                 |
                    -----------------------------------
                    |                                 |
               Operations                    Fundamental Concepts
                    |                                 |
  -----------------------------------------------     ------------------
  |           |             |              |          |                |
Addition  Subtraction  Exponents  Logarithms     Brackets  Order of Operations
```

The mind map I use for my students is displayed in Figure. 7.3. This visual organisation not only clarifies the relationships between these terms but can also explicitly illustrate, for instance, how the operations of exponents and logarithms are applied within algebraic manipulation, and how the strategic use of brackets dictates the procedural sequence. This personalised visual representation offers a powerful tool for students to revisit, consolidate, and master the subject material. In my view, the NSLE's dynamic generation of personalised mind maps represents a true stride forward in personalised learning. It offers students far more than just a concise visual reminder of the material; it acts as an intelligent compass, proactively highlighting areas where focused attention and further exploration might be most beneficial.

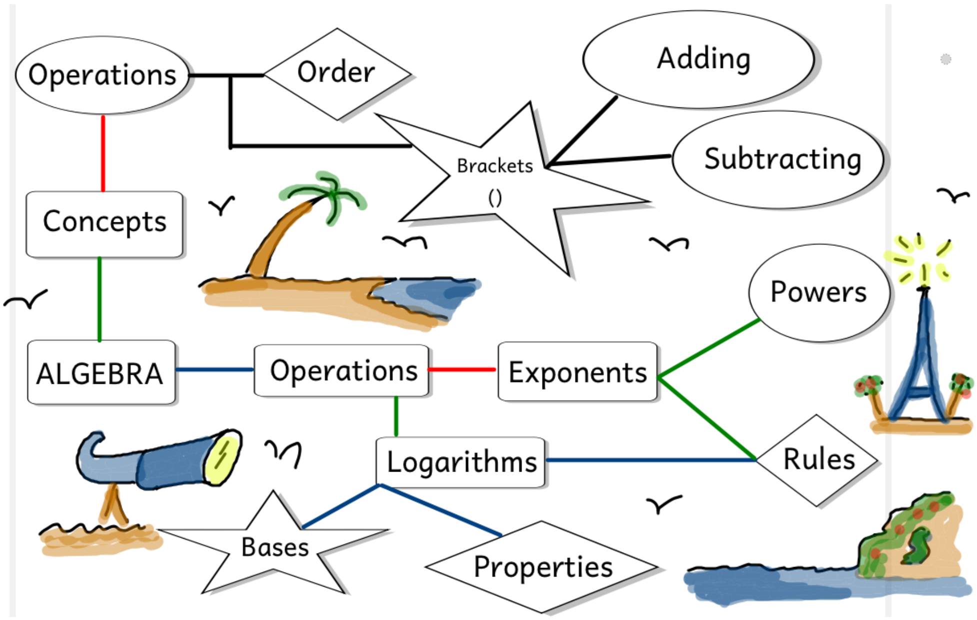

Figure 7.3. Teacher's perspective on key term relationships.

This proactive reinforcement of knowledge, intelligently facilitated by the AI-driven mind mapping capabilities, holds immense potential to substantially improve overall learning outcomes and encourage the efficacy of educational interventions. Indeed, a core objective of this research is to evaluate the specific impact of the AI mind mapping feature on student learning, thereby contributing meaningfully to the body of literature on AI assisted pedagogy and its transformative potential within educational contexts.

Assessment Models

A cornerstone of effective pedagogy, as I see it, lies in assessment that empowers students to not only gauge their current progress but also to intelligently adapt their learning strategies moving forward. The NSLE distinguishes itself by integrating sophisticated AI-powered assessment models designed to cultivate a more holistic and interactive experience than traditional methods often afford. These models go beyond simply marking right or wrong; they track a student's ability to form correct and meaningful associations, providing nuanced, real-time feedback that actively fosters a deeper and more interconnected understanding of the subject matter. Through the continuous, real-time analysis of student responses, the NSLE possesses the remarkable capacity to pinpoint individual strengths, specific areas of weakness, and even preferred learning styles. I envisage the NSLE operate in such a way that its AI algorithms thoughtfully incorporate a multi-sensory approach to learning, recognising the profound impact of engaging multiple senses on both student engagement and the long-term retention of knowledge.

7.5 Gamification

The strategic integration of gamification, the incorporation of game design elements into non-game contexts, as Surve and colleagues [*Surve et al. 2024*] have recently underscored, represents, in my view, a particularly promising avenue for enhancing student engagement and intrinsic motivation within the educational landscape. Indeed, the summary below illustrates a range of potential AI-driven gamification strategies across several subject areas. It serves as a snapshot into what AI may suggest in applying gamification to specific subjects or even topics. I suggest allowing AI to provide concrete examples of its remarkable capacity to facilitate deeper learning and heightened engagement for both students and educators alike.

Language arts

- Narrative network
  - Students collaboratively build stories, with AI creating branching paths. The student continue along the branching pathways and allow AI feedback on their ideas and writing.
- Vocabulary voyage
  - Students explore the planets representing vocabulary categories. The planets symbolise synonyms, antonyms, verbs and nouns. AI feedback personalises learning and identifies areas for practice.

Mathematics

- Fractal farm
  - Students manage a virtual industry of their choice, using math to improve product management. AI analyses their strategies and gives recommendations.
- Equation expedition

Students solve math equations in an adventure game. AI adjusts the difficulty to match their skill level.

Science

Ecosystem engineer
Students build and manage virtual ecosystems. AI models of ecological interactions are employed. AI also gives feedback on the stability and sustainability of the system.
Molecular maestro
Students create new virtual compounds. AI analyses their designs and gives feedback on properties and potential uses.

This potential strategies, I believe, is amplified significantly when thoughtfully combined with the adaptive capabilities of AI. Indeed, one of the key areas I am exploring is how the incorporation of AI-powered gamified learning experiences, can actively allow and encourage students to build and generate meaningful associations as they progress through the curriculum. Building upon the potential of gamification, I've found that the integration of AI offers a powerful catalyst for creating transformative learning experiences. AI significantly strengthens gamified learning by enabling the personalisation of instruction, the delivery of immediate and adaptive feedback, and the dynamic adjustment of challenges to meet individual student needs. This synergy, in my analysis, fosters a learning environment that is not only more engaging but also demonstrably more effective in promoting deep understanding.

Gamification through immersive RPG design for Mathematics and Physics education

My research investigations into the transformative potential of a sophisticated and highly interactive Role-Playing Game [RPG] as a vehicle, significantly enhance student engagement and fostering a deeper understanding of core subject concepts. At its heart, this investigation explores how creating a truly captivating learning environment, one where abstract scientific principles are not merely presented but actively experienced and applied within an immersive narrative, can remodel student learning. This innovative approach is guided by the NSLE framework, a model grounded in the principles of cognitive science. To evaluate the impact of this NSLE-integrated RPG on a range of critical learning outcomes, including conceptual understanding, student motivation, and attitudes towards STEM (Science, Technology, Engineering, and Mathematics) subjects, my study employs a mixed-methods research design [Chapter 13.3].
My concept for an educational game designed to deeply engage students with mathematics and physics, is outlined below. I believe that by carefully intertwining compelling game mechanics with a rich narrative and educational integration, we can create a powerful tool for fostering both understanding and a love for these subjects. The walk-through of the core elements of this design, from character attributes rooted in subject-specific skills to the strategic application of knowledge in a dynamic combat system is laid out in detail in Appendix AL, . The game's design incorporates a range

of reward systems, as summarised below together with possible interactive elements to maximize student engagement.

Reward systems

AI provides points, badges, or recognition for completing tasks, reinforcing positive behaviours.

Challenges and quest

AI creates engaging tasks and daily and weekly challenges that require students to apply their knowledge and build associations.

Interactive simulations

The NSLE incorporates AI-powered simulations for experimentation and problem-solving.

Social learning

AI facilitates collaboration and knowledge exchange among students.

Adaptive difficulty adjustment

AI dynamically adjusts the difficulty level based on student performance.

Feedback and reflection

AI provides personalised feedback and opportunities for reflection.

I'm particularly interested in the role of AI in driving these features, from providing motivating rewards like points and badges to generating dynamic challenges and facilitating collaborative learning. In the following section, I will outline how AI will be used to create interactive simulations and deliver a rewarding learning experience.

Core game mechanics: Fostering conceptual understanding through active participation

The game's core design directly links in-game actions and progress to mathematical and physical principles. Instead of standard classes, students choose roles like "Engineer," "Scientist," or "Magician," each inherently tied to specific math and physics strengths. For example, an Engineer might excel at mechanics problems, while a Scientist is strong in data analysis, encouraging students to see these subjects in action.

Character attributes move beyond generic stats to represent specific mathematical and physical skills, such as "Precision" for calculation accuracy or "Insight" for understanding complex formulas, reinforcing their importance. A branching skill tree mirrors the interconnectedness of math and physics topics like Algebra, Calculus, Mechanics, and Electromagnetism, allowing for specialization and exploration.

Experience points are earned through engaging with the subject matter in in-game puzzles testing knowledge (like projectile motion simulations or circuit design) and quest-based learning. Research quests involve investigating real-world science, while experimental design quests simulate scientific processes. Collaborative quests require teamwork and the combined skills of different roles. The turn-based combat system demands the practical application of these principles through resource management based on scientific constraints and tactical decisions using mathematical and physical reasoning. Even special abilities are rooted in science, like an "electromagnetic pulse" or "gravitational pull," creating a tangible connection between theory and application.

Engaging narrative: Contextualizing learning within a compelling world

The creation of the game is explained in *Appendix AL*, featuring a compelling narrative to provide context and drive learning. An immersive science fiction or fantasy setting enables imaginative yet realistic applications of scientific principles, showcasing their wide-ranging relevance, including physics governing space travel and mathematics underpinning advanced technology. Integrating real-world issues like environmental challenges within the story promotes critical thinking about the practical importance of scientific knowledge. Exploring ethical considerations surrounding scientific progress, such as genetic engineering or AI, encourages students to think about the wider societal impact of their learning.

By allowing player choices to significantly shape the narrative and its outcomes, the game fosters a sense of ownership and engagement. Dynamic and branching storylines based on player decisions encourage re playability and highlight the complex nature of problem-solving and scientific exploration. Non-linear gameplay gives students the freedom to explore the game world and tackle challenges at their own pace, catering to different learning styles and interests.

Educational integration: Bridging the gap between gameplay and curriculum

The seamless integration of educational content is key. An accessible in-game encyclopedia will offer detailed explanations of scientific ideas, biographies of key scientists, and real-world examples, providing support right when it's needed. Engaging mini-games will specifically teach and reinforce math and physics concepts, like a "rocket launching" simulation demonstrating Newton's Laws. Interactive data visualisations will help students grasp complex datasets and scientific phenomena, making abstract information more concrete.

Student learning will be assessed through their in-game actions, problem-solving strategies, and successful completion of quests, offering a more complete and relevant evaluation than traditional tests. By encouraging students to create their own in-game content, such as puzzles or stories, they can demonstrate their understanding creatively and practically. Collaborative projects will require students to work together to solve complex problems and present their results, fostering teamwork and communication skills alongside subject knowledge.

Technical considerations: Ensuring an accessible learning platform

Successful implementation demands careful technical planning. This includes selecting a strategic game engine, e.g. Unity or Unreal Engine, that provides the necessary tools for both game development and smooth educational integration. Designing an intuitive and user-friendly interface is also key to ensure ease of navigation and understanding for students with different technical skills. Finally, prioritising universal accessibility is a fundamental design principle to ensure the game is usable by all students, including those with disabilities.

Next steps

I propose future research and development to concentrate on refinement of the specific mathematics and physics concepts integrated into the game and aligning them with relevant educational standards. Focussing on iterative prototyping and user testing, developing a functional prototype to test core gameplay and gather valuable feedback from students are essential, once the NSLE framework is implemented. Building upon the inherent motivational power of game-based learning, I've become particularly interested in how the integration of AI can profoundly augment its educational impact within this framework.
In my analysis, AI moves beyond simple game mechanics to truly personalise the learning journey by dynamically adapting game content and difficulty in direct response to individual student learning styles and performance. This allows for the provision of immediate, actionable feedback, an element in guiding students and effectively addressing misconceptions as they arise. The strategic deployment of gamification rewards, such as points and badges, when intelligently orchestrated by AI, serves to reinforce positive learning behaviours in a more nuanced and adaptive manner. AI can also be employed to generate engaging challenges that necessitate the active application of knowledge in novel and stimulating contexts.
Within the NSLE, I envision AI-powered simulations playing a role in fostering both experimentation and collaborative learning opportunities. The capacity of AI to personalise feedback and reflection prompts by dynamically adjusting task difficulty based on a student's evolving performance creates a truly responsive and supportive learning ecosystem. The interactive and immersive environments that are characteristic of gamified platforms naturally foster greater student participation and a deeper level of engagement. The rich data streams generated by these AI-powered platforms offer invaluable insights into individual and collective learning patterns. This data, when thoughtfully analysed, can empower educators to continuously refine their instructional strategies and create even more deeply personalised learning experiences within the NSLE, optimising learning outcomes for every student.

7.6 Overcoming Bias

As I investigate the exciting possibilities of enabling AI to operate within the NSLE, I feel it's paramount to address the ethical considerations and potential challenges that accompany this powerful technology. The literature, including the recent work by *O'Connor et al. 2024*, rightly highlights the critical risk of AI algorithms trained on biased data inadvertently perpetuating harmful stereotypes, potentially leading to inequitable and unfair educational experiences for our students. These biases, as I understand it, can unfortunately creep in at various stages, from the inherent biases present within the training datasets themselves to subtle yet significant flaws in the

very design of the algorithms. To proactively mitigate these very real risks, I believe a comprehensive and multi-pronged approach is needed.
This necessitates a commitment to utilising as much as possible, unbiased datasets for training our AI models. It requires a focused effort on developing AI models that are not only effective but also transparent and explainable in their decision-making processes, moving away from the "black box" phenomenon. Implementing human review processes at key stages of AI development and deployment is providing a necessary layer of oversight and ethical scrutiny. Fostering diversity within the AI development teams themselves can bring a wider range of perspectives to the table, potentially mitigating unconscious biases.
Finally, and perhaps most importantly, the integration of ethical considerations must be woven throughout the entire AI development lifecycle, from initial conceptualization to ongoing implementation and evaluation. Beyond the issue of bias, ethical considerations surrounding the usage of personal student data are also a concern that demands careful attention and safeguards. Additionally, the very implementation of sophisticated AI-driven gamification within the NSLE requires a degree of technical expertise and a technological infrastructure, aspects that must be carefully planned and resourced to ensure equitable access and effective deployment.

7.7 Scalability and Accessibility

As I envision the widespread adoption and implementation of the NSLE framework, the critical considerations of scalability and ensuring genuine accessibility for our student population come sharply into focus. This necessitates proactively addressing challenges, such as the effective management of the vast datasets inherent in AI-driven systems and the imperative of maintaining both algorithmic accuracy and fairness as the NSLE scales to accommodate a growing number of learners [Davuluri. 2021].
Further, it requires a deep commitment to designing user interfaces that are not only intuitive but also thoughtfully cater to the needs and abilities of all students. Drawing on existing research, including the work of Wang et al. 2013 on cloud-based infrastructure, Miraz et al. 2021 on adaptive user interfaces, Jessner et al. 2017] on multilingual support, and Wendler et al. 2002 on cultural sensitivity, I believe several key strategies can help us navigate these complexities. Looking ahead, I see future research playing a role in prioritising the further development of AI algorithms that can truly adapt and personalise learning pathways to the unique needs of individual learners [Gligorea et al. 2023]. Also to enhancing the sophistication of natural language processing for more intuitive interactions [Hirschberg et al. 2015], and deeply integrating user-centred design principles throughout the NSLE's development [Margetis et al. 2021].
Creating an inclusive learning ecosystem, in my view, demands a strategic and multifaceted approach. This includes offering learning materials in multiple languages to break down linguistic barriers, providing comprehensive closed captions and alternative text descriptions to ensure accessibility for students with sensory disabilities. To build the system using modular components that allow for flexible expansion and adaptation to evolving needs. Prioritising an exceptional user experience through intuitive and user-friendly interfaces and incorporating assistive

technologies that adapt to individual learning differences are also necessary components of the system. Actively seeking and incorporating feedback from both students and educators throughout the design and implementation process will lead to a successful system. It's about building an environment that not only scales effectively but also genuinely empowers every learner to thrive.

7.8 The value of case studies

In my exploration of the NSLE, I've found that case studies offer a particularly valuable lens through which to examine complex educational phenomena, especially the interaction between challenging topics and the power of associative learning. As foundational research, such as that by Atkinson et al. 1975, has demonstrated, the process of associative learning truly thrives when we actively weave connections between new information and a learner's knowledge. This inherent human tendency to connect the unfamiliar with the familiar, I believe, holds clear implications for instructional design within the NSLE. Drawing on pedagogical insights from studies like those by *Stigler et al. 2009*, I experienced and observed the effectiveness of my colleagues, consciously employing analogies and relevant real-world examples as powerful tools to bridge the cognitive gap that often exist between novel information and a student's existing understanding. By strategically building these associative bridges, we can make abstract concepts more tangible and relatable, fostering deeper comprehension and more lasting retention within the NSLE framework.

Mathematics and Physics

Drawing upon my own experience lecturing in both Mathematics and Physics, I consistently integrated and applied mind mapping techniques, as introduced by *Buzan. 2024*, as a collaborative strategy with my students to visually encapsulate the core properties of the subjects [*Fig. 7.4 ; Fig. 7.5*]. I found that their active participation in this process was not merely engaging but also profoundly instrumental in fostering their academic success, often leading to truly exceptional learning outcomes.

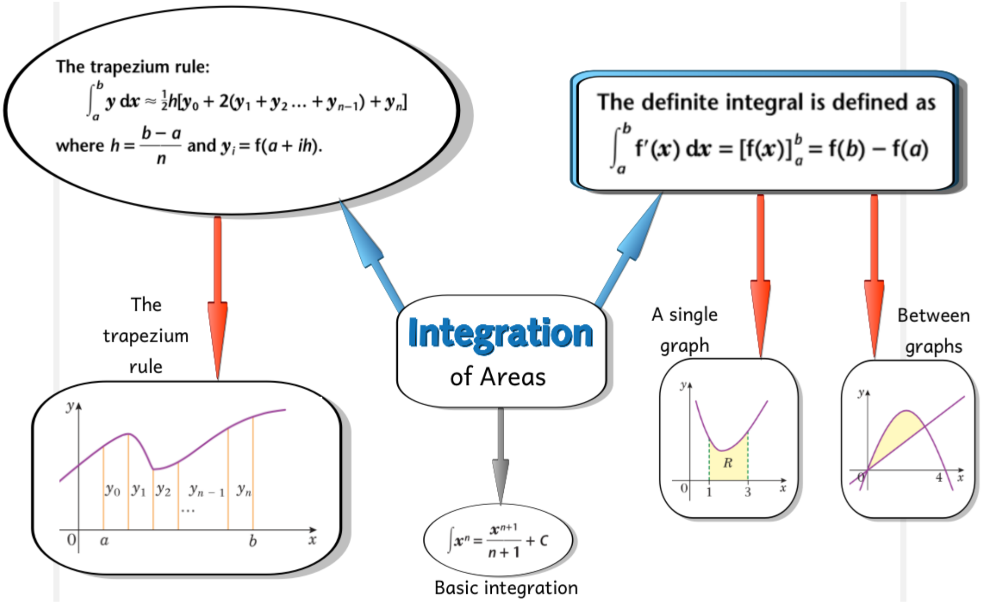

Figure 7.4. Knowledge structure for integral calculus in area problems and applied sciences.

A notable example, as illustrated in *Figure 7.4*, is the Mathematics mind map I created to illuminate the fundamental principles of calculating areas using integral calculus. What struck me as particularly powerful was the way this visual representation empowered my students to effectively transfer and apply these same core principles not only within the specific domain of Mathematics, but also across seemingly disparate disciplines such as Physics, displayed in *Figure 7.5*. This tangible cross-disciplinary application of integral calculus, I believe, illustrates the inherent interconnectedness of knowledge and the potential for visual associative tools like mind mapping to facilitate its recognition and utilisation.

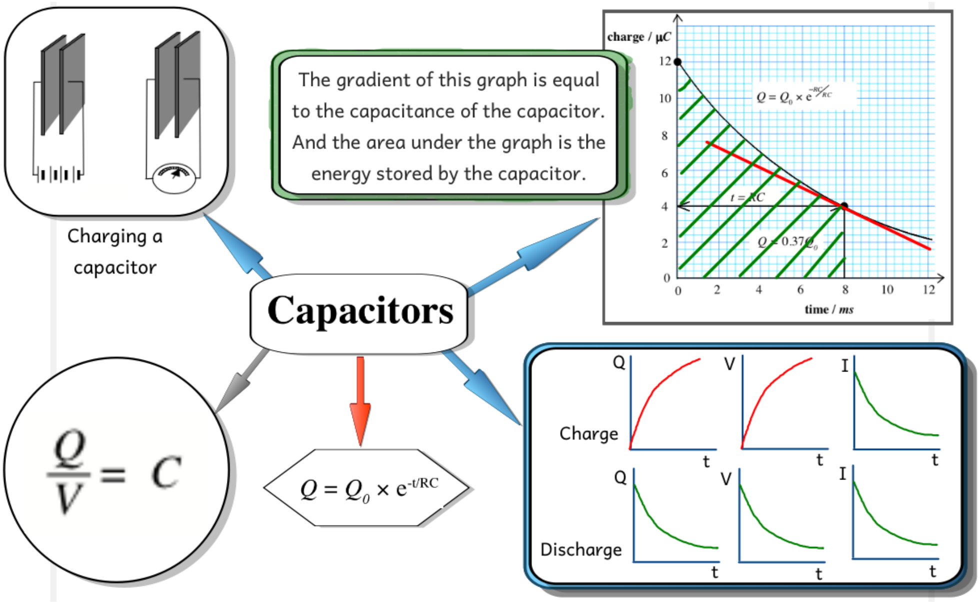

Figure 7.5. Knowledge organization of capacitor properties using mind mapping and integral calculus.

Language Learning

In my exploration of effective pedagogical tools within the NSLE, I've been particularly struck by the inherent synergy between mind mapping techniques and the unique demands of language acquisition. I find the visual nature of mind maps, renders them a highly effective learning tool in this domain. By providing a structured yet flexible framework for organising grammatical concepts, new vocabulary, and even the often-subtle nuances of a language's culture, mind maps actively facilitate a deeper level of understanding and, promoting more long-term retention for language learners. One of the key reasons I've found mind mapping to be such a potent tool, lies in the cognitive processes it actively engages. The very act of creating a mind map necessitates active recall, which, as cognitive science suggests, is a powerful mechanism for strengthening memory consolidation.

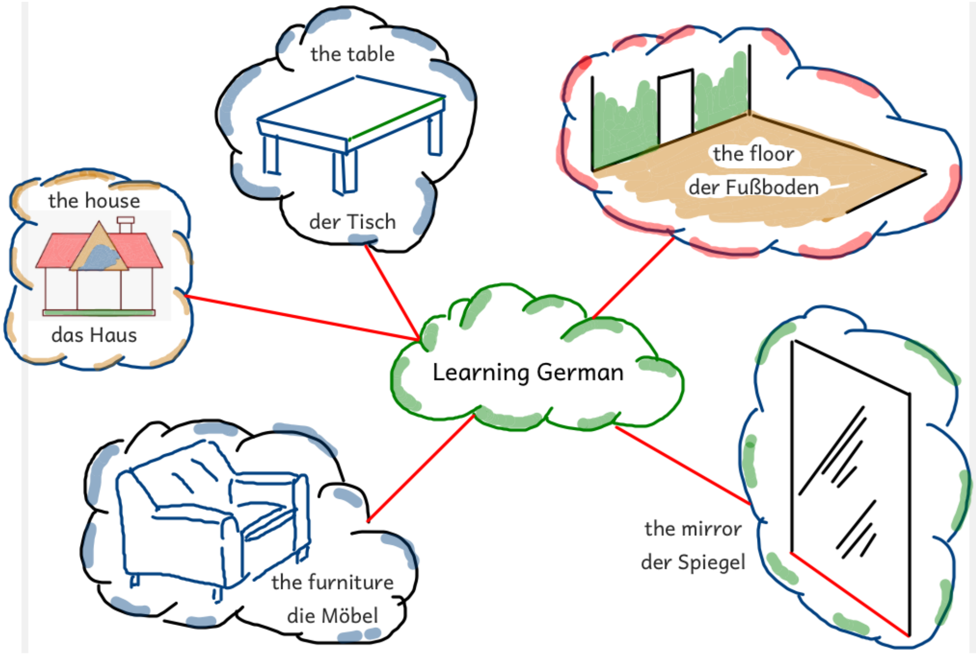

Figure 7.6. Educational mind map for German household vocabulary acquisition.

The visual connections inherent in mind maps significantly strengthen a learner's comprehension of the often-complex relationships that underpin a language's structure. Beyond these cognitive benefits, I've also observed that the personalised nature of mind maps empowers learners to tailor their study approach in a way that suits with their individual learning style, leading to increased engagement and a greater sense of ownership over their learning. The strategic establishment of connections between new vocabulary and grammar with a learner's existing knowledge base, a principle supported by the work of *Stigler et al. 2009*, through techniques like vocabulary webs and contextual cues, actively facilitates deeper understanding and contributes to improved fluency.

These associative techniques, in essence, increase memory by providing multiple retrieval pathways, making it easier to recall both vocabulary and grammatical rules. This, in turn, not only boosts retention but also increases learner engagement and their perceived control over the often-daunting process of language acquisition. I recall, for instance, a particularly effective strategy my students employed when learning German articles, illustrated in *Figure 7.6* and *Figure 7.7*. By consciously associating the location of a specific vocabulary item on the mind map diagram with its corresponding German article ('der,' 'die,' or 'das'), they reported a significantly easier time learning and subsequently remembering the correct articles.

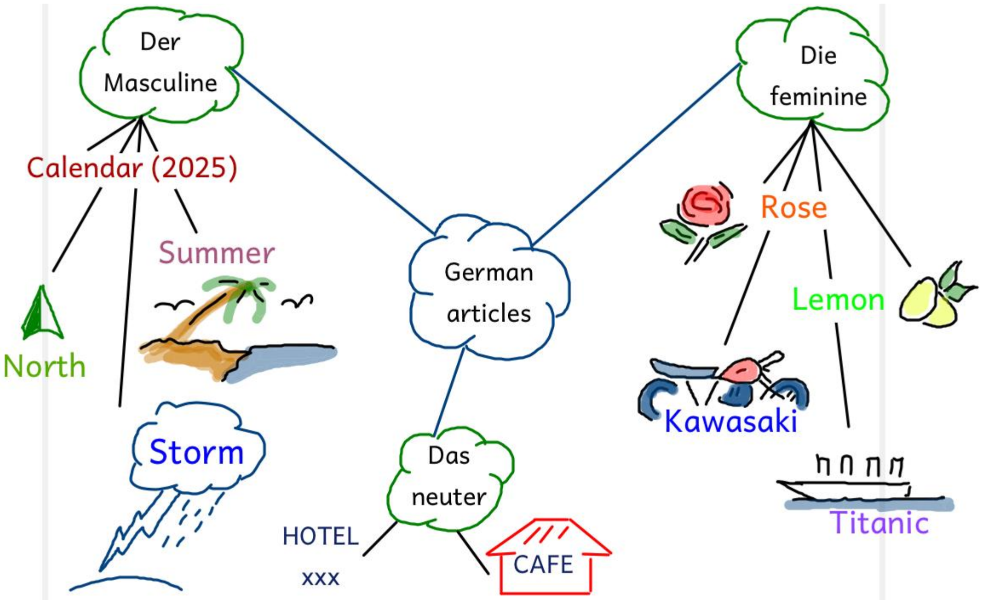

Figure 7.7. Application of mind mapping for German article acquisition.

This simple spatial-linguistic association proved remarkably effective. Building on this observation, the NSLE algorithms are designed to dynamically adapt the complexity of these visual association tasks. As a student demonstrates proficiency in recalling the articles, the system will generate subsequent diagrams with an increasing number of items, thereby progressively challenging and reinforcing their learning. Conversely, if a student struggles, the number of items will be temporarily reduced to provide more focused practice and support. As part of my research into innovative pedagogical tools for second language acquisition, I explored the potential of AI algorithms in generating cognitive organisers. A specific challenge frequently encountered by learners of German is the acquisition of grammatical gender and its corresponding definite articles (der, die, das).

To investigate the efficacy of AI-generated visual aids in this domain, I prompted an algorithm to construct a mind map designed to facilitate this association of German articles with various noun categories and linguistic patterns. The resulting mind map, an example of which is presented below, represents an attempt to utilise a simple organisation for better grammatical understanding. An AI generated mind map that help my students learn German articles: der, die, das. The structure is designed for visual learning and memorization. When comparing this AI version with the human generated mind map in Figure 7.7, the similarities are apparent.

GERMAN ARTICLES

Mind map
root((German Noun Genders (Der, Die, Das)))
Der (Masculine)
Most male people (der Mann, der Hund)
Days of the week (der Januar)
Points of the compass
Motorcycles (der BMW)
Die (Feminine)
Most female people (die Frau, die Katze)
Most trees (die Rose)
Abstract nouns (die Freiheit)
Das (Neuter)
Diminutives (-chen, -lein) (das Mädchen)
Most colours (das Blau)
Most metals and elements (das Gold)
Nouns ending in -ment (das Dokument)

7.9 Challenges and Future Directions

As I envision the goal of education, it's clear that the future lies not in the passive absorption of information but in active, multi-sensory engagement that truly captivates and involves the learner. The emergence of AI-powered education, as highlighted in recent work by Bușu. 2024 and Srinivasa et al. 2022 offers a compelling glimpse into this future, promising the creation of dynamically and adaptive learning environments. As lecturer in an Engineering Technical College, I've observed firsthand the power of hands-on activities [Oladele. 2024] and immersive simulations in various subjects, such as Motor Engineering, Physics and Mathematics, to allow students to interact with abstract concepts in a tangible and meaningful way, fostering a demonstrably deeper level of understanding.
However, as Vrabie. 2023 points out, the seamless implementation of advanced features like AI-driven gamification necessitates a degree of technical expertise and a technological infrastructure. The ethical considerations surrounding the use of personal learning data and the potential for algorithmic biases, as underscored by Hanna et al. 2024 and Fernández. 2022, are paramount and demand careful and ongoing scrutiny. Looking ahead, I believe that further research to fully understand the long-term effectiveness of AI in cultivating not just surface-level knowledge but truly profound and lasting comprehension is ongoing. The key, in my estimation, lies in forging a powerful and synergistic partnership between artificial intelligence and human pedagogical expertise. In this symbiotic relationship, AI can take on the role of intelligently personalising the learning journey, freeing educators to focus on what they do best: fostering critical thinking skills, nurturing creativity, and cultivating that human connection that is so vital to meaningful learning and holistic development. It is in this harmonious convergence of technology and human insight that I see the greatest potential for the Neuro-Synaptic Learning Environment to truly advance education.

CHAPTER 8
STUDENT MODELLING AND PROFILING

My research explores the potential of the NSLE, to move beyond conventional teaching [McElwee. 2020], by adopting an approach using AI, neuroscience, and social network analysis to personalise learning [*Murthy et al. 2025*]. My investigation focuses on several key areas. Firstly, I am developing sophisticated student profiling techniques. These techniques aim to capture nuanced individual learning styles and needs, moving beyond traditional assessments. Secondly, I am focused on the design and practical implementation of personalised learning pathways. These pathways will adapt content and pace to optimise individual progress. A particularly compelling aspect of my work involves the integration of neurofeedback-driven learning techniques, which hold the promise of enhancing focus and engagement. Finally, a consideration is the practical side, ensuring the seamless and effective integration of these AI-powered solutions within our existing educational infrastructures [Kayal. 2024].

8.1 Foundation of modelling and profiling

The NSLE is founded on the integration of AI with a deep understanding of human learning. This synergy enables sophisticated student modelling and profiling to create personalised learning pathways that adapt to each student's unique needs, abilities, and learning style [Bayly-Castaneda et al. 2024]. By allowing machine learning algorithms to analyse a wealth of student data [Hussain et al. 2019], we can generate dynamic profiles that not only inform but actively guide instructional strategies [*Chapter 12.1*]. Indeed, the entire NSLE framework is fundamentally grounded in this process of student modelling and profiling [*Halloun. 2012*].

Implementation and evaluation

A critical aspect of realising the full potential of the NSLE ecosystem lies in the careful implementation and evaluation of its student modelling and profiling capabilities. To this end, I propose a controlled pilot study program in *chapter 12.4,* that will allow for a thorough assessment of the system's initial strengths and weaknesses, the findings of which will directly inform subsequent iterative refinements. Integral to this process is a data collection and analysis plan designed to monitor student performance over time, identifying key trends that can guide ongoing optimisation. This commitment to continuous evaluation and refinement, which includes incorporating feedback from all stakeholders, students, educators, and administrators, will be paramount in ensuring the system's long-term efficacy and its adaptability to the complexities of real-world educational settings.
The data that will fuel these insights will be drawn from a variety of sources, including learning management systems, educational software, and applicable assessment tools. This rich dataset, in conjunction with the NSLE's sophisticated machine learning algorithms [*Chapter 9.1*], will be analysed to uncover meaningful patterns that can provide valuable information for educators and policy makers. Complementing this, adaptive assessments [Iqbal. 2023] will dynamically adjust the difficulty level, to

provide a more precise understanding of student mastery, while the incorporation of student self-assessment questionnaire results, aims to foster metacognition and cultivate self-directed learning. Teacher feedback, often streamlined by AI tools [*Chen et al. 2020*], will offer invaluable qualitative insights for making targeted instructional adjustments. A commitment to regularly reviewing and refining the profiling process, actively incorporating feedback, and thoughtfully embracing emerging technologies will be required for the sustained success and evolution of the NSLE.

8.2 Learning pathway analysis

The rich insights gleaned from student profiles are instrumental in a detailed analysis of learning pathways. This analysis, in turn, empowers educators to pinpoint specific areas ripe for improvement, paving the way for more targeted interventions, personalised learning experiences, and more refined and effective instruction. To achieve this comprehensive understanding, the NSLE framework thoughtfully integrates the power of machine learning [*Chapter 9.1*], the analytical depth of educational data mining [*Chapters 6.4 and 6.7*], and the cognitive principles of cognitive load theory. My methodological approach employs a mixed-methods design, drawing on a range of data sources, including online learning platforms, learning management systems, various forms of assessments and student survey questionnaires.
The application of machine learning techniques allows for the identification of subtle yet patterns within student learning behaviours, according to Orji et al. 2020, while educational data mining methodologies [Romero et al. 2010] enable a deeper examination of the relationships between these behaviours and the effectiveness of different instructional strategies. The framework is designed to generate actionable outputs, including detailed student profiles, clear visual maps of learning pathways, and precisely tailored interventions [*Donaldson et al. 2021*], all aimed at empowering personalised support for each learner. I believe the potential of this framework extends beyond individual student learning, offering valuable applications in educational settings and even in teacher training programs, fostering a richer understanding of the nuances of student learning by directly connecting individual profiles to demonstrably effective learning pathways.

8.3 AI-driven learning algorithms

The very essence of the NSLE ecosystem is rooted in a neuro-inspired approach to learning. Here, sophisticated AI algorithms work to analyse individual learning patterns, in a way that mirrors the brain's own remarkable process of forming neural connections. This dynamic analysis, coupled with the provision of continuous real-time feedback and assessment, is central to ensuring a truly personalised and, more effective learning journey for each student. In developing the NSLE, I've drawn inspiration from key principles of neuroscience, including the remarkable capacity for neuroplasticity, Hawkins et al. 2021, the foundational mechanisms of Hebbian learning, *Strom. 2007*, and the brain's elegant process of synaptic pruning, Zhang. 2020.

These neurobiological principles inform the AI-driven adaptive learning engine that lies at the heart of the NSLE, enabling it to tailor the educational experience precisely to individual student needs. This includes the provision of continuous, real-time feedback and assessment, allowing for immediate adjustments and a more responsive learning environment. Reinforcing the importance of inclusivity within the NSLE framework, a valuable supporting study by Burgstahler et al. 2004 highlights the system's commitment to accessibility through comprehensive language support and a range of other accessibility features.

8.4 Interactive learning experiences

The NSLE is designed to enhance learning across all subjects by cultivating more effective and interactive educational encounters. The findings of Takona. 2024 lend strong support to this direction, illuminating the considerable potential of AI to not only refine existing teaching practices but also to nurture truly personalised learning pathways for each student. A particularly compelling dimension of the NSLE involves the strategic integration of Augmented Reality [*AR*], Virtual Reality [*VR*], Extended Reality [*XR*], and Mixed Reality [*MR*] modules. These immersive technologies effectively enhance the understanding of abstract concepts, fostering a more intuitive grasp of complex ideas [Dembe. 2024]. These technologies are described below.

Augmented Reality [*AR*]

AR overlays digital information onto the real world, enhancing the user's perception of their environment. It fundamentally alters the user's immediate surroundings by adding layers of digital content, such as images, text, or 3D models, typically through devices like smartphones or specialised headsets. This integration of virtual elements with real-world stimuli allows for interactive and context-aware experiences, distinct from fully immersive virtual environments.

Virtual Reality [*VR*]

VR creates a fully immersive, computer-generated environment that replaces the user's perception of the real world. By utilising headsets and motion tracking, VR isolates the user from their physical surroundings, transporting them into a simulated space. This complete immersion enables users to interact with and explore virtual environments, offering a high degree of presence and engagement, and is often used for training, simulation, and entertainment.

Extended Reality [*XR*]

XR is an umbrella term encompassing all real-and-virtual combined environments and human-machine interactions generated by computer technology and wearables. It is a superset that includes AR, VR, and MR, as well as any future technologies that blur the lines between the physical and digital disciplines. XR emphasises the continuum of immersive experiences, highlighting the interconnectedness and evolution of these technologies.

Mixed Reality [*MR*]

MR blends real and virtual worlds, allowing digital objects to interact with and be anchored in the user's physical environment. Unlike AR, which primarily overlays digital information, MR enables virtual objects to behave as if they exist within the real world, with accurate spatial mapping and real-time interaction. This integration facilitates more complex and realistic interactions, where virtual and physical elements coexist and influence each other.

Expanding on this, I propose the seamless incorporation of a social learning network within the NSLE ecosystem. This will further catalyse meaningful collaboration and invaluable peer-to-peer learning, promoting a vibrant exchange of knowledge and perspectives that transcends disciplinary boundaries. To further amplify engagement and the practical application of knowledge, the NSLE will feature interactive simulations tailored to specific subjects. The convergence of augmented, virtual, extended and mixed reality heralds a transformative epoch for education, promising to transcend the limitations of traditional pedagogical frameworks. These immersive technologies offer the potential to create dynamic, interactive learning environments that foster deeper engagement and comprehension.

8.5 Integration with learning management systems

A core tenet of the NSLE is its design to seamlessly integrate existing Learning Management Systems [LMS] platforms, such as Canvas, Blackboard, and Moodle [Swerzenski. 2021], creating a central and dynamic learning hub. My vision is that this integration will foster significantly deeper student engagement through more interactive and enriching experiences [*Mpungose et al. 2022* ; *Falcone. 2018*], while simultaneously personalising the learning journey, streamlining administrative tasks, and improving overall access to resources. Achieving effective LMS integration within the NSLE framework necessitates a thoughtful approach to Application Programming Interface [*API*] connectivity, the development of compelling digital content, and the application of established best practices in online learning design.
Extending this integration, connecting the NSLE with Student Information Systems [*SIS*] promises to further optimise administrative processes. I believe that this synergy between SIS and educational software will facilitate real-time data exchange, substantially reducing administrative burdens [Rodrigues et al. 2003] and establishing a foundation for truly data-driven instruction. To this end, my research proposes a comprehensive platform for seamless data exchange, incorporating a sophisticated

data integration layer, a powerful analytics engine, and user-friendly reporting tools. It is important that we continuously evaluate this platform to ensure not only the accuracy and reliability of the data but also a positive and intuitive user experience, maximizing its positive impact on student learning outcomes.
Complementary to these systems, Curriculum Management Systems [*CMS*] hold the potential to further enrich the educational ecosystem. By thoughtfully integrating CMS with both LMS and SIS, educators can ensure greater curricular coherence, effectively monitor student progress in relation to learning objectives, further streamline administrative tasks, and make more informed instructional decisions based on readily available data. This integrated approach, in my view, will foster stronger collaboration among educators and other stakeholders, contributing to an improved and more cohesive overall learning experience. While the specific implementation of these systems may vary across different institutions [Lai et al. 2012], the overarching trend points towards their success in enhancing educational practices [Yulieana et al. 2020].
I am exploring how technology assessments, as researched by *Ryan. 2024* can reconfigure student learning evaluation within the NSLE. Such systems offer the potential to provide instant, actionable feedback to students, adapt dynamically to individual learning needs, and offer educators invaluable insights into the depth of student understanding. By streamlining the often time-consuming assessment processes, reducing grading time, and providing rich, data-driven insights [*Tippins. 2011*], these tools will empower educators to make more informed pedagogical decisions and guide instruction with greater precision [*Hense et al. 2011*].

Teacher training

Looking ahead, I propose that the NSLE framework be strategically integrated into teacher training programs. My vision for this integration centres on a comprehensive platform that employs the power of local networks and operating systems to provide educators with readily accessible instructional materials, relevant resources, and practical pedagogical tools. The NSLE ecosystem encompasses a collaborative network of students, educators, and institutions, all working together to harness the benefits of personalised learning experiences and equip educators with the necessary tools and knowledge to thrive in this evolving educational landscape.
Realizing the full transformative potential of the latest educational technology, as I see it, demands a comprehensive and context-aware approach. This includes conducting thorough needs assessments to understand the unique requirements of each educational setting, providing ongoing teacher training to ensure effective utilisation, and establishing continuous feedback mechanisms to ensure the equitable and significant integration of technology in education. Successful implementation, therefore, necessitates careful and detailed planning, encompassing thorough needs assessment, platform development, seamless mobile app integration, sophisticated data analytics capabilities, pilot testing, and a commitment to ongoing evaluation and refinement.

CHAPTER 9
ALGORITHM DESIGN

In this chapter, I examine the core of my doctoral research: the design of the NSLE algorithms. Here, I'll be laying out the development and refinement of several key components. This includes the graph-based algorithms I've crafted to personalise learning pathways, the methods I've implemented for pinpointing individual knowledge gaps, and the strategies embedded within the NSLE to foster sustained learner engagement. Beyond these core elements, I will also address system considerations such as training protocols, validation procedures, and ongoing maintenance strategies.

9.1 Algorithm development

The NSLE personalises learning through sophisticated machine learning algorithms, empowering students to build interconnected concept networks. In this chapter, I articulate the design principles behind these algorithms, detailing their structure to mirror the complex interconnectedness of neural connections [Schmidgall et al. 2024]. This biomimicry fosters a dynamic and engaging learning environment. By analysing student data, the NSLE tailors content, identifies knowledge gaps, and recommends targeted resources to optimise the learning journey. This personalised approach fosters deeper understanding, critical thinking, and a love of exploration, unlike traditional methods that often isolate facts [Amunga. 2019].

9.2 Graph algorithm development

The development of our graph-based algorithms represents what I believe is a fresh perspective on designing truly integrated learning systems, one that deeply harnesses the principles of associative learning. This development process, which I've detailed below, involved a series of carefully considered and iterative steps. My aim is to identify the unique knowledge gaps of each learner, optimise their individual learning pathways for maximum impact, and cultivate a more enriching and effective overall learning experience. To assess the impact of this algorithm, I will be conducting a continuous and comprehensive evaluation, as outlined in *chapter 12.6*.

Concept graph construction

> Analyse the learning material to identify the relationships between concepts using natural language processing and graph theory techniques [Gross et al. 2018]. Construct a concept graph, which represents the relationships between concepts in the learning material.

Knowledge gap identification

Analyse the learner's current knowledge level and compare it to the required knowledge level for a particular concept. Identify areas where the learner requires additional support using machine learning algorithms.

Adaptive learning path optimisation

Use optimisation techniques to identify the most effective learning path [Gligorea et al. 2023] for the learner, taking into account the learner's knowledge gaps, learning style and preferences. Search for the most effective sequence of learning activities using a combination of genetic algorithm, simulated annealing and particle swarm optimisation.

Learning path generation

Generate the adaptive learning path for the learner based on the optimised learning path. Provide the learner with a personalised learning plan that includes the most effective sequence of learning activities.

Learning path evaluation

Evaluate the effectiveness of the adaptive learning path using metrics such as learner engagement, knowledge retention and transfer of learning. Use the evaluation results to refine the algorithm and improve the learning path.

Algorithm refining

Refine the algorithm by incorporating feedback from the evaluation results. Use the refined algorithm to generate a new adaptive learning path for the learner.

Learning path deployment

Deploy the adaptive learning path to the learner. Provide the learner with a personalised learning experience that is tailored to their needs and preferences.

This evaluation will focus on demonstrating its effectiveness in fostering deeper learner engagement, promoting lasting knowledge retention, and facilitating the smooth transfer of concepts to new contexts.

9.3 Algorithm optimisation

One of the bedrock principles of how we learn is that individuals build knowledge by naturally forming associations between different concepts, according to *Shanks. 2010*. However, what I've observed is that many traditional learning methods often struggle to truly empower learners to forge these meaningful connections. This limitation, I believe, can significantly hinder the development of deep understanding and contribute to weaker knowledge retention. To tackle this challenge, I've developed this integrated learning system design approach that places algorithm optimisation at its core. This approach strategically blends the power of graph theory [*Section 9.1*], machine learning methodologies, and a suite of optimisation techniques, which I've summarized above, with the specific aim of personalising learning pathways and demonstrably improving knowledge retention. My conviction is that by carefully optimising these underlying algorithms, we can unlock the potential to create truly dynamic and adaptive learning environments that are far more conducive to effective and lasting learning.

9.4 Optimisation techniques

A key aspect of the NSLE algorithms are its use of powerful optimisation techniques, Genetic Algorithms [Deb. 1999], Simulated Annealing [Delahaye et al. 2019] and Particle Swarm Optimisation [Lazinica. 2009]. I incorporated these methods because they enable the system to intelligently determine the most effective learning sequence for each student. These techniques systematically explore a vast landscape of potential learning paths, each with its own unique characteristics, to pinpoint the ones most likely to lead to successful learning outcomes.

Genetic algorithms

Drawing inspiration from the elegant mechanisms of natural selection, the Genetic Algorithms are designed to mimic the process of biological evolution to optimise individual learning paths [*Diao et al. 2015*]. The process begins with generating an initial set, a population of potential learning sequences. Then, the system evaluates each path based on key factors for effective learning: learner performance, engagement, and time efficiency. Following this evaluation, the "fittest" learning paths, those demonstrating the best results, are then selected to "reproduce". This reproduction occurs through two main mechanisms, *crossover*, where elements from different high-performing paths are combined and *mutation*, which introduces small, random variations to explore new possibilities. This iterative cycle of selection, crossover, and mutation allows the algorithm to progressively refine the population of learning paths, gradually leading to the discovery of sequences that are not only increasingly effective in promoting learning but also more efficient in their delivery.

Simulated Annealing

Simulated Annealing, a technique that, as *Morales-Castañeda et al. 2019* insightfully explain, takes its inspiration from the fascinating metallurgical process of annealing, offers a clever way to optimise learning paths within the NSLE. The core idea is to iteratively explore slightly different, or 'neighbouring,' learning sequences. We begin by selecting an initial learning path and setting an initial 'temperature' parameter. The algorithm then probes small variations of this current path. What's particularly interesting is how it decides whether to accept these changes: any improvement to the learning path is automatically accepted, while deteriorations are accepted with a probability that gradually decreases as the 'temperature' of the system cools down.

This carefully controlled exploration allows the algorithm to escape potentially suboptimal solutions, what we often call 'local optima' and converge towards a highly effective, near-optimal learning path, much like how the annealing process in metallurgy yields a strong and stable material structure.

Particle swarm optimisation

Drawing on fascinating research, such as the work by *Chao et al. 2024*, Particle Swarm Optimisation offers another possible compelling approach to optimising learning paths within the NSLE. Inspired by the elegant collective intelligence we see in bird flocking, this technique works by simulating the behaviour of a 'swarm' of individual particles. In our context, each potential learning path is represented as one of these particles navigating through the landscape of possible solutions. What I find particularly insightful about this method is how each particle's movement is influenced. They adjust their focus not only based on their own past successes, their personal best-performing position, but also by the collective wisdom of the swarm, specifically the best position any particle has discovered so far. Their current velocity also plays a role in shaping their next move.

This iterative process of movement and adjustment, guided by both individual exploration and the shared experiences of the swarm, effectively drives the entire group towards the most promising regions of the solution space, helping us pinpoint the most efficient and effective learning paths for our students. It emphasise that by strategically employing this suite of optimisation techniques, including Genetic Algorithms and Simulated Annealing, as previously discussed, the NSLE algorithm gains an advantage. It allows us to thoroughly explore the vast and complex space of potential learning paths, identify highly effective sequences of learning activities, and, most importantly, personalise the learning experience to meet the unique needs of each individual student [*Chapter 12.1*].

9.5 Network training

A foundational step in the NSLE is the construction of what I've come to think of as a dynamic "knowledge landscape." This involves a comprehensive analysis of the learning materials that will be uploaded into the system, which includes everything from curriculum documents and textbooks to teacher’s own notes, assessments, and even the associated mark schemes [*Chapter 6.2*]. This also encompasses all the visual, auditory, and kinaesthetic elements specifically designed for user engagement, as well as the feedback messages embedded within the learning experience. This digital network represents each concept as a distinct node. The connections between concepts are defined by "edge embeddings" [*Song* et al. 2018], which specify the relationships, such as "prerequisite" or "related to."

While techniques like word embeddings [*Gutiérrez* et al. 2019] are valuable for capturing the general semantic relationships between individual words, I've found that the NSLE's strength lies in its ability to utilise edge embeddings to explicitly define the specific connections between concepts within the learning material itself.

By specifying the nature of these relationships, such as "prerequisite," "example-of," or "related-to", these edge embeddings enable the construction of a rich and granular knowledge graph that accurately represents the structure of the subject matter.

Neural networks

At the heart of the NSLE lies the power of neural networks, those fascinating AI tools directly inspired by the workings of the human brain. Much like our students learn from examples and experiences, these networks learn from vast amounts of data, uncovering subtle patterns and relationships that might otherwise remain hidden. In the NSLE, I've implemented two primary training approaches for these networks: supervised learning [*Cunningham et al. 2008*], which refines the connections within the network by minimizing errors, learning from its 'mistakes', and unsupervised learning [*Dayan et al. 1999*], which allows the network to autonomously discover underlying structures and patterns in the data. Just as we assess student understanding through exams, validation of data, the network has never seen before, ensure its ability to generalise its learning and effectively handle new information. However, the NSLE framework extends far beyond these core AI components. I've intentionally integrated a rich variety of visual, auditory, and tactile elements to cultivate a more engaging and truly memorable learning experience.
Students can actively explore concepts through images, diagrams, videos, podcasts, interactive simulations, and hands-on activities. This multisensory approach, I believe, fosters a much deeper level of understanding and, importantly, makes the learning process more enjoyable. The true potential of the NSLE framework, in my view, lies in its capacity to fundamentally transform the educational landscape. By applying principles drawn from network science, it enables the creation of dynamic and richly interconnected learning environments. Concepts are no longer presented as isolated facts but rather as interconnected threads, inviting exploration and discovery. This empowers students to navigate complex information with greater confidence, uncover novel connections between ideas, and gain a more profound and integrated understanding of the world around them.

9.6 Network validation

A cornerstone of the NSLE framework, and something I've dedicated attention to, is its validation process. This isn't just about checking for errors; it plays a role in the very personalisation of the learning experience and in maximizing how engaged our students are. Alongside this, what I term 'network validation' is to ensure that all the interconnected elements within our learning ecosystem, the students, the educators, the tools, the technologies, work together seamlessly. My aim here is to foster genuine collaboration and the effective sharing of knowledge.
This multi-faceted validation approach allows the NSLE to truly tailor the learning journey. It continuously assesses a student's evolving understanding and proactively identifies areas where they might be struggling. The machine learning algorithms I plan to integrate, analyse student performance data and pinpoint specific knowledge gaps. This enables the framework to provide targeted support precisely where it's needed, especially when students are grappling with complex concepts, thereby

preventing them from feeling overwhelmed or discouraged. The framework actively monitors a student's cognitive load, the mental effort they're expending during learning. By analysing patterns in this data, the framework can dynamically adjust the pace of learning to maintain optimal engagement without pushing a student beyond their cognitive capacity.
Validation also extends to assessing student engagement levels in real-time. If the system detects that a student's focus is waning, it can intervene with personalised feedback, subtle adjustments to the learning pace, or even introduce gamified elements designed to reignite their curiosity and re-engage them with the material. From my perspective, network validation is a non-negotiable component in designing an integrated learning system that employs associative learning principles. It's about ensuring that all the interconnected pieces of the puzzle, learners, educators, tools, and technologies, function harmoniously to facilitate effective knowledge sharing and meaningful collaboration.
This validation process, as I envision it, begins with educators gaining a deep and comprehensive understanding of the entire learning environment. Following this, we establish clear and measurable performance criteria to gauge success in areas like learner engagement, knowledge retention, and collaborative interactions. These clear guideposts ensure that the network is functioning as intended and provide the basis for data-driven improvements [*Chapter 12.1*]. To gather the necessary data for this validation, I employ a range of methods, including surveys, in-depth interviews, and sophisticated data analytics. This allows us to comprehensively assess the network's strengths and identify any weaknesses. For instance, this data might reveal a dip in student engagement with a particular learning resource, signaling a need for review. Regular assessments and evaluations are therefore necessary to ensure the network remains a dynamic and effective learning environment. Based on the insights gleaned from this ongoing data collection, educators can strategically introduce new resources, refine existing learning strategies, or seamlessly integrate the latest relevant educational technologies. This continuous cycle of data-informed refinement is for maintaining an efficient, engaging, and effective learning environment for our students.

Holistic Approach to Training and Validating the Neural Network

My vision for the NSLE framework centres on a truly holistic approach to both training and validating its underlying neural network. This is in my view, to empower the network to not just function, but to genuinely adapt and flourish within a dynamic learning environment. This holistic philosophy extends directly to how we train and validate the network. My aim isn't simply to create a system that memorizes facts; rather, I'm striving for a network that truly comprehends the relationships between those facts. In essence, we're cultivating a form of 'critical thinking' within the network itself, mirroring the deeper cognitive processes we aim to foster in our students.
By intentionally factoring in the ways in which individuals learn, the network acquires a powerful ability to generalise knowledge. This generalised understanding can then be effectively applied to novel situations, leading to a much deeper and more transferable understanding for our learners. This holistic approach, I believe, is what truly paves the way for an effective associative learning ecosystem. My goal with this

intelligent framework is to empower both educators and researchers to create a learning environment where students are actively encouraged to forge meaningful connections between stimuli and responses, leading to lasting learning outcomes.

9.7 Scalability and flexibility

A critical consideration in the design of the framework, and one I've focused on intently, is ensuring both scalability and inherent flexibility. My goal here is to provide a framework that not only allows for the design of truly adaptive and personalised learning systems but also readily accommodates a wide spectrum of learning needs and educational environments. Scalability, as I see it, is paramount to ensure the framework can comfortably accommodate a growing number of users and their varied learning requirements. The system is designed to expand seamlessly, welcoming new students from all backgrounds without any compromise in performance or effectiveness. Several key design choices contribute to this remarkable scalability.
The framework's inherent flexibility allows it to adapt gracefully to these learning needs and environments. I've aimed for a system that can be implemented seamlessly across a range of settings, from traditional classrooms to fully online platforms and even informal learning contexts. To further complement scalability, the NSLE integrates a rich and varied library of learning materials, specifically curated to cater to different learning styles. For instance, visual learners can benefit from images and simulations, auditory learners can thrive with engaging podcasts, and kinaesthetic learners can fully participate through hands-on activities. This approach to learning resources is key to effective scaling, as the framework is designed to adapt existing materials to cater to new needs, eliminating the often cumbersome requirement of a complete overhaul for each new environment or student cohort. Flexibility, in my view, is what truly transforms the framework into a powerfully adaptive learning environment. Moving beyond a rigid, one-size-fits-all approach, the NSLE is designed to cater to the unique needs of each individual student. With adaptability as a core design principle, the learning remains engaging and effective as the framework intelligently personalises each student's learning journey.

9.8 Security and data protection

The increasing prominence of digital learning platforms, as *Parker. 2023* rightly points out, makes security measures an absolute necessity to safeguard sensitive learner data. Within an associative learning environment like the NSLE, where exploration and active engagement are so vital, providing a secure and protected learning experience is, in my view, paramount. To address this critical challenge, I've proposed a multi-layered security framework that thoughtfully integrates technical safeguards, organisational protocols, and human factors. Strong data encryption and stringent access controls are in place to ensure that only authorized individuals can access sensitive information. Alongside these technical measures, regular security audits and timely updates will continuously fortify the system's defenses.
Clear and accessible policies and procedures guide both educators and learners on responsible data handling practices. Comprehensive training programs are designed to raise awareness of potential security threats and empower everyone to actively

contribute to maintaining a secure environment. My aim is to cultivate a genuine culture of cybersecurity awareness within the NSLE community, encouraging vigilance and the prompt reporting of any suspicious activity. Open and transparent communication channels between educators, learners, and administrator, for building trust and ensuring that everyone feels comfortable raising any security-related concerns. By carefully integrating these interconnected elements, the NSLE strives to create a secure and trustworthy environment where learners feel empowered to explore freely and confidently, knowing their data is protected. This security, in turn, allows educators to create truly innovative learning opportunities without having to compromise on data protection. Identifying potential key vulnerabilities and proposing effective mitigation strategies, are building a resilient learning ecosystem.
A comprehensive understanding of the various security concerns, coupled with practical and actionable recommendations for both educators and administrators, is key for establishing and maintaining a safe and trustworthy learning environment for all. My commitment with the NSLE is to create not just a secure, but also an inspiring learning environment. This is achieved through the implementation of these multi-layered security measures, detailed below, combined with a human-centred approach that prioritises the protection of both educators and learners. Secure data, in my view, is not a barrier to innovation but rather the very foundation that empowers educators to be creative and learners to explore with genuine confidence.

Technical measures

My firm belief is that by thoughtfully incorporating technical safeguards, organisational protocols, and human-centred design principles, associative learning ecosystems like the NSLE can effectively ensure the confidentiality, integrity, and availability of sensitive learner data.

Data encryption
- End-to-end encryption
  - Implement end-to-end encryption to ensure data is protected.
- Key management
  - Establish a key management system to generate, distribute and manage encryption keys.

Access control
- Role-based access control
  - Implement to restrict access to learner data based on user roles and permissions.
- Attribute-based access control
  - Utilise to grant access to learner data based on attributes, such as learner profiles and enrolments.

Data storage
- Secure data storage
  - Store learner data in secure, tamper-proof storage solutions, such as encrypted databases or cloud storage.

Regular backups
Perform regular backups of data.

This comprehensive framework, in my vision, serves as a solid foundation for the development of data protection strategies specifically tailored for associative learning environments, fostering a strong sense of trust among learners, educators, and the institutions that support them.

Organisational measures

Data governance
Data ownership
Establish clear data ownership and responsibility.
Data classification
Classify learner data based on its sensitivity and importance.

Training
Employee training
Provide regular training and awareness programs for employees to ensure they understand the importance of data protection and data security.
Learner education
Educate learners about data protection best practices, such as password management and data sharing.

Human-Centred Measures

Learner consent
Informed consent
Obtain informed consent from learners before collecting, processing, or sharing their personal data.
Data subject rights
Ensure that learners have the right to access, rectify and erase their personal data, as well as the right to object to data processing.
Data minimization
Data retention
Implement data retention policies to minimize the amount of learner data stored and processed.
Data anonymization
Anonymize learner data to prevent identification.

9.9 User interface and feedback mechanisms

The user interface (UI) of the NSLE in *chapter 12.1* and its embedded feedback mechanisms [*Fig 9.1*] are, to my mind, critical components of the NSLE's overall

holistic design. In today's increasingly learning ecosystems, I believe it's paramount to prioritise a user experience that is both seamless and deeply engaging. My approach to designing this integrated learning system has been resolutely user-centric in its UI development. This means placing a strong emphasis on intuitive navigation, a visually appealing design, and rich interactive features. The very framework I've developed for the UI aims to directly support the associative learning process, drawing valuable insights from cognitive psychology, educational technology, and human-computer interaction.
A well-designed UI, in my experience, is key to enhancing user engagement and promoting truly effective learning, thoughtfully catering to the unique needs of both learners and educators. The core of this integrated learning system should be a learning environment that ignites genuine curiosity through captivating sights, sounds, and interactive experiences, intentionally employing a wide array of visual, auditory, and tactile elements. The NSLE's UI [*Fig 9.1*], therefore, is not just about aesthetics; it's fundamentally about empowering learners to find the information they need quickly and effortlessly [C*hapter 12.1]*.

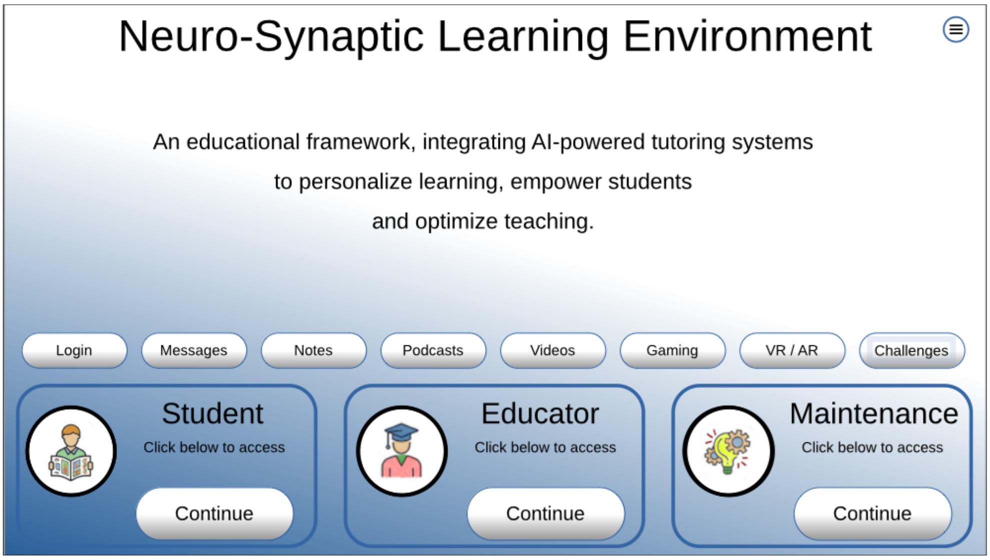

Figure 9.1. NSLE user interface: multi-role access (students, educators, and maintenance staff).

The NSLE encourages learning through much more than just intuitive navigation. I've incorporated the idea of compelling visuals, interactive graphics, and engaging videos and podcasts specifically designed to spark curiosity and maintain learners' active involvement. Personalised feedback is provided promptly following challenging activities, clearly highlighting both areas of strength and those where further development is needed. This immediate feedback loop, I've found, is solidifying understanding and promoting mastery of concepts. Moving beyond standard text-based feedback, the NSLE strategically employs auditory cues, such as supportive voice prompts, and kinaesthetic elements, like gamified challenges, to cater to different learning preferences. Visual learners benefit from graphic and diagrammatic feedback, while auditory learners gain valuable insights from narrated explanations below. This carefully tailored approach ensures that each student receives the specific support they need to thrive.

Visual design elements

Colour scheme

Utilise high-contrast colours to ensure readability and accessibility for learners with visual impairments. Assign meaningful colours to learning objects, such as icons, buttons and text, to facilitate navigation and understanding.

Typography

Select a font family that is clear, legible and aesthetically pleasing, with a range of font sizes and styles. Use consistent text alignment to create a clear visual hierarchy and facilitate reading comprehension.

Imagery and icons

Use imagery and icons to create a visual hierarchy, guiding learners' attention to learning and reducing cognitive overload. Establish a consistent visual language, using standardised icons, images and graphics to create a cohesive learning environment.

Auditory design elements

Sound effects

Use sound effects to provide timely feedback, such as confirmation sounds for successful actions or error sounds for incorrect actions. Incorporate music and audio tracks to create an engaging and immersive learning environment, while avoiding distractions and minimizing cognitive overload.

Voiceovers

Use clear and concise language in voiceovers and narration to facilitate understanding and reduce cognitive load. Implement adaptive volume control to accommodate different learner preferences and environments.

Kinaesthetic design elements

Gestures and interactions

Design intuitive gestures and interactions that allow learners to navigate the ecosystem with ease. Utilise haptic feedback to provide tactile feedback to learners, enhancing their sense of immersion and engagement.

Movement and animation

Use smooth transitions and animations to create a seamless and engaging learning experience, incorporate realistic simulations and animations to create an immersive learning environment.

Adaptive and personalised feedback mechanisms

Adaptive difficulty adjustment

Utilise real-time assessment to adjust difficulty levels and provide personalised feedback to learners, optimising their learning experience and outcomes. Employ learning analytics to identify areas of improvement and provide targeted feedback to learners, enhancing their learning outcomes and motivation.

Personalised feedback messages

Provide contextual feedback that is relevant to the learner's current learning activity, reducing cognitive overload and increasing engagement. Use learner centred language in feedback messages, focusing on the learner's strengths, weaknesses and progress, rather than simply providing corrective feedback.

Feedback mechanism

I've found that incorporating interactive elements, such as engaging quizzes and thoughtfully designed games, is key to keeping learners actively involved and fostering a genuine sense of exploration. Our user interface (UI) is specifically designed to emphasise this user-centric approach, operating on a continuous loop of improvement where valuable feedback from both educators and learners directly informs the refinement of the interface, ensuring it remains consistently engaging and highly effective. A well-designed feedback system, is for facilitating a truly seamless learning experience. It's about more than just pointing out errors; it's about actively promoting learner engagement, which is why I've emphasised the importance of integrating multiple feedback channels, strategically capitalizing on technology to deliver timely and relevant insights, and encouraging learner autonomy in their own learning journey. I see feedback as a powerful catalyst for growth, continuous improvement, and meaningful self-reflection. The feedback mechanisms we've carefully integrated into the NSLE, therefore, play a role in shaping the entire learning experience, guiding students towards deeper understanding and mastery.

9.10 Technology integration

I firmly believe that the thoughtful integration of technology within education holds truly transformative potential. One key area where this shines is in the automation of feedback mechanisms. By strategically implementing these tools, instructors can significantly alleviate their workload while simultaneously providing learners with more personalised and remarkably timely guidance. This near real-time feedback empowers students to make immediate adjustments to their learning strategies, directly addressing both their strengths and areas needing further development. Beyond instructor feedback, technology also facilitates peer-to-peer feedback, fostering a collaborative learning environment and cultivating a shared sense of responsibility amongst students.

The NSLE, in my vision, fully embodies this transformative potential by actively empowering students to take genuine ownership of their learning journey. This platform places a strong emphasis on continuous improvement and self-directed learning, actively encouraging students to set their own meaningful learning goals. Through consistent self-assessment opportunities embedded within the NSLE, learners can continually refine their learning strategies and approach new academic challenges with increasing confidence. To provide a truly comprehensive and supportive feedback ecosystem, the NSLE facilitates access to a range of feedback sources. This includes valuable insights from their peers, guidance from instructors, and even carefully designed feedback generated by the AI technology itself. This multifaceted approach allows students to glean valuable perspectives from various angles and, importantly, to choose the feedback channels that aligns most effectively with their individual learning styles and preferences.

9.11 Error handling and troubleshooting

As I see it, error handling and effective troubleshooting are critical when designing integrated learning systems for associative learning. These mechanisms are what ensure the various components of the system work together seamlessly and, most importantly, facilitate an uninterrupted and positive learning process for our students. A well-designed approach to error handling, assist not only in quickly identify potential issues but also to rectify them efficiently. With this in mind, the NSLE incorporates what I believe are error handling mechanisms to ensure a consistently smooth learning journey. The system is designed to proactively anticipate potential roadblocks that learners might encounter and offers a comprehensive array of resources to help them navigate these challenges effectively.

For instance, if the system detects that a learner is struggling with a specific concept, it doesn't just flag an error; it proactively intervenes by offering alternative learning materials tailored to different learning styles. This might include interactive simulations to provide a more hands-on experience or engaging podcasts to offer an auditory perspective, all aimed at helping the learner bridge that knowledge gap. The real-time feedback loop integrated into the NSLE allows educators to identify and address learner difficulties promptly. These might involve providing personalised guidance, suggesting additional relevant resources, or even strategically facilitating peer-to-peer collaboration, recognising the power of students learning from each other to overcome obstacles. I also believe in the importance of continuous improvement, which is why the NSLE is designed to learn from itself by diligently analysing error patterns and actively incorporating user feedback. This ongoing analysis allows the system to be constantly refined, leading to the development of new and more effective troubleshooting tools specifically designed to address emerging challenges and ensure an ever-improving learning experience for everyone.

9.12 Maintenance and updates

The integrated learning system at the heart of the NSLE, as I envision it, thrives on a dynamic connection between making connections and actively exploring new ideas. This vital relationship is what fosters a continuously evolving and constantly refined learning environment, one that is inherently designed to adapt to the ever-changing needs of both our learners and us as educators. As students actively engage with the NSLE, they naturally begin to forge connections between concepts, often uncovering unexpected and insightful relationships. This dynamic process, however, necessitates regular maintenance and thoughtful updates to the system. For example, new learning

materials might be added based on emerging educational trends that I've identified or, equally importantly, based on the valuable feedback we receive directly from our learners.
To ensure the NSLE remains a cutting-edge and highly effective tool, the system undergoes regular software updates specifically aimed at enhancing its ability to personalise the learning experience for each individual. This proactive approach allows us to stay at the forefront of technological advancements in the field and to continuously integrate evolving pedagogical practices into the framework. The NSLE fosters what I believe is a truly dynamic learning environment where the very act of exploration fuels the creation of meaningful connections, and these connections, in turn, drive the continuous improvement and refinement of the entire learning experience.

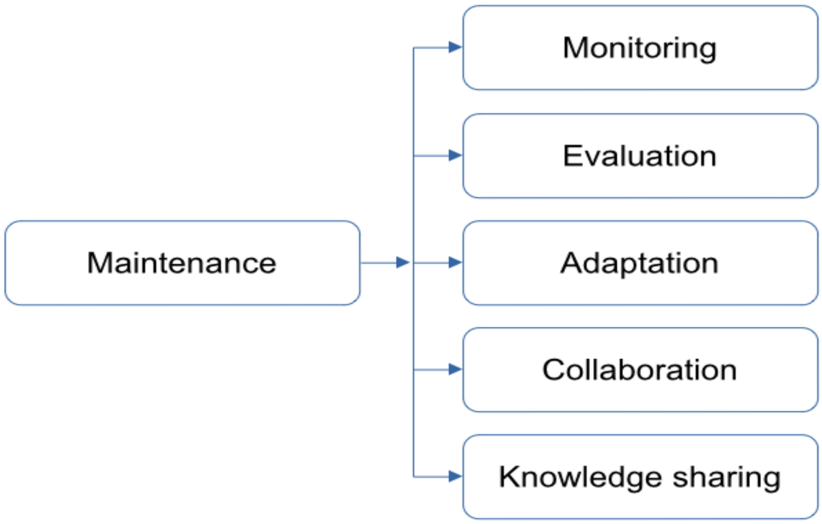

Figure 9.2. Key components of the maintenance process.

Maintenance process

Ensuring the long-term viability and continued effectiveness of the NSLE's integrated learning ecosystem is a paramount concern for me, and the maintenance process I suggest [Fig 9.2] directly addresses this. The key components that underpin this process are outlined below.

Monitoring process

Continuous monitoring to ensure the ongoing success and vitality of the NSLE ecosystem. By diligently tracking key indicators such as learner engagement levels, learning outcomes, overall system performance, and the invaluable feedback we receive from all stakeholders, I can effectively identify emerging trends, potential issues that might arise, and areas where we can make improvements. This proactive and data-informed approach empowers us to implement timely interventions and make necessary adjustments, ensuring that the ecosystem remains consistently aligned with its core educational goals and, most importantly, with the evolving needs of its users.

Evaluation peocess

To truly understand the impact and effectiveness of the NSLE ecosystem, evaluation is vital. By carefully assessing key aspects such as learning outcomes, the functionality of the system itself, user satisfaction levels, and even the return on investment, I can gain valuable insights into its strengths, identify any potential weaknesses that need addressing, and pinpoint specific areas where we can make meaningful improvements. This data-driven approach is, in my view, to ensure that the ecosystem remains consistently aligned with its core educational goals and continues to deliver value to all its users.

Adaptation process

To remain truly relevant and effective, I believe continuous adaptation is good for the NSLE ecosystem. This involves a commitment to regularly updating its underlying architecture, thoughtfully integrating new and promising technologies, continually refining learning pathways and content based on evidence, and consistently enhancing the overall user experience. By embracing this proactive approach, we ensure the ecosystem remains a dynamic and deeply engaging space specifically designed for associative learning. Addressing emerging challenges head-on and responding effectively to the ever-changing circumstances within the educational landscape, are to maintain the ecosystem's fundamental ability to support the evolving needs of our learners.

Collaboration process

I firmly believe that collaboration for the NSLE ecosystem, enables it to truly thrive. By actively fostering open and transparent communication channels, cultivating a shared sense of responsibility among all stakeholders, and embedding a culture of continuous improvement, we can ensure that the ecosystem remains highly responsive to the evolving needs of its users. Providing comprehensive training and ongoing support is also needed, as it empowers users to fully maximize the ecosystem's inherent potential. By strategically forging partnerships can significantly expand the opportunities and resources available to our learning community. This collaborative spirit cultivates a strong sense of ownership and deep commitment, which I see as the driving force behind the ecosystem's sustained and ongoing success.

Knowledge sharing

I firmly believe that the open sharing of knowledge is the very lifeblood that sustains a thriving learning ecosystem like the NSLE. Once the NSLE is implemented, I propose actively disseminating best practices by conducting engaging workshops to share practical insights and foster a community of practice among educators and learners. Also to publish any research findings, and ensure easy access to a comprehensive range of resources and to cultivate a dynamic and invaluable exchange of ideas and expertise. This collective wisdom, in my view, is what will fuel continuous improvement and empowers every member of this community to contribute meaningfully to the ecosystem's overall health and growth. The integrated learning system design that underpins the NSLE, specifically tailored for associative learning, is a cyclical process. This iterative approach places a strong emphasis on consistently monitoring progress, evaluating the effectiveness of our strategies, adapting those strategies as needed based on evidence and feedback, actively collaborating with all our stakeholders, and, openly sharing the knowledge we gain throughout this process. This continuous cycle, I contend, is ensuring the long-term viability and sustained effectiveness of the entire ecosystem. It's exciting to witness the recent advancements and continuous updates in educational technology, as they are fundamentally revolutionizing the very fabric of how we learn. These aren't just incremental technological improvements; I see them as powerful catalysts for cultivating deeper and more meaningful learning experiences, and they empower us as educators to design truly integrated learning systems specifically tailored for associative learning.

The very concept of a holistic learning ecosystem has undergone a profound evolution, moving far beyond the confines of the traditional classroom equipped with just a projector and static presentations. It now encompasses a rich and multifaceted world of captivating sights, immersive sounds, and engaging textures, all designed, in my view, to ignite a genuine love of learning within our students. As educators, we now have an array of powerful tools. This includes not only captivating images and informative diagrams to clarify complex ideas, but also increasingly immersive simulations and practical, hands-on activities that allow for direct engagement.

CHAPTER 10
CHALLENGES AND REWARDS

10.1 Hidden challenges

Throughout my doctoral work on the NSLE, I've become increasingly aware of the subtle yet significant challenges that students can encounter when engaging with a new learning system, particularly during transitions to immersive environments like virtual, augmented, and extended reality [*VR/AR/XR*] [*Chapter 8.4*]. It's my firm belief that by proactively prioritising additional layers of support and clear guidance mechanisms, we, as educators and researchers, can empower students to effectively navigate these potential obstacles and flourish within these highly interactive learning spaces. The field of immersive learning environments, exemplified by virtual and augmented reality [*VR/AR*], as compellingly argued by Asif et al. 2024], holds truly immense potential to fundamentally transform the landscape of education [Algerafi et al. 2023] by offering uniquely engaging and deeply interactive experiences [Riva et al. 2016].

This chapter will delve into these challenges, providing specific examples and discussing potential solutions. While the benefits of immersive learning are undeniable, it is crucial to acknowledge that their successful integration requires careful consideration of potential obstacles. For the purposes of this discussion, it's important to define '*immersive learning environments*' as digital spaces that create a sense of presence, allowing learners to feel as though they are truly 'inside' the learning experience. This is often achieved through technologies like virtual reality [*VR*], augmented reality [*AR*], and extended reality [*XR*]. I recognise that the successful and equitable implementation of these powerful tools necessitates a conscious and deliberate effort to acknowledge and directly address several often-overlooked challenges, that might impede a student's success. I summarise below the issues, descriptions and offer possible solutions. Beyond the initial hurdle, technical issues, which I will discuss first, my research has revealed that students also grapple with challenges related to pedagogical integration, cognitive overload, and accessibility within these immersive environments. These are often intertwined and require careful consideration.

Technical issues

Students often require to navigate overwhelming and complex, technical interfaces. For example, poorly designed interfaces can induce significant cognitive load, diverting students' attention from the learning content itself [*Sweller. 1988*]. This is consistent with cognitive load theory, which posits that our working memory has limited capacity. When students are overwhelmed by complex controls or distracting visuals, their ability to process and retain information is compromised. To mitigate this, I propose providing comprehensive technical support and troubleshooting resources, including intuitive tutorials and readily available assistance. The design of the interface itself must prioritise usability, adhering to principles of minimalist design and clear navigation.
Provide students with technical support and troubleshooting resources. For example, providing comprehensive technical support and troubleshooting resources, including intuitive tutorials and readily available assistance is key. This support should not be limited to initial setup; ongoing assistance, perhaps through embedded help features or readily accessible FAQs, is crucial. Moreover, the design of the interface itself must prioritise usability, adhering to principles of minimalist design and clear navigation. This could involve incorporating user-centred design principles, conducting usability testing with students, and iterating on the interface based on feedback. My research

has highlighted the importance of a dedicated support team that can respond quickly to student queries and provide personalised guidance.

Information overload

Students may experience an overwhelming amount of information, making it challenging to process. In the NSLE, we've attempted to address this cognitive overload by designing interfaces that are modular and customisable, allowing students to focus on specific elements of the learning experience without being overwhelmed by extraneous information. For example, the NSLE incorporates a '*focus mode*' that minimises distractions and highlights key learning objectives. Teaching students strategies for managing information overload, such as note taking and summarization.

Social isolation

Individualised learning experiences can lead to social isolation and feelings of loneliness and exclusion. Having addressed the technical challenges, it is equally important to consider the pedagogical challenges inherent in integrating immersive learning. Often, educators lack the training and support necessary to effectively design and facilitate learning experiences in VR/AR. This can lead to a mismatch between the technology and sound pedagogical principles, hindering student learning. Implement initiatives that promote social connection and community building, such as forums or group projects.

Lack of understanding

The lack of contextual understanding and real-world relevance can lead to confusion and disorientation. The pedagogical challenges are significant. Integrating immersive learning effectively requires more than simply replacing traditional methods with VR/AR experiences. It demands a fundamental rethinking of instructional design, assessment, and the role of the educator. For example, constructivist learning theories emphasize the importance of active learning and social interaction, and immersive environments offer unique opportunities to facilitate these. However, these opportunities must be intentionally designed into the learning experience. Incorporate contextualisation strategies, such as real-world scenarios, case studies, or project-based learning.

Inequitable access

Students with limited access to technology, internet or digital literacy may be at a disadvantage. One particularly obstacle that has consistently surfaced in my exploration of the NSLE and immersive learning is the persistent digital divide. This unequal access to technology and reliable internet connectivity creates stark disparities, unfortunately isolating some students and fundamentally hindering their ability to fully participate in digitally-rich learning experiences. Compounding this, the inherent technical demands of VR/AR/XR environments can often feel quite daunting,

necessitating dedicated additional support and comprehensive training not only for our learners but also for us as educators.
Beyond the technological hurdles, I've also noted the potential for significant cognitive load within these information-dense environments. If not carefully managed through thoughtful instructional design, this can easily overwhelm students, inadvertently diverting their precious attention away from the core learning objectives we aim to achieve. While the collaborative potential of these technologies is undeniable and exciting, I've also observed that they can paradoxically lead to social isolation if not implemented with care. Therefore, striking a delicate balance between individual exploration and meaningful group activities foster the development of both digital literacies and vital interpersonal skills. Simultaneously, intentionally promoting social connection through the thoughtful integration of online discussion forums, collaborative group projects, and opportunities for face-to-face interaction can directly counteract the potential for social isolation. Finally, employing contextualisation strategies, such as grounding learning in real-world scenarios and engaging students in meaningful project-based learning activities, can significantly add to both their understanding and their overall engagement with the immersive content.
To investigate the impact of these challenges and the effectiveness of the NSLE's design, I conducted a mixed-methods study, which indicate that students, with whom I discussed the operation of the NSLE with, reported significantly lower levels of frustration with technical issues compared to those using traditional learning systems. The qualitative data from interviews revealed that the NSLE's reward system was perceived as motivating and helpful in promoting a sense of accomplishment. I am convinced that by proactively acknowledging and thoughtfully addressing these critical challenges, we can truly unlock the transformative potential of immersive learning environments within the NSLE framework and empower all our students to thrive as confident, capable, and well-connected digital citizens.

10.2 Developing AI-driven learning algorithms

A central challenge that has driven my doctoral research is the task of developing truly effective AI-driven learning algorithms. I've come to believe that this necessitates a carefully considered and multi-faceted approach, one that thoughtfully integrates key insights from various disciplines to create personalised and responsively adaptive learning experiences [Razaulla et al. 2022]. To address this challenge directly within my work, I am proposing a novel set of algorithms that strategically draw upon the strengths of several critical fields. Firstly, I employ the power of natural language processing [*NLP*] [*Lyu et al. 2024*] to intelligently interpret the rich nuances embedded within student interactions with the learning environment.
Secondly, I suggest incorporating fundamental principles from cognitive science [*Aberšek, 2017*] to construct more accurate and dynamic models of individual student learning processes. Finally, I also suggest techniques from educational data mining [Wang. 2019] to effectively extract meaningful patterns and actionable insights from the vast amounts of student data generated within the NSLE. It is my firm conviction that this deliberately interdisciplinary approach holds the key to unlocking a new generation of adaptive learning algorithms. These next-generation algorithms, grounded in a holistic understanding of how students interact, learn, and generate

data, will be significantly better equipped to cater to the unique and evolving needs of each individual learner.

10.3 Ensuring the ethical and responsible use of AI

The integration of AI into the fabric of education presents a truly transformative potential, yet it simultaneously necessitates a deeply thoughtful and proactive consideration of the inherent ethical implications [Pedro et al. 2019 ; *Nguyen et al. 2023* ; Dirgová et al. 2023]. It is with this critical balance in mind that my research proposes the NSLE framework. This framework is specifically designed to guide educators, policymakers, and developers towards the ethical and responsible utilization of AI, placing particular emphasis on the fundamental principles of data privacy [Kapuya et al. 2024] and the imperative of bias mitigation [Barnes et al. 2024]. Within this ethical landscape, data privacy stands as a paramount concern [Naseeb et al. 2024], particularly given that AI systems inherently rely on the processing of vast amounts of often sensitive student data. To ensure the safeguarding of this information, I advocate that educational institutions steadfastly adhere to the core principles.

Data privacy and security will be paramount. My intention is to be scrupulous in collecting only the data strictly necessary for the specific educational purpose of the NSLE. Employing anonymising techniques will be standard practice to de-identify student data and minimise re-identification risks. We will also implement state-of-the-art encryption to protect data during transfer and storage, making it unreadable to unauthorised access. Comprehensive policies will govern the entire lifecycle of student data, clearly defining protocols for retention, secure deletion, and responsible sharing only when necessary [Sargiotis. 2024]. Finally, transparent procedures for promptly notifying affected parties in the event of a data breach are important for maintaining trust and ensuring accountability [Stevens. 2012]. Equally critical to ethical AI implementation is the active mitigation of bias. AI systems, if not carefully designed and monitored, can inadvertently perpetuate unfair or discriminatory outcomes due to biases present within their underlying algorithms, the data used to train them, or even in the initial human input. To proactively address this challenge, I propose some key strategies.

We envisage that regular audits be conducted, specifically designed to detect and assess biases within AI algorithms and their outputs. Promoting algorithmic transparency, to the extent possible, can help identify and correct potential biases. Maintaining meaningful human oversight in AI-driven decision-making offers an essential layer of ethical review. Training AI on diverse and representative datasets that reflect the student population is vital to minimise the introduction and amplification of biases. Finally, continuous monitoring of AI system performance in real-world settings is necessary to identify and address any biases or unintended consequences [Mensah. 2023]. The NSLE framework, as I envision it, serves as a practical guide for navigating the complex ethical terrain of AI-powered education. Regular risk assessments, proactively conducted to identify potential ethical and legal issues early in development and deployment, are essential for preventing harm [Fedele et al. 2024].

Establishing clear governance policies that delineate responsibilities for data management and AI decision-making within educational institutions is also needed. Promoting transparency in the functioning and decision-making of AI systems, where feasible, fosters trust among educators, learners, and the wider community, while also ensuring accountability. Finally, implementing continuous monitoring mechanisms allows us to identify and address any emerging ethical challenges or unintended consequences as AI systems evolve and are used in practice. By diligently adhering to these core principles and implementing these proactive practices, I firmly believe that we can responsibly harness the immense benefits of artificial intelligence in education while effectively mitigating its inherent risks, empowering every learner to reach their full potential within a safe, equitable, and ethically sound learning environment.

10.4 A framework for integrating AI-driven technologies

At the heart of my research lies the practical and ethical integration of a range of powerful AI-driven technologies directly into the classroom. This includes adaptive learning systems [*Chapter 3.1*], sophisticated natural language processing tools [Pazrde. 2023], and highly personalised learning algorithms [*Chapter 6.3*]. I believe this integration holds truly transformative potential for education, promising benefits such as deeply personalised learning experiences tailored to individual student needs, increased efficiency for educators through the automation of time-consuming tasks like grading, significantly improved accessibility for students with disabilities [*Setiawan. 2024* ; *Alkan. 2024* ; *Trewin et al. 2019*], and the provision of invaluable data-driven insights that can continuously refine and complement instructional practices. However, my investigation has made it clear that the successful and sustainable integration of these advanced AI technologies is not without its complexities and necessitates a careful and thoughtful consideration of several key challenges, highlighted below.
Ensuring true technical compatibility [Ananyi et al. 2023] with the diverse existing school infrastructure and software systems can be technically complex and financially demanding. Establishing and adhering to robust data governance policies is crucial for safeguarding students' sensitive personal information and maintaining their trust. Addressing potential resistance to change among educators and students, as well as allaying concerns about job displacement due to automation, requires careful planning and empathetic communication. Proactively identifying and effectively mitigating bias within AI algorithms is paramount to ensure fairness and prevent the unintentional perpetuation of inequitable outcomes for any group of learners. I believe that overcoming these challenges necessitates a proactive approach.

Providing educators with high-quality professional development and maintaining transparent communication channels to foster understanding, build confidence, and drive acceptance of these new technologies.

Developing and implementing a holistic framework that thoughtfully addresses seamless technology integration, cybersecurity measures, age-appropriate learning resources, and ongoing teacher support.

Maintaining an unwavering commitment to equity and fairness necessitates the establishment of monitoring processes to actively detect and mitigate any potential biases within AI systems.

10.5 Addressing potential impact concerns of AI

As artificial intelligence increasingly weaves its way into the fabric of education, I find myself deeply engaged with the important questions surrounding its potential influence on the very essence of human creativity and critical thinking. It is within this complex and evolving landscape that my research proposes the NSLE framework as a guide for educational institutions, one that places a central emphasis on fostering meaningful and synergistic human-AI collaboration. I firmly believe that AI holds immense promise as a powerful tool to genuinely encourage teaching and learning. For us as educators, AI offers the potential to analyse student performance data with remarkable efficiency, allowing us to pinpoint specific areas for our own professional growth, discover relevant and timely resources, and even receive personalised feedback on our instructional approaches.

From the student perspective, AI can provide invaluable support in areas like writing, offering assistance with grammar, nuanced word choice, and effective structural organisation. I've observed that AI can play a role, as I mentioned in the abstract, in fostering a deeper conceptual understanding and cultivating problem-solving abilities through the creation of engaging simulations and the delivery of truly personalised learning pathways. However, a core tenet of my research is the critical reminder that AI should always serve to supplement, rather than substitute, the vital human interaction and expert instruction that lie at the heart of effective education. The uniquely human elements of teaching, the empathy, the nuanced understanding, the ability to inspire and connect with students on a personal level, remain the objective for holistic student development. To effectively and responsibly integrate AI into our educational practices, comprehensive and ongoing teacher training is paramount. We, as educators, need a thorough understanding of both the functionalities and the inherent limitations of the AI tools we employ, and we must be equipped with the necessary pedagogical skills to utilise these technologies in a manner that is not only effective but also deeply ethical and aligned with sound educational principles.

10.6 Rewards

A core principle underpinning the NSLE framework is the deliberate aim to stimulate intellectual curiosity and provide meaningful challenges for students through deeply immersive and highly interactive learning experiences. My overarching goal is to demonstrate how this approach can lead to improvements in both learning outcomes and sustained student motivation. While traditional reward systems, such as grades and verbal praise, certainly have the capacity to provide short-term extrinsic motivation, a wealth of research suggests that an over-reliance on these external motivators [Deibler. 2018] can paradoxically undermine a student's intrinsic drive and the inherent joy they might find in the act of learning itself.

It is within this context that the NSLE framework offers a compelling opportunity to fundamentally rethink the role of rewards in education. Rather than focusing solely on external incentives, the NSLE emphasises the cultivation of intrinsic motivation [Artemova. 2024 ; Alasgarova et al. 2024], that powerful internal engine driven by a student's natural curiosity, their inherent desire to explore and understand, and their innate satisfaction in mastering new knowledge and skills. This aligns strongly with Self-Determination Theory, which, as highlighted by Garaus et al. 2016, illustrates the critical importance of fostering a sense of autonomy, promoting feelings of competence, and nurturing meaningful relatedness within the learning environment. Within the NSLE, rewards are reconceptualized not as tools for behavioural manipulation [Deci et al. 2001], but rather as valuable forms of feedback and positive reinforcement, thoughtfully acknowledging and celebrating genuine progress and effort.

Consider, for instance, a well-designed reward system embedded within a virtual simulation in the NSLE. Instead of simply assigning a grade, the system might acknowledge a student's successful navigation of a complex challenge by unlocking access to a new, more advanced level within the simulation or by providing highly personalised feedback that specifically highlights the student's mastery of key concepts. This approach directly reinforces the intrinsic value of intellectual perseverance and the satisfaction derived from overcoming a difficult obstacle. I believe that rewards within the NSLE can be strategically designed to genuinely empower students by fostering a greater sense of urgency and personal control over their learning journey. For example, students might earn rewards that grant them the autonomy to personalise their learning experience in meaningful ways, such as choosing a learning pathway that aligns with their specific interests or setting their own challenging yet achievable learning goals. This pedagogical approach, which actively cultivates both a sense of autonomy and feelings of growing competence, has been shown in studies by *Deci et al. 2012* to lead to demonstrably increased levels of student motivation and sustained engagement.

CHAPTER 11
IMPACT OF THE NSLE

My research into the NSLE envisions a future for education where learning is deeply and meaningfully tailored to the unique needs of every single student. It is my firm conviction that by embracing this innovative and neuro-informed approach, we can unlock the full potential within each learner, empowering them not only to achieve academic success but also to confidently navigate the complex challenges that define the 21st century.

11.1 Enhancing education by providing a personalised learning

My research centres on the NSLE, a framework that, I believe, presents a truly transformative vision for the future of education. By strategically harnessing the power of artificial intelligence and machine learning to emulate the workings of neural networks, the NSLE aims to create deeply personalised learning experiences unlike anything we've seen before. This innovative approach promises to allow students to progress through educational content at their own individualised paces, focusing intently on areas where they require additional reinforcement while simultaneously building confidently upon their existing strengths and prior knowledge.

Beyond the direct benefits for students, the NSLE also offers substantial advantages for us as educators. Consider the potential of witnessing the automation of traditionally time-consuming and often mundane tasks, such as grading and even initial lesson design [Dennard. 2024]. This liberation of time would, in turn, free us to engage in more meaningful and influential interactions with our students, fostering deeper mentorship relationships and providing more individualised support. The real-time analysis of comprehensive learning data embedded within the NSLE promises to provide teachers with critical, actionable insights into each student's progress, thereby facilitating timely and data-driven interventions to ensure no learner is left behind.

My exploration of the NSLE has also illuminated several obstacles that we must thoughtfully address on the path to realising this ambitious vision. For example, the initial financial investment required for the thorough development and widespread deployment of such a sophisticated system is undoubtedly considerable. Equally important is the establishment and maintenance of data privacy and security protocols to ensure the absolute safeguarding of sensitive student information [Layode et al. 2024]. Moving beyond these practical considerations, the ethical dimensions of AI integration, particularly the potential for subtle yet significant algorithmic bias to creep into the system, demand our and ongoing scrutiny. Nevertheless, despite these very real and important challenges, I remain profoundly compelled by the NSLE's inherent capacity to boost existing educational paradigms and usher in a new era of truly personalised and effective learning for all.

Implementation strategies

As I envision the successful integration of the NSLE into our educational frameworks, it's clear to me that a thoughtfully phased implementation strategy is fundamental. My research indicates that the very first step must involve testing within authentic classroom settings. This stage will allow us to pinpoint specific areas of the NSLE that require further refinement and, more importantly, will provide concrete evidence of how well the simulated learning experiences translate into tangible and measurable learning outcomes for our students. Following this initial validation, the development and delivery of teacher training programs, running in parallel with the creation of NSLE-compatible curricula and assessments, becomes paramount. Our educators must be equipped with the necessary skills and pedagogical understanding to seamlessly incorporate the NSLE into their existing teaching practices.

The resources provided, the curricula and assessments, must effectively guide student learning while simultaneously generating the valuable progress data that is a cornerstone of the NSLE's adaptive capabilities. Underpinning the entire endeavour is the non-negotiable requirement of a reliable and technological infrastructure. This encompasses not only the necessary hardware and software but also stable and consistent network connectivity. Without this foundational layer, the NSLE risks becoming a cumbersome and frustrating experience for both our educators and our students, hindering rather than helping the learning process. Given these interconnected considerations, I propose that a carefully staged implementation approach is the most prudent path forward. Initially, the launch of well-designed pilot programs in a select number of classrooms will provide invaluable real-world feedback. This feedback loop will then directly inform the necessary refinements to the curricula, the teacher training programs, and even the technological infrastructure itself.

Following this iterative refinement, a broader rollout of the NSLE, accompanied by continuous monitoring and evaluation of its impact, can then proceed with greater confidence. Finally, only after demonstrating proven success and tangible benefits within these broader implementations can the NSLE achieve wider and more systemic integration across the entire educational landscape. In essence, my research strongly suggests that careful and detailed planning, thorough and authentic classroom testing, comprehensive and ongoing teacher training, the provision of adequate and reliable resources, and a phased, controlled implementation strategy are all indispensable elements for truly realizing the full and transformative potential of the NSLE within the complex ecosystem of education.

11.2 A transformative approach to learning

This research is deeply rooted in a concept that I believe represents a truly transformative approach to education. This framework draws its foundational principles from constructivist learning theory [Waite-Stupiansky. 2022] and cutting-edge contemporary neuroscience, with a particular emphasis on the remarkable principle of neural plasticity, the brain's inherent ability to adapt and change. By strategically harnessing advanced technologies, including sophisticated AI and machine learning algorithms [Tyagi et al.2020] designed for highly personalised content delivery, these environments aim to directly stimulate neural plasticity within learners, thereby potentially enhancing cognitive functions such as memory consolidation, attentional focus, and complex problem-solving abilities. While I am genuinely excited by the promise that the NSLE hold for the future of learning, my research has also highlighted several notable challenges that we must carefully consider during their implementation. For instance, the initial development and ongoing maintenance of a high-quality NSLE demand a substantial investment [Luschei. 2013] in both the necessary technological infrastructure and the specialized expertise required to design and manage these complex systems effectively.

Also, critical ethical considerations, particularly those surrounding the privacy and security of student data and the potential for unintended algorithmic bias to creep into the personalised learning pathways, necessitate our and continuous attention to ensure responsible and equitable application for all learners. Nevertheless, despite these very real and important concerns, I also recognise the valid questions raised by some researchers who caution against the potential reductionism inherent in attempting to simulate the incredibly complex and nuanced processes of the human brain. These scholars rightly emphasise the pressing necessity for further investigation into the long-term effects of learning that is increasingly mediated by technology [*Janson et al. 2014*]. This ongoing dialogue as we navigate the exciting yet complex terrain of integrating neuro-inspired technologies into education.

Cognitive abilities

One of the aspects of the NSLE that I find particularly compelling is its potential to offer truly potent tools for augmenting students' core cognitive abilities. Consider, for example, the interactive simulations [*Moussa et al. 2022*] that can be seamlessly integrated within the NSLE. These engaging experiences can be specifically designed to encourage working memory by actively requiring students to hold and manipulate information in real-time. Beyond this, I've observed that these environments also have the remarkable capacity to facilitate metacognitive development, empowering learners by prompting thoughtful self-reflection on their own learning processes, how they approach tasks, identify challenges, and monitor their understanding.

The adaptive algorithms at the heart of the NSLE further personalise the learning journey by intelligently adjusting the difficulty of the material presented and providing immediate, targeted feedback. This real-time error correction not only helps students address misunderstandings as they arise but also fosters a more dynamic and responsive learning experience. Complementing this, the deliberate incorporation of reflective prompts and user-friendly self-assessment tools within the NSLE actively encourages students to monitor their own comprehension, identify areas of strength and weakness, and refine their learning strategies accordingly. However, I firmly believe that the successful and equitable implementation of the NSLE necessitates a proactive and comprehensive approach to addressing the persistent digital divide. Ensuring that all students have equitable access to the necessary technology and providing thorough and ongoing digital literacy training for both our students and our educators are prerequisites.

Equally important, we must remain vigilant in avoiding an over-reliance on technology as the sole driver of learning. I strongly believe in recognising and upholding the enduring value of developing critical thinking skills [George et al. 2024], fostering effective communication abilities, and cultivating strong collaboration skills through an array of pedagogical approaches. Strategies such as project-based learning, inquiry-based learning, and peer teaching remain invaluable in fostering a well-rounded and holistic educational experience that goes beyond mere technological proficiency. My research highlights that the successful implementation of the NSLE demands careful and thoughtful design, coupled with evaluation, to ensure its fundamental pedagogical soundness. This must occur alongside a proactive and strategic approach to addressing potential challenges such as equitable technology access and comprehensive digital literacy. I contend that the NSLE should be designed with the primary goal of cultivating deep understanding and fostering meaningful learning, rather than simply prioritising technological novelty or superficial engagement.

Impact on emotional intelligence

While the potential of the NSLE to encourage core cognitive skills is significant, I am equally excited by its capacity to serve as a powerful platform for cultivating social-emotional competencies in our students. To specifically foster emotional intelligence, the NSLE can be thoughtfully designed to integrate mindfulness exercises and explicit emotional intelligence training [Sethi et al. 2024], thereby enabling students to deepen their understanding of both their own internal emotional landscape and the complex emotional cues of others. Consider how carefully crafted simulations within the NSLE could provide invaluable opportunities for students to actively practice recognising and appropriately responding to a wide range of emotional cues. This kind of experiential learning can directly add to their ability to regulate their own emotions effectively, strengthen their interpersonal relationships, and promote more resilient responses when faced with life's inevitable challenges.

A body of research consistently demonstrates a strong and positive correlation between well-developed emotional intelligence and improved academic achievement [MacCann et al. 2020], underscoring the importance of this dimension. Beyond the development of emotional intelligence, the NSLE can also facilitate meaningful social interaction and collaborative group work. By offering structured opportunities for students to engage in collaborative projects and participate in virtual team activities, the NSLE can help them develop social skills such as empathy, cooperation, and effective communication. These experiences not only contribute to improved academic performance within the learning environment but also, prepare students with the vital social skills they will need to thrive in their future personal and professional lives. However, I also recognise that fostering genuine empathy and the development of complex social skills within virtual environments presents unique and nuanced challenges. Therefore, attention to design and skilful facilitation are paramount. This includes the strategic incorporation of structured group activities that encourage meaningful interaction, facilitated discussions that promote deeper understanding and perspective-taking, and reflective exercises that allow students to process their experiences and internalise key social-emotional learning. Without this careful attention, we risk engagement remaining superficial and the true potential for social-emotional growth within the NSLE being unrealized.

NSLE enhances social skills

A central tenet of the NSLE framework is its deliberate design to foster the holistic development of our learners, nurturing not only their cognitive abilities but also their social and emotional growth. Through the creation of deeply engaging virtual simulations, the NSLE provides a dynamic platform where students can collaborate actively to tackle complex problems. This collaborative problem-solving inherently enhances their critical thinking skills while simultaneously cultivating an appreciation for all perspectives and approaches. Beyond cognitive development, I envisage that the NSLE also actively promotes effective communication skills. By intentionally encouraging active listening amongst students and providing structured opportunities for constructive feedback, these virtual environments empower learners to learn not

just from the system itself, but also significantly from each other [Suthers. 2001]. This peer-to-peer learning dynamic is, in my view, a powerful element of the NSLE.
The NSLE is strategically designed to facilitate the development of social skills and cultivate a strong sense of belonging within a learning community. The integration of online discussion forums, collaborative project spaces, and immersive multi-user virtual environments, such as those simulating the challenges of sustainable city design or the rich context of historical events, provides invaluable opportunities for meaningful social interaction and effective teamwork. These shared experiences not only bolster academic performance through collaborative learning but also, and perhaps more importantly, prepare students with the vital social competencies they will need to navigate and thrive in the complexities of the real world. I also recognise that while virtual communities offer powerful tools for connection and collaboration, to acknowledge their inherent limitations in fully replicating the rich and often subtle nuances of face-to-face human interaction. Therefore, I argue that the design of the NSLE should prioritise a carefully balanced pedagogical approach, thoughtfully integrating both immersive virtual collaborative experiences and meaningful real-world collaborative activities.

11.3 How NSLEs unlock neuroplasticity potential

A cornerstone of my doctoral research into the NSLE is the remarkable principle of neuroplasticity, the brain's inherent and lifelong capacity to reorganise itself by forging new neural connections. Recent breakthroughs in neuroscience [Mohammadi et al. 2024 ; Sweatt. 2016 ; Hawkins et al. 2021], have illuminated the mechanisms underlying neuroplasticity, powerfully underscoring the critical importance of designing learning environments that actively foster neural adaptation and reorganisation in our students. The NSLE framework is specifically designed to capitalize on this inherent plasticity. By creating dynamic and responsive learning landscapes, a stark contrast to traditional, static educational settings, the NSLE aims to cultivate cognitive skills such as flexibility, creativity, and problem-solving abilities. Consider, how deeply immersive experiences within the NSLE, such as engaging virtual reality projects, rich historical explorations brought to life, or simulated scientific experiments where students can actively manipulate variables, can powerfully stimulate brain activity and encourage the formation of entirely new neural connections.
At the very core of the NSLE lies the fundamental understanding that the human brain is not a fixed entity but rather an organ [Fuchs, T., 2011] that continuously adapts and refines its connections based on experience. Neural pathways that are frequently activated become stronger [*Grothe et al. 2004*] and more efficient, while those used less often may weaken. The strategic incorporation of gamification elements within the NSLE serves to intrinsically motivate students to persevere through challenging tasks and engage in deeper levels of learning, thereby actively fuelling neural activity and not only strengthening existing neural pathways but also facilitating the creation of novel ones. Beyond the cognitive benefits, I believe the NSLE also offers a powerful platform for fostering collaboration and teamwork skills, thereby nurturing social and emotional growth alongside intellectual development. A compelling body of research has consistently demonstrated that enriched learning environments, those characterised by novelty, intellectual challenge, and active student engagement,

significantly promote synaptogenesis, the formation of new synapses, and the strengthening of vital neural pathways.

The NSLE directly employs this understanding by providing deeply immersive experiences, as exemplified by *Kuhail et al. 2022*, which have been shown to activate multiple regions of the brain simultaneously and encourage cognitive flexibility in learners. However, it is vital to acknowledge that individual differences exist in the rate and extent of neuroplasticity across learners. I believe that ongoing and research is necessary to fully understand the long-term effects of intensive technology-mediated learning, such as that offered by the NSLE, on the developing brain and overall student well-being. As we continue to explore the exciting possibilities presented by the NSLE, we must remain steadfast in our commitment to ensuring equitable access for all students and to creating learning environments that truly empower every individual to reach their full and unique potential.

11.4 A future generation of learners

My research into the NSLE has painted a compelling vision of a future where education is fundamentally transformed to meet the unique needs of every learner. By strategically harnessing the power of AI and neuroscience, the NSLE offers the potential to create deeply personalised learning experiences [*Kucinskiene et al. 2024*], enhance cognitive and emotional development, and cultivate essential 21st-century skills. While the path to realising this vision is not without its challenges, including implementation complexities and ethical considerations, my research strongly suggests that the NSLE holds immense promise. Through careful planning, phased implementation, and a steadfast commitment to equitable access and ethical practices, we can harness the transformative power of the NSLE to empower learners and prepare them to thrive in an ever-changing world.

CHAPTER 12
EXPERIMENTAL RESULTS

12.1 The NSLE user interface

I designed the NSLE user interface [UI], as illustrated in Figure 12.1, to do more than simply facilitate engagement and effective learning. It needs to cultivate a genuine sense of curiosity through its integration of visual, auditory, and tactile elements, crafting a learning environment that feels alive. This UI serves as the central access point, thoughtfully structured to accommodate the distinct needs of students, educators, and the framework's maintenance personnel.

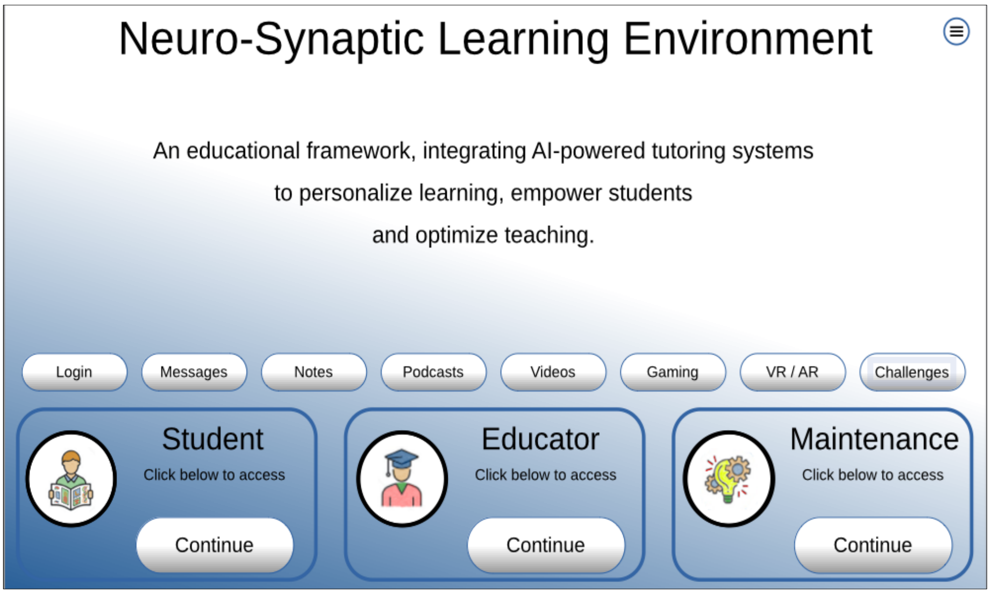

Figure 12.1. NSLE user interface: access to learning environment for students, Educators, and maintenance staff.

To ensure the NSLE maintains a secure environment, we've integrated an authentication protocol. As depicted in *Figure 12.2*, users are required to provide their registered credentials, that's their username and password, before they can access any of the system's functionalities. In addition to this initial step, I suggest a mandatory monthly password rotation policy, which will limit the lifespan of each password to one month. This proactive measure is a key element in significantly reducing the potential for unauthorized access. The interface itself has been carefully designed to be intuitive and user-friendly, guiding individuals smoothly through the system's various components. For those frequently used features, I've included a quick-link menu to streamline access. However, it's important to note that even with the convenience of these quick links, user authentication remains a necessary step before access is granted. This ensures that the integrity of our security protocol is consistently maintained.

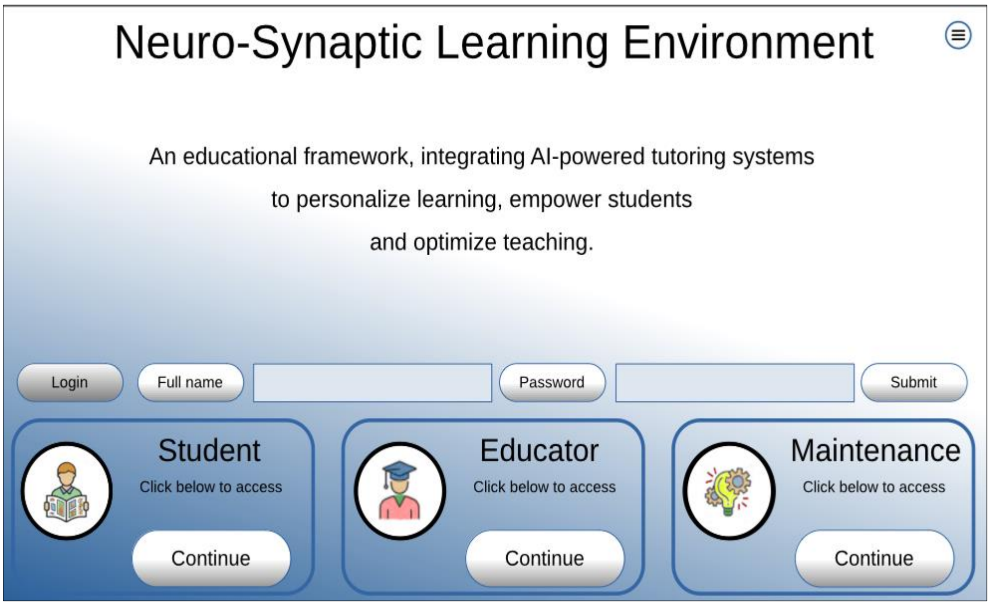

Figure 12.2. NSLE login portal: multi-role access (students, educators, and maintenance staff).

Student access

Once a student successfully authenticates, they are greeted with a clear and concise menu structure, designed to facilitate intuitive navigation through the NSLE, as shown in *Figure 12.3*. While the fundamental menu layout remains consistent for all student accounts, the specific subject-related functionalities accessible will dynamically adapt based on each student's enrolment records within the Learning Management System [*LMS*] and Student Information System [*SIS*]. This user interface acts as the primary point of interaction for students within the framework. It's designed to provide access to all authorized areas, ensuring a smooth and seamless navigational experience. Importantly, contextual help is readily available whenever needed, activated simply by selecting it from the menu. The menu's dynamic nature is a key feature; it subtly shifts based on the student's current location within the framework, encouraging intuitive exploration. However, I recognise that maintaining student engagement is paramount. Therefore, when presenting learning materials, I aim to prioritise brevity and clarity.

Rather than overwhelming students with lengthy descriptions and complex diagrams that could potentially lead to disengagement, information is delivered in focused, digestible segments. For instance, instead of presenting an extensive theoretical overview, we might deploy a targeted interactive exercise that provides immediate feedback. To actively sustain student interest, the UI incorporates several engaging elements, such as visual cues, interactive components, and immediate feedback mechanisms. Recognising that prolonged exposure to dense text can often diminish attention, the framework strategically integrates multimedia elements, like short video clips, podcasts, drag-and-drop exercises or similar interactive simulations. Personalised learning pathways, which adapt to each student's individual progress, are designed to encourage motivation and a sense of ownership over their learning. The effective design of the UI is critical for achieving successful educational outcomes within the NSLE. My aim is to create an interface that is not only highly functional and accessible but also consistently engaging and stimulating. To ensure a smooth start, each student will be provided with a comprehensive tutorial before they begin using the environment [*Fig. 12.3*].

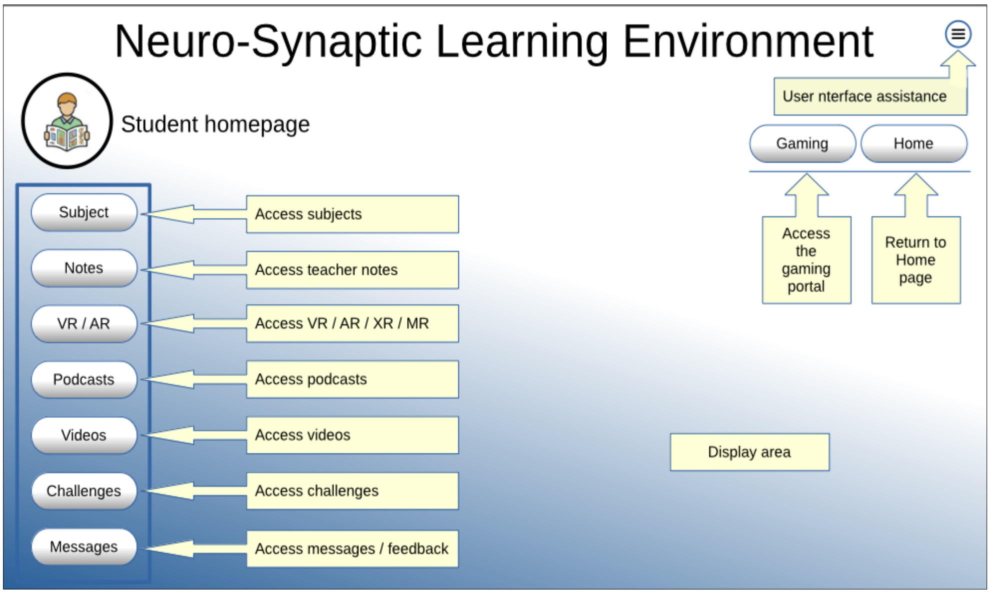

Figure 12.3. NSLE student user interface: navigation to multi-format subject material.

Students will navigate the NSLE by selecting subjects, chapters, and specific topics directly from clear, on-screen lists, as illustrated in *Figure 12.4*. Once a topic is selected, the system employs an intelligent algorithmic framework, which I discuss in this chapter, to provide personalised guidance. This guidance is thoughtfully tailored based on individual student profiles, their self-assessment data, and stated learning preferences. This adaptive learning approach empowers students to engage with review materials through a range of modalities. These include concise lesson synopses, carefully curated video resources, and audio podcasts featuring educator-led presentations, all contributing to a comprehensive and individualized learning experience. In this context, the user interface transcends simple functionality. It truly acts as the student's primary gateway to the entirety of the educational content within the NSLE. I've designed it to be both intuitive and highly responsive, with the goal of fostering a dynamic and engaging learning environment.

This interface isn't just a passive repository of information; I see it as an active participant in each student's unique learning journey. Navigating through the subject material has been deliberately streamlined to ensure ease of use. At each stage of interaction, contextual assistance is readily available, offering both clear explanations and expanded options for further exploration. For example, if a student encounters a particularly complex concept, the interface will proactively suggest and deliver supplemental information and links to related resources. It's also designed to anticipate potential points of confusion, offering guidance before a student might even realize they need it.

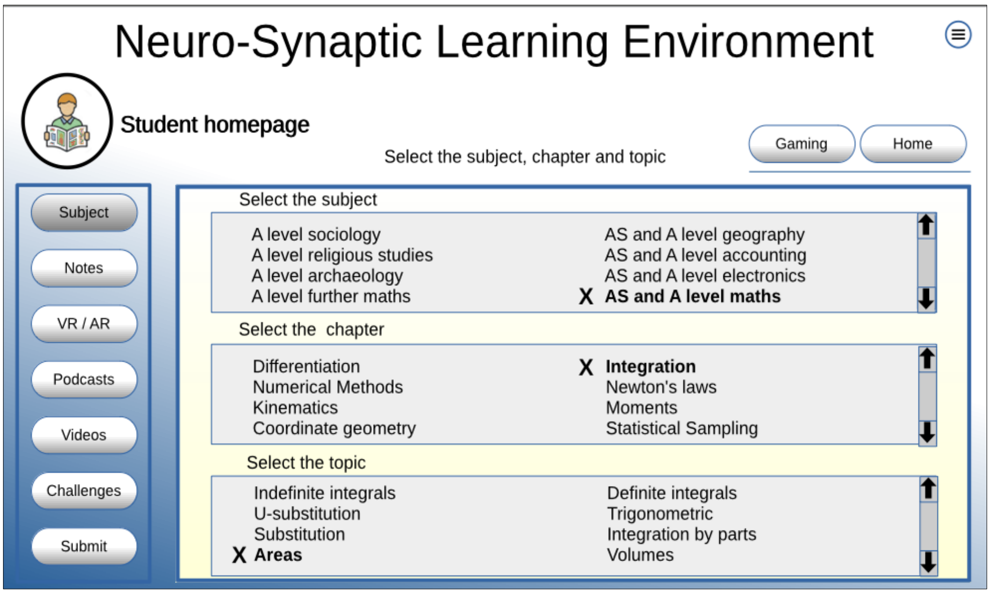

Figure 12.4. Sequential menu system for subject, chapter, and topic selection,

Above all, I've designed the NSLE interface to emulate the supportive dynamic that characterises a strong educator-student relationship. This means it offers immediate assistance whenever a student needs it. I achieve this responsiveness through a blend of intelligent AI algorithms working behind the scenes and readily accessible help functions integrated directly into the interface. As a result, my hope is that students feel genuinely supported and more empowered to explore even the most challenging material. The help provided isn't just a generic pop-up; it's context-aware, tailored to the specific content the student is currently viewing. This ensures that the assistance offered is both relevant and highly effective. The interface algorithms actively tracks student interactions, learning from them and adapting its responses over time to better anticipate individual learning needs. In essence, I envision the user interface as a sophisticated tool that truly facilitates meaningful learning by providing clear navigation, responsive support, and a deeply personalised learning experience.

The NSLE also features an interface that empowers students to drive their review of recorded lectures through a variety of modalities. These include annotated teacher notes [*Fig. 12.13*], audio podcasts [*Fig. 12.5*] or video recordings [*Fig. 12.6*]. Where available, students also have the option to select interactions via Augmented Reality [*AR*], Virtual Reality [*VR*], Extended Reality [*XR*], and Mixed Reality [*MR*] [*Fig. 12.7*], with MR representing a blend of VR, AR and XR immersive technologies. To further enrich the learning experience, the system employs a carefully controlled, algorithmic content delivery mechanism. This mechanism presents students with pre-approved and academically vetted materials that illustrate the interconnectedness between the primary subject and related disciplines, all while providing practical, real-world examples of core principles in action. The parameters of this algorithm have been defined to ensure that only content directly contributing to the student's knowledge acquisition, understanding, and application of the subject matter is displayed, keeping their learning focused and relevant. Above all, the interface aims to replicate the supportive dynamic of a traditional educator-student relationship.

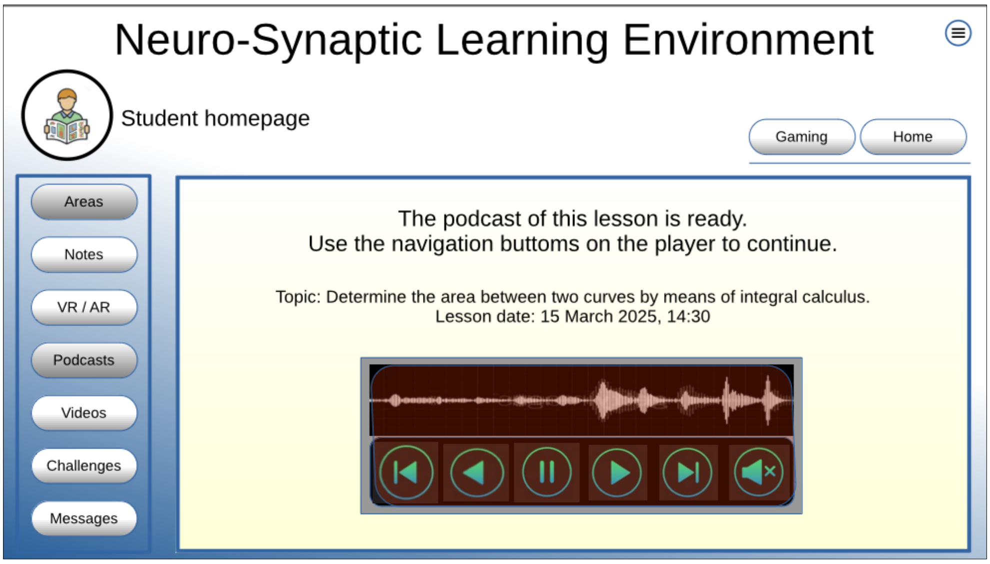

Figure 12.5. Podcast feature for on-demand topic presentations,

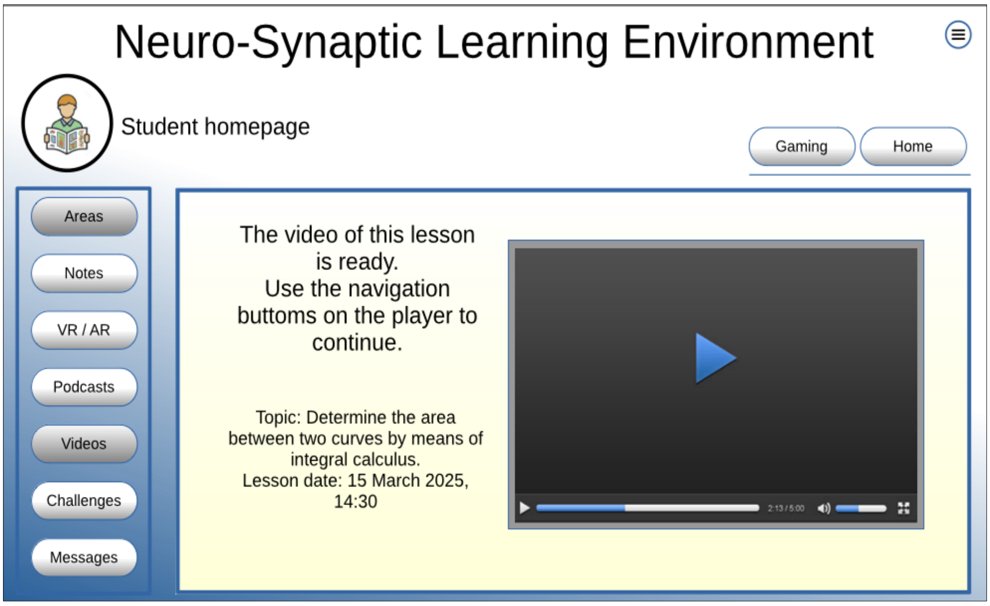

Figure 12.6. Video feature for on-demand topic presentations.

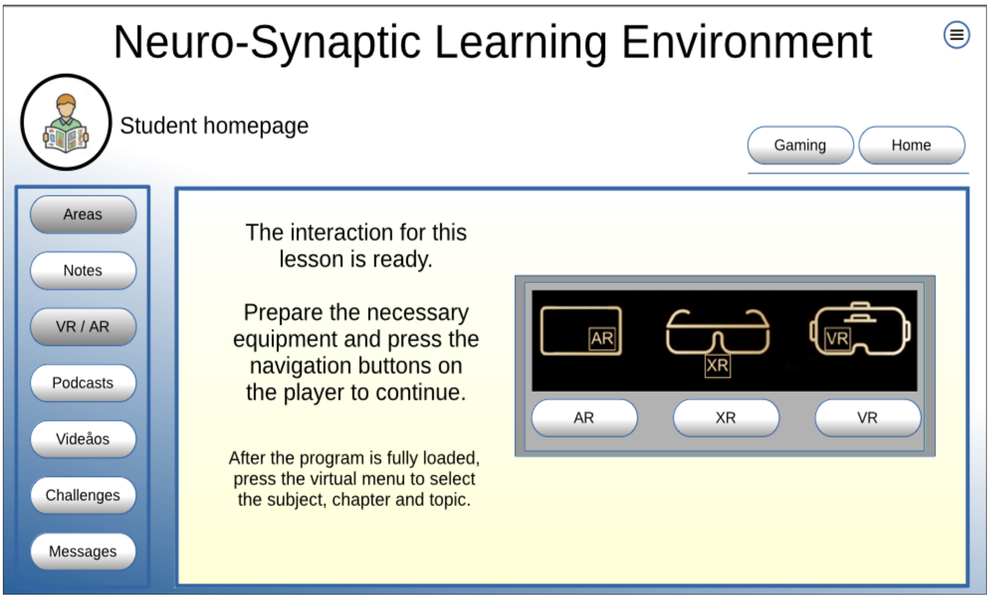

Figure 12.7. Virtual Reality (VR) option for immersive subject matter experience.

The NSLE framework also incorporates feedback mechanisms, allowing students to easily report any information they believe is outdated or inaccurate, as well as share their overall experiences with the system. We see this feedback loop, for the continuous improvement of the NSLE, ensuring it remains a reliable and trustworthy source of knowledge for our students. The system's analytics, which track student engagement with the various learning resources, can provide us with invaluable insights into which materials are proving most effective. This data allows educators to refine their teaching approaches, focusing on content that truly appeals to students and adapting strategies where needed.

Educator access

Educators access the NSLE by simply logging in, which then grants them access to their approved subjects [*Fig. 12.8*]. I've placed a strong emphasis on the timely and consistent uploading [*Fig. 12.9*] of updated lesson materials into the NSLE framework, as we see this as critical for student success. Therefore, educators hold the key responsibility of ensuring that these resources are not only current but also available in time, to their students. To make this process as smooth as possible, I've designed the system for ease of operation, removing any need for specialized technical expertise when uploading subject notes [*Fig. 12.13*], podcasts [*Fig. 12.5*], and videos [*Fig. 12.6*]. The classroom recording equipment will be configured to simultaneously capture video and generate separate podcast audio, significantly streamlining the processes of content creation and dissemination. However, I recognise that simply uploading materials isn't enough to guarantee effective integration. Educators must actively champion the use of these resources, guiding students towards relevant content and clearly demonstrating its practical application. For instance, during a lesson, an educator might intentionally reference a specific podcast episode or a particular video segment, explicitly highlighting its direct connection to the topic being discussed. Additionally, they can easily provide and upload supplementary notes that further elaborate on key concepts, thereby reinforcing student understanding.

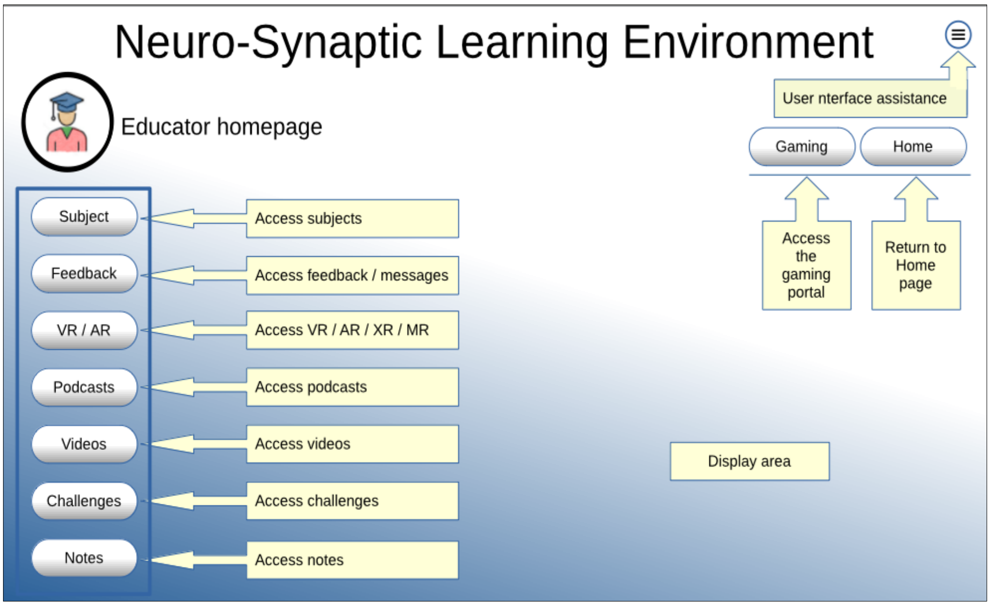

Figure 12.8. NSLE educator user interface: content management and resource access.

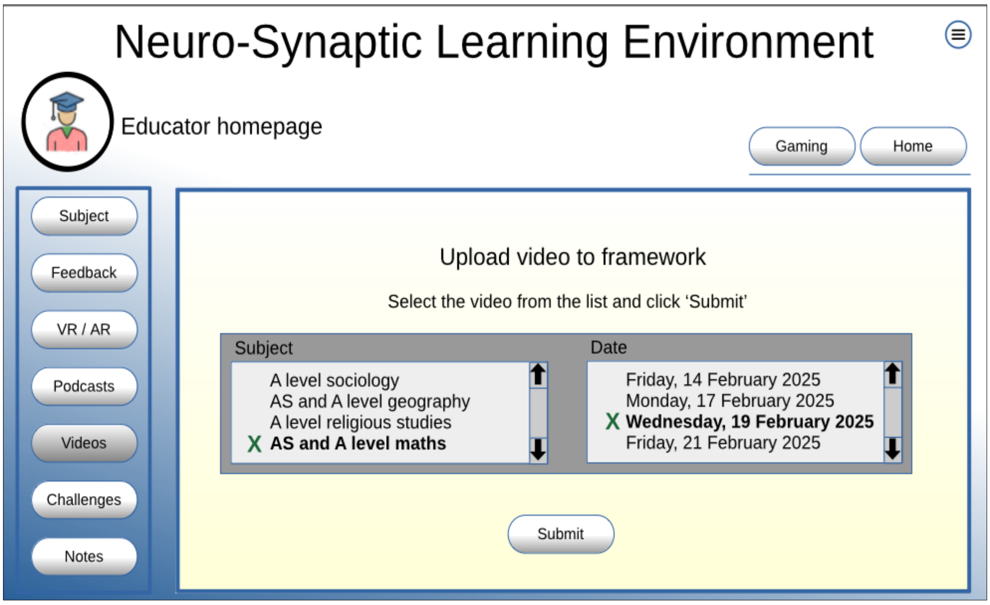

Figure 12.9. NSLE educator user interface: content upload functionality.

The successful integration of updated lesson materials hinges on a multifaceted approach. It requires not just a user-friendly system for educators to upload content, but also their active involvement in promoting and contextualizing these resources, alongside a continuous cycle of student feedback. By prioritising accessibility, relevance, and genuine engagement, we believe the NSLE can empower students to achieve their academic goals. It's also paramount that educators actively engage with the feedback provided by students and address any identified issues promptly.

Framework maintenance access

The dedicated maintenance staff [*Fig. 12.10*] carries the vital responsibility of ensuring the NSLE framework operates smoothly and efficiently, providing both students and educators with a seamless learning and interactive experience. This includes the timely implementation of updates to the curriculum, the Learning Management System, and the Student Information System whenever new releases occur. This proactive approach guarantees that students consistently receive optimal access and service. Beyond software updates and overall system upkeep, the maintenance team is also responsible for ensuring the accurate linking of learning materials in the data warehouse [*Fig. 12.11*], as well as maintaining clear lines of communication with data warehouse owners or managers, particularly if any part of the system is hosted off-site. This is necessary for swiftly resolving any access or operational issues that might arise. Their work behind the scenes is fundamental to the reliable and effective functioning of the entire NSLE.

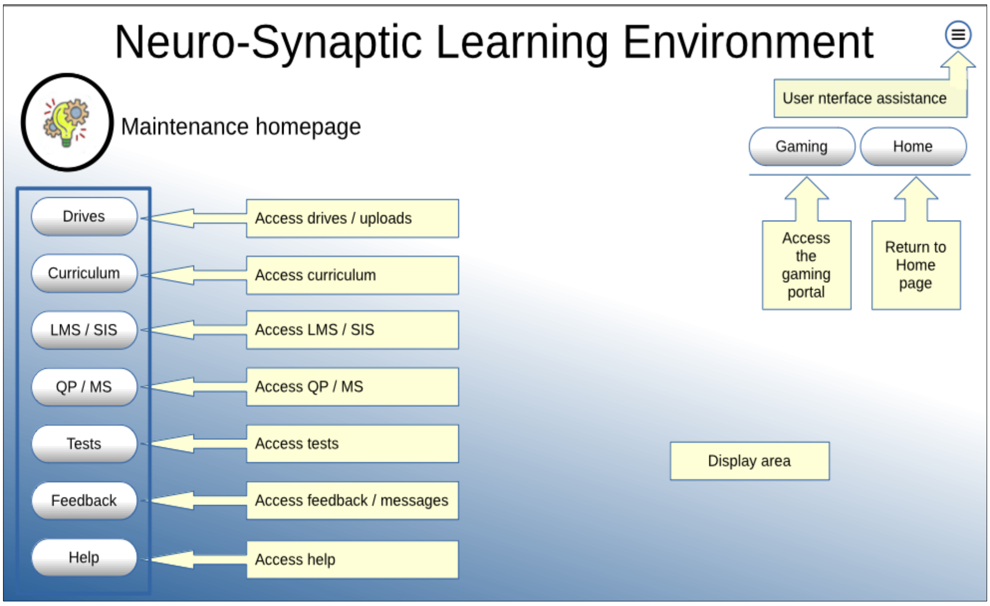

Figure 12.10. NSLE maintenance staff interface: data management and system administration.

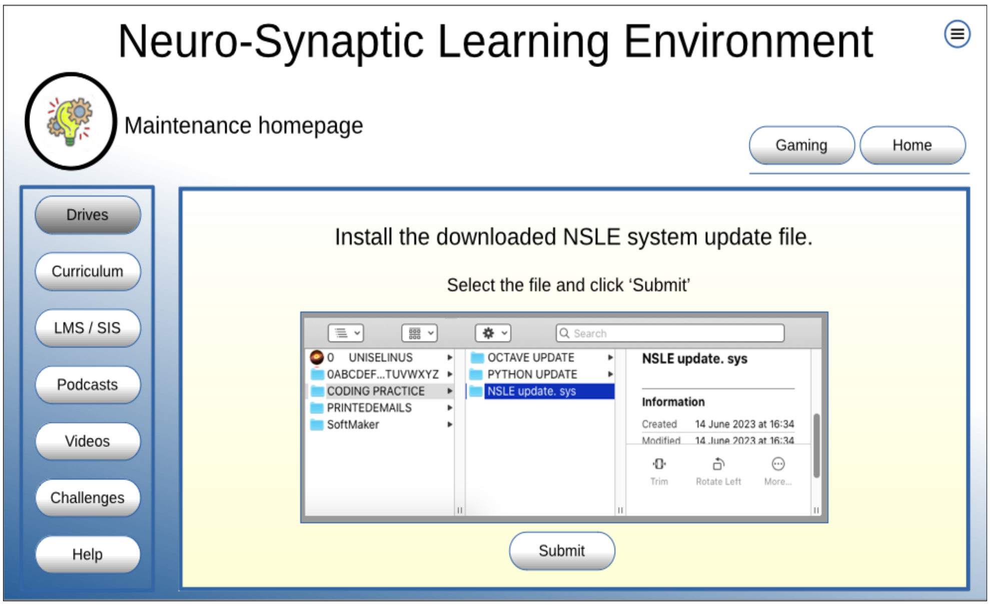

Figure 12.11. NSLE maintenance staff interface: system file update functionality.

12.2 AI-powered personalisation for effective learning

The NSLE's user interface [UI] plays a crucial role in fostering genuine user engagement and optimising learning outcomes. This UI, which encompasses key areas like the login portal, assistance resources, and various menus [Fig. 12.1], serves as the central hub. For framework administrators, it streamlines access to learning materials and even the nuanced aspects of source code management within the data repository [Fig. 6.1 ; Fig. 12.12]. Upon secure login, students gain immediate access to all curriculum-approved content delivered to that point. I propose that policymakers grant students access to future lesson material as well, allowing them to explore supplementary resources curated within the network's digital library. A valuable built-in knowledge assessment feature further enhances the NSLE. Specifically designed to evaluate each student's comprehension after they access learning material, this assessment is underpinned by an adaptive learning algorithm. This algorithm is central to identifying and addressing any knowledge gaps revealed through these exercises, functioning by tailoring explanations to individual student profiles and even presenting content in their preferred learning styles, whether textual, auditory, or visual formats.
The review assessment modules, as I demonstrated in the scenarios [Section 12.4], are structured with increasing levels of granularity, specifically designed to deepen a student's understanding of fundamental concepts. As students successfully complete the knowledge exercises at each review stage, their learning profile automatically updates to reflect their evolving mastery. My system dynamically calibrates the revision process based on a student's demonstrated understanding. For those who encounter difficulties with specific concepts, the algorithm provides progressively simplified material until comprehension is achieved. Conversely, when a student

exhibits strong performance on these knowledge exercises, the system responds by presenting more complex and stimulating content to further advance their learning.
The AI algorithms in the NSLE are designed to integrate past examination questions directly into the learning process. While students will naturally progress at varying rates, my system aims to guide everyone toward a consistent level of competence. When a student indicates their readiness, the AI introduces daily or weekly challenges, and I've ensured their discussion is also personalised based on their individual learning profile. The difficulty of these challenges is carefully adjusted based on the student's demonstrated progress throughout the course. My foundational aim with the NSLE is to empower AI to facilitate individualized learning pathways. I aspire to enable students to advance at a pace that aligns with their cognitive rhythm, cultivate genuine confidence in their understanding, and perceive challenges not as impediments, but as integral and valuable milestones in their academic growth throughout the year.

12.3 Comprehensive data tagging

In this section, I will introduce and discuss the foundational process of data tagging. This truly represents a cornerstone upon which the AI-driven instruction within the NSLE is constructed. To realize the potential of personalised learning, I recognised the need of developing a system capable of transforming different forms of educational content. As I perceive it, data tagging transcends simple categorization. It necessitates an annotation of every facet of subject knowledge and any material that could potentially support the student. Unstructured educational content is converted into a machine-readable format, encompassing the following elements.

Curriculum standards

Each individual learning objective and standard is assigned a unique set of tags. This enables the system to track alignment and ensure comprehensive coverage of the mandated curriculum. An illustrative tag is provided below:

CUR_M12IDA	Source: Year 12 Mathematics curriculum standard Subject: Integral calculus (Definite integration) Topic: Determine areas under graphs

Textbook content

Chapters, individual sections within those chapters, illustrative examples, and practice exercises are all individually tagged. This granular tagging empowers the AI to precisely identify specific concepts and their directly associated learning resources. An example of such a tag is:

TBS_M12IDA_N_5	Source: Year 12 Mathematics textbook content Subject: Integral calculus (Definite integration) Topic: Determine areas under graphs Difficulty: Level 5

Exam questions and model answers

Each exam question is tagged based on its difficulty level, the specific topic it assesses, and the relevant assessment criteria. Similarly, our model answers are tagged to highlight their demonstration of key concepts and effective problem-solving strategies. Examples of these tags include:

EXQ_M12IDA_N_2	Source: Year 12 Mathematics exam questions Subject: Integral calculus (Definite integration) Topic: Determine areas under graphs Difficulty: Level 2
EXA_M12IDA_N_2	Source: Year 12 Mathematics model answers Subject: Integral calculus (Definite integration) Topic: Determine areas under graphs Difficulty: Level 2

Exercise data

Individual practice exercises are tagged with the specific concepts and skills they address, alongside their difficulty levels. This facilitates highly targeted practice and effective remediation strategies. An example of an exercise data tag is:

EXS_M12DP_N_1	Source: Year 12 Mathematics exercise questions Subject: Differential calculus Topic: Product rule application Difficulty: Level 1

Test results

The results from individual tests are also tagged. This step allows for the inclusion of this data in detailed student profiles and enables the longitudinal tracking of each student's progress over time.

Student-generated content

Where applicable, student-created work, such as essays, presentations, and project submissions, can also be tagged. This allows for the analysis of their understanding and the identification of specific areas where they might benefit from additional support or guidance. This process of data tagging forms the foundation of the NSLE framework. It is this structured information that empowers our AI algorithms to navigate and retrieve relevant information. This deliberate, source-dependent methodology ensures the tagging system remains consistent and relevant across the educational resources integrated within the NSLE. By tailoring the tags to the specific characteristics of each source, we maintain a high degree of accuracy. The tagging methodology is multifaceted. It begins with a careful dissection of all learning materials into what I term '*discrete learning objects*'. Each of these objects is then tagged with comprehensive metadata, as an example is outlined in Table 12.1.

Table 12.1. Tagging of specific mathematics topics from a textbook source.

Source	Textbook (**TBS**)			
Subject	Year **12** Mathematics (**M**)			
Chapter	Exponents (E)	Trigonometry (T)	Differentiation (D)	Integration (**I**)
Topic	Basic laws (L)	Basic Principles (P)	Product Rule (P) Chain Rule (C) Quotient Rule (Q)	Definite integral (**D**) Indefinite Integral (In) Areas (**A**)
Medium	Notes (N), Video (V), Podcast (P) Kinesthetic (K)	Notes (N), Video (V), Podcast (P) Kinesthetic (K)	Notes (N), Video (V), Podcast (P) Kinesthetic (K)	Notes (**N**), Video (V), Podcast (P) Kinesthetic (K)
Difficulty	1 - 5	1 - 5	1 - 5	1 - **5**
Code	TBS_MEL_N_1	TBS_MTP_N_2	TBS_MDQ_N_3	**TBS_M12IDA_N_5**

While this metadata certainly encompasses information such as the subject matter and its inherent difficulty, its scope extends to the identification of specific cognitive skills addressed, the preferred learning styles it may accommodate, and even the assumed level of prior knowledge a student might require. To illustrate the operational dynamics of the tagging system within the user interface, let us consider the example presented in Figures 12.13 – 12.15. Here, the framework retrieves a teacher's annotated notes, labelled TBS_M12IDA_N_5, as detailed in Table 12.1. Deconstructing this code, '*TBS*' indicates that the example originates from a textbook, while '*M12*' signifies Mathematics for Year 12. The '*I*' denotes that the chapter focuses on integral calculus, specifically definite integrals ('*D*'). The '*A*' specifies that the particular topic concerning the determination of areas. The '*N*' indicates that the student is currently viewing annotated educator notes, and the difficulty level for this particular example is set at the highest, '*5*'.

Should a student find this level of difficulty overly challenging, our adaptive algorithm will select a relevant example from earlier foundational material, with a difficulty level below 5. Critically, this alternative example will then be presented in the student's preferred learning format, be it visual, auditory, or text-based, ensuring engagement with the material in a manner that best aligns with their individual learning style. The student retains the autonomy to select any other available display option. I anticipate that nearly all topics within the NSLE will feature accompanying educator notes, video presentations, and podcast versions of each lecture readily accessible for students to review and learn from at their own pace. This comprehensive tagging process, while very demanding in its initial implementation, forms the core of the NSLE.

Utilisation of tagging data

The personalisation of the learning experience is predicated on the following elements. Each student's profile incorporates specific information, including their preferred learning style, articulated preferences, self identified strengths and weaknesses, and prior knowledge across different subject domains. This prior knowledge level is adopted from previous test or exam results on the same topics. The salient characteristics gathered from self-assessment questionnaires are tagged and made accessible to the NSLE algorithms [Appendix L]. Throughout their interaction with the NSLE, the framework continuously monitors each student's progress. This encompasses their performance in examinations, exercises, and assessments, as well as their engagement with the learning materials. The algorithms capture and analyse real-time data regarding their performance, level of engagement, and demonstrated comprehension. This information is utilised to maintain a consistently up-to-date student profile.
Drawing upon the rich data within a student's profile and their ongoing progress, the NSLE's algorithm selects and presents the most relevant learning materials in their preferred format. This means if a student learns most effectively through visuals, auditory input, kinesthetic activities, or reading and writing, the system adapts accordingly. Achieving this level of personalization requires accurately tagging each student's learning preferences. The system transcends mere content presentation, I've designed it to dynamically adjust the entire learning process based on the student's performance. This means if a student encounters difficulties with a particular concept, the system can immediately suggest and provide targeted remediation activities. Conversely, if a student demonstrates mastery in a specific area, the system offers opportunities for accelerated learning and more challenging material.

Data updates and educator alerts

To ensure the NSLE framework's efficacy, I've prioritised the recency and precision of its foundational data. This means the system [Figure 12.12] requires daily updates across several critical areas to guarantee a responsive and pertinent learning experience. For example, by accessing student attendance and absence records, the system can account for potential learning deficits from missed sessions. I've also designed our algorithms to identify atypical student behaviours. This includes observing unexpectedly long engagement with a single question, frequent reference to prior lessons, or persistent struggles with certain exercise types. When the system detects such anomalies or deviations from anticipated performance, it automatically generates timely alerts for educators. This immediate notification empowers them to intervene promptly and provide targeted support. Ultimately, this feedback mechanism keeps educators closely informed about each student's progress and any challenges they might face. The adaptive algorithms employ machine learning techniques to identify recurring patterns in student interactions and, significantly, to predict their future learning trajectories.

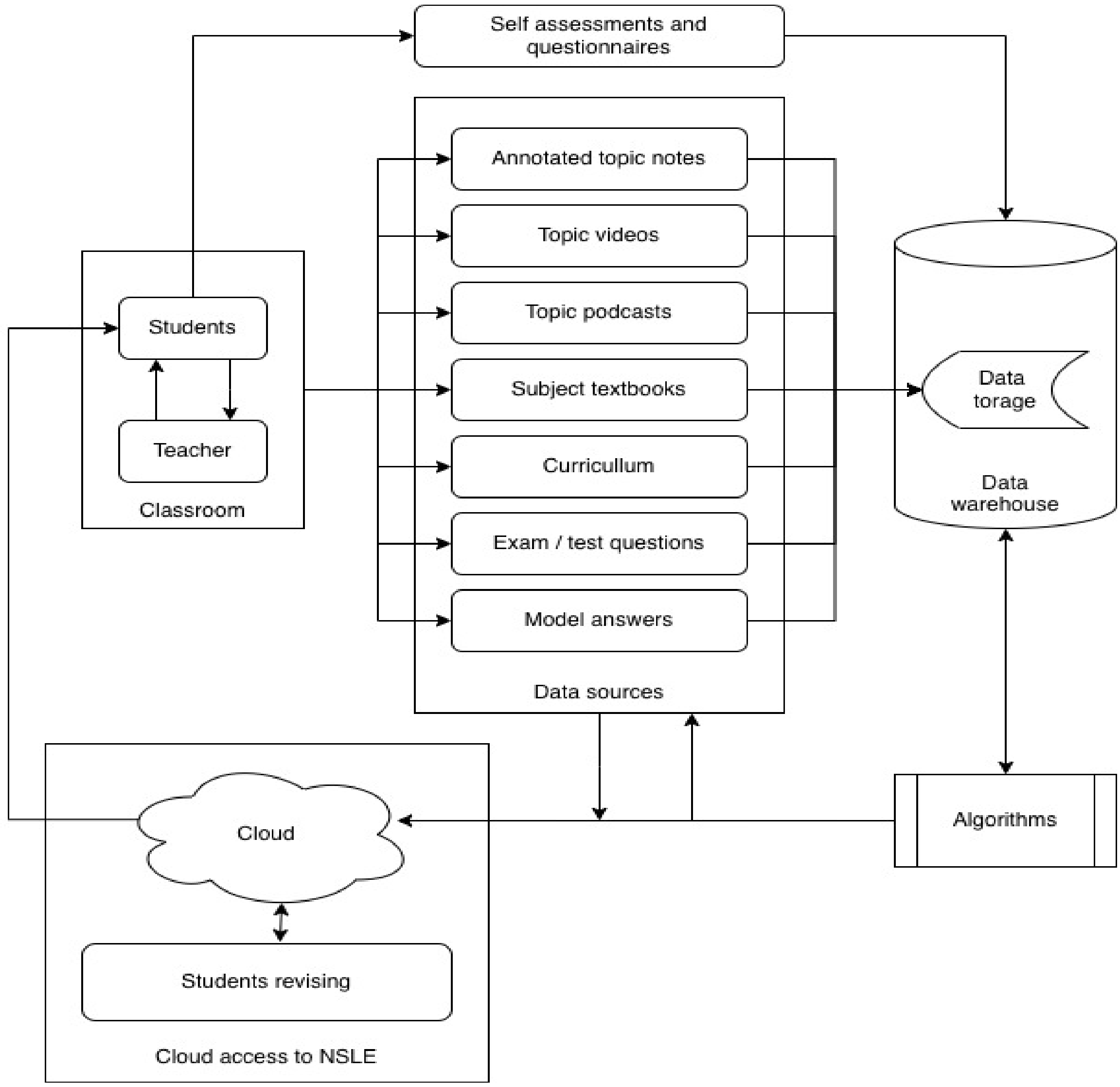

Figure 12.12. Data flow within the learning analytics system: students, data warehouse, and algorithms.

This predictive capability allows the system to proactively recommend specific content or subtly adjust individual learning pathways to optimise the learning experience. In essence, the NSLE framework is designed to evolve with each student interaction, ensuring that their learning remains personalised and effective. However, it is vital to emphasise that even with these sophisticated algorithms in place, human oversight remains indispensable. Educators fulfil a major role in validating the content, interpreting complex student needs, and providing the nuanced guidance that only a human can offer.

12.4 Pilot studies

Concerning this part of my PhD, I'm deeply invested in designing and applying the NSLE to demonstrate its real-world viability. A significant challenge is that a fully functional NSLE isn't yet available for extensive testing. To address this, I've taken a proactive approach: I've implemented pilot studies with a simulated student cohort. I meticulously constructed this cohort to mirror the diverse learning needs and skill levels typically encountered in educational environments, drawing insights from self-assessment questionnaire data I extrapolated. To bring this simulation to life, I developed a bespoke Javascript algorithm to generate realistic, randomized responses for each questionnaire [*Appendix K*], essentially replicating how a student might genuinely engage with it. This simulation has proven to be an indispensable tool for thoroughly evaluating the NSLE's core AI algorithms.

My primary aim in this initial phase is to compellingly illustrate the practical operational capabilities of these algorithms before we move to a full-scale deployment. What's particularly exciting is how the simulation clearly demonstrated the system's inherent capacity to personalise learning pathways and dynamically adapt to each simulated student's unique characteristics. It effectively showcased the NSLE's promising potential to pinpoint individual learning gaps and subsequently recommend highly targeted resources. While I recognize that real-world implementation data will ultimately provide a more complete picture, this initial study stands as a robust foundation for the NSLE's future development, offering critical preliminary insights into its transformative potential for student learning outcomes.

Dynamic student profiling through data aggregation

For my pilot studies, I began by collecting baseline data from five of our simulated students. This involved administering detailed self-assessment questionnaires, which allowed me to capture key aspects of their individual characteristics, preferred learning styles, and perceived strengths and weaknesses, as summarized in *Appendices M to Q*. This initial information is then systematically organize and stored within a dedicated data warehouse, effectively building what I consider dynamic student profiles [*Fig. 12.12*]. These profiles are not static; they are living records that evolve over time. Following the initial data input, the system continuously refines them by incorporating academic performance metrics, including updated self-assessment questionnaire data. As a result, the system gradually constructs a rich and adaptive understanding of each student's unique educational experience. To illustrate, if a student shows improvement in a particular subject or indicates a shift in their learning preferences, these changes are automatically reflected within their profile. The system employs an iterative cycle of data collection and refinement to ensure it maintains an up-to-date and nuanced understanding of each learner.

The integrated AI classroom

The central tenet of this system rests upon its application of AI to augment educational practices. The process typically commences with educators, or a dedicated support team, tagging lesson materials [Table 12.1]. Live lessons are captured as both video and podcast recordings and are accompanied by detailed lesson notes, all of which are uploaded to the NSLE platform. This approach not only enable students to engaging with the content but also empowers the AI to personalise their learning path to success. New and updated materials should therefore, regularly be uploaded. Irrespective of physical presence, students have complete access to both live and recorded lessons via the NSLE platform. This, coupled with the continuous updating of learning materials, strives to guarantee uninterrupted learning opportunities. The system aims to mitigate educational disparities by providing consistent and personalised access to a wealth of learning resources for every student.

The pilot study scenarios

To illustrate the NSLE's capabilities and its potential to support a range of learners, I have developed five simulated scenarios encompassing Mathematics, Biology, Chemistry, Geography, and Economics. Each scenario adheres to a consistent structure, commencing with a concise overview of a simulated student's self-assessment data analysis, followed by a representation of an interaction between the AI algorithm and the student, guided by their unique learning profile. To generate realistic student self-assessments for these simulations [*Appendices A to H*], I employed JavaScript-generated code [*Appendix K*] to produce randomized responses for each assessment question. The resulting combinations of answers are detailed within the corresponding assessment summaries [*Appendices M to Q*]. The data gathered from each student's self-assessment questionnaire is then analysed and securely stored, forming a foundational element of their individual learning profile. Specific characteristics identified within these profiles are subsequently tagged, providing information to guide the algorithm's decision-making processes. I posit that the true strength of the system resides in its capacity to transform raw self-assessment data into actionable insights, moving beyond mere data collection to actively and intelligently shape the learning experience for each student.
While these simulations are necessarily simplified representations of the complexities inherent in real-world educational settings, they offer a valuable proof of concept, clearly demonstrating the potential of AI to significantly increase educational outcomes. Upon initial registration with the NSLE, students are provided with resources, including their unique login credentials and the suite of self-assessment questionnaires [*Appendices A to H*], carefully designed to initiate the process of mapping their individual learning profiles. It is critical to emphasise that the analyses and insights derived from these self-assessments and the subsequent algorithmic tagging are sensitive in nature and demand careful interpretation. Access to this information should be strictly limited to registered and appropriately vetted educators. These analyses are private and must be handled with the utmost respect for privacy and confidentiality.

Scenario 1 – Student A is studying Year 12 Mathematics

Background

Student A's academic journey, marked by successful completion of Year 11 Mathematics (83% [*Tag: ER_mat_83*]) and Physics (76% [*Tag: ER_phy_76*]), led to their enrolment in Year 12, continuing with both subjects.

Learning profile

The NSLE's response to student A encompasses the Year 11 results, the self-assessment questionnaire data [*Table 12.2*] and ongoing dynamic information.

Table 12.2. Student A's self-assessment responses: random example.

Mathematics	
Questionnaire forms	**Random generated selections**
Cognitive profiling form	abccadbdcbca153453125535535
Cognitive task performance record	53441
VARK questionnaire	dccbbbabcadbddac
Gad-7 form	aacaeca
Student behaviour observation form	nnnnnnnyynnnyynnynynn
Mayer Salovey Caroso form	aabaabaaabaabbaabbababaabaabbaabbabaabbb
Emotional intelligence questionnaire	babdaddabcbcbbd
Cognitive processing	24423432421211212334

Learning profile analysis

I observe several key characteristics that stand out in student A's profile, which are tagged for AI attention [*Appendix M*] when selecting the most appropriate learning material. While they demonstrate strong creative abilities, the profile also indicates challenges in areas such as attention, memory, and problem-solving. There are also potential indicators of anxiety and deficits in emotional intelligence. Interestingly, their preferred learning modalities appear to be auditory and visual, yet they seem to experience difficulties with kinesthetic activities. In my view, a professional evaluation would be highly beneficial in more fully understanding these cognitive, emotional, and learning style discrepancies. Following such an evaluation, targeted interventions could be designed and implemented to address these specific areas, with the goal of enhancing both their academic performance and overall well-being.

Revision media selection

Student A has the option to review the teacher's notes [*Fig. 12.13–12.15*], listen to a podcast [*Fig. 12.5*] or review a video recording [*Fig. 12.6*] of the lesson material. They opted to review the teacher's notes for this revision session. Although this decision is not according to their preferred medium, they have the option to use all the possible presentations.

The student – AI interaction

To illustrate how the NSLE supports student A, I demonstrate their engagement with a specific lesson. Based on their learning profile, student A opted to review the teacher's notes, which have been similar to that presented in the classroom. The lesson content included a visual representation, an image illustrating the area enclosed between the curves y = x^2 and y = x, within the boundaries of x = 0.4 and x = 0.6 [*Fig. 12.13–12.15*]. Together with the teacher's lesson notes, the interaction between the AI and the student is represented by the flow diagram, as detailed in *Appendix R*. The student's interaction with the AI is via the user interface.

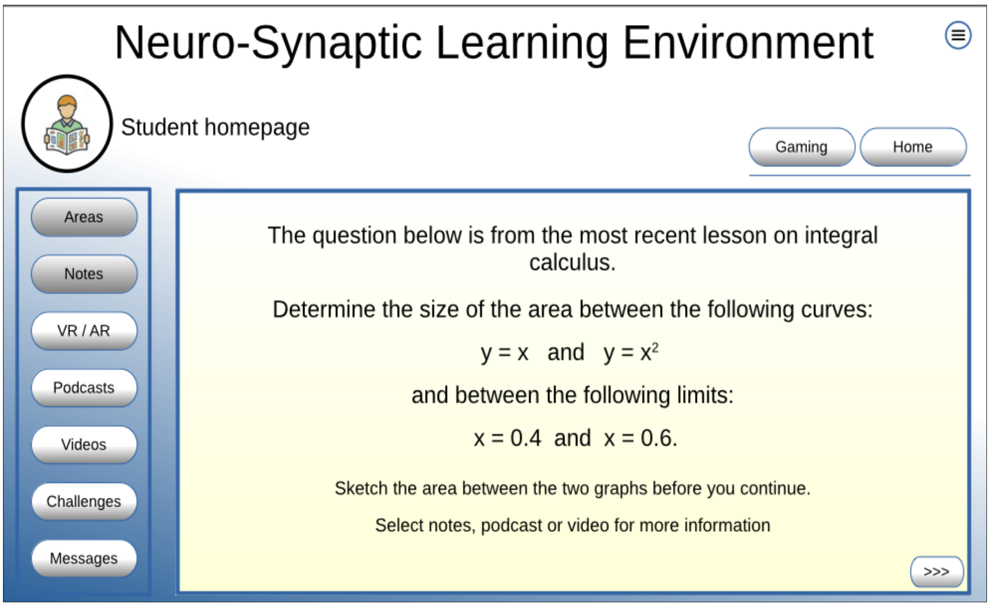

Figure 12.13. NSLE Student interface: accessing teacher's notes with alternative media options.

In this example the student is presented with a question involving an area generated between 2 graphs and limits on the x-axis. The student are requested to sketch the area, which is a specific topic the student would have completed before starting this topic in the classroom. The UI allows the student to exit the lesson at any stage and access any other topic using any media available.

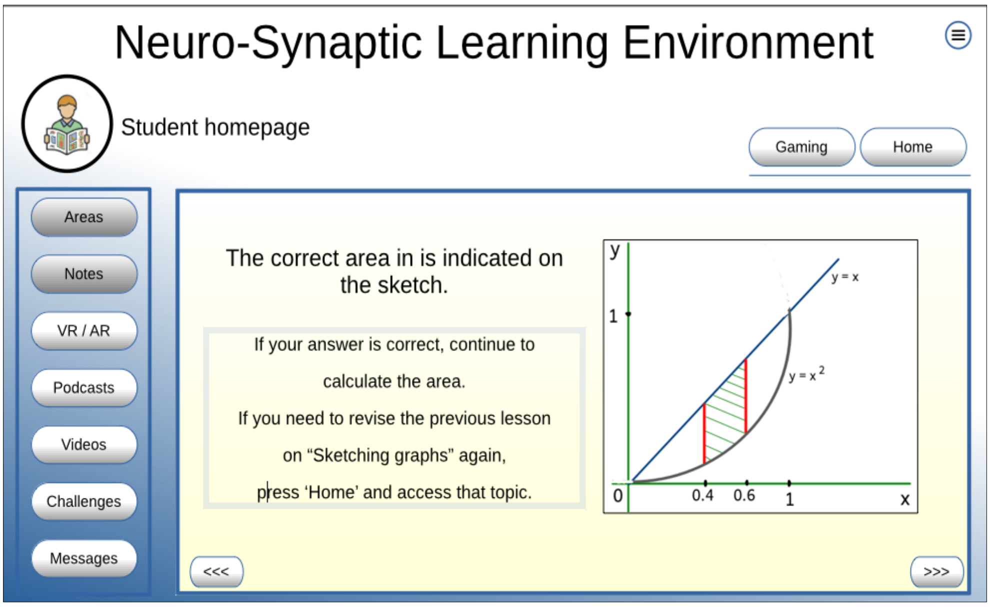

Figure 12.14. NSLE student interface: access to teacher's notes for revision.

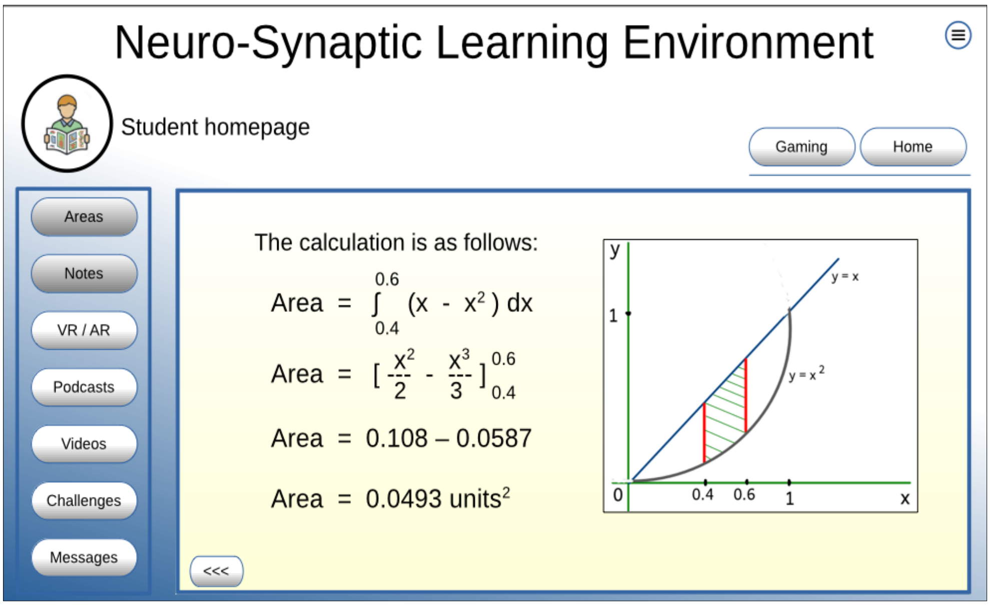

Figure 12.15. NSLE student interface: answer display with multimodal revision options.

It's important to highlight that the AI in this context is intentionally modelled to emulate the qualities of an ideal tutor, guiding the student through the material step by step. This structured approach aims to empower student A to build a solid understanding of the concepts as they progress through the lesson at their own pace.

AI generated quiz

After each presentation, the student is given the option to complete a content related AI-generated quiz, to confirm their understanding of the topic. The following quiz is a demonstration of the AI algorithm's ability to create such assessment questions. The answers are supplied after the student's attempt to answer the questions.

Question 1:

Find the area of the region enclosed by the curves $y = x^2$ and $y = 2x$, between the intersection coordinates.

Answer:

The intersection coordinates are (0, 0) and (2, 4).
The area = $\int [0, 2] (2x - x^2)\, dx$
Area = 4 / 3 units^2.

Explanation:

Determine the intersecting coordinates first by equating the two functions. Thereafter, integrate the difference between the functions, integrating normally.

Question 2:

Determine the area of the region bounded by the curves $y = x^{1/2}$ and $y = x^2$, between the intersection coordinates.

Answer:

The intersection coordinates are (0, 0) and (1, 1).
The area = $\int [0, 1] (x^{1/2} – x^2)\, dx$
Area = 1 / 3 units^2.

Explanation:

Determine the intersecting coordinates first by equating the two functions. Thereafter, integrate the difference between the functions, integrating normally.

Scenario 2 – Student B is studying Year 12 Biology

Background

Student B's academic journey, marked by successful completion of Year 11 Biology (56% [*Tag: ER_bio_56*]) and Science (45% [*Tag: ER_sci_45*]), led to their enrolment in Year 12, continuing both subjects.

Learning profile

The NSLE's response to Student B encompasses the Year 11 results, the self-assessment questionnaire data [Table 12.3] and ongoing dynamic information.

Table 12.3. Student B's self-assessment responses: random example.

Biology	
Questionnaire forms	**Random generated selections**
Cognitive profiling form	bdbbaaacaccc225341414451445
Cognitive task performance record	44125
VARK questionnaire	dbacaaddbccdcddb
Gad-7 form	cccacda
Student behaviour observation form	nnnnnnynyyyyynnyyynny
Mayer Salovey Caroso form	abbabaaabaaabbabbababaaaababbbaabbbbbaaa
Emotional intelligence questionnaire	aacdbadadcbbcdb
Cognitive processing	44414211144142121231

Learning profile analysis

Turning our attention to student B's profile, as summarised in *Appendix N*, we see a fascinating combination of strengths and challenges. They clearly demonstrate strong analytical and creative thinking abilities. However, the profile also indicates difficulties with working memory, attention, and processing speed. This appears to contribute to a notable discrepancy between their perceived cognitive abilities and their actual performance on certain cognitive tasks. Interestingly, their preferred learning style leans towards auditory and read/write methods, suggesting they benefit from structured information and visual supports. While student B reports experiencing some anxiety, they also exhibit commendable self-awareness and resilience. Areas where they seem to face more hurdles include emotional regulation and social skills.

The Cognitive Processes Assessment further highlights a disconnect, revealing a potential overestimation of their executive functions despite underlying deficits. To best support student B, I believe targeted interventions focusing on enhancing cognitive efficiency, emotional intelligence, and sensory integration would be particularly valuable. The aim of these interventions would be to bridge the gap between their strong cognitive potential and their practical application of these abilities in various learning contexts.

Revision media selection

Student B has the option to review the teacher's notes, listen to a podcast [Fig. 12.5] or view a video recording [Fig. 12.6] of the lesson material. They opted to review the teacher's notes for this revision session, but still has the options to review any recorded video material or to listen to available podcasts. This decision confirms their learning profile's identified preference for auditory and read/write methods.

The student – AI interaction

Student B reviews the lesson on the function of myelin and the role it plays in the human brain and revise the work that the AI algorithm presents, as simulated in the flow diagram in *Appendix S*.

AI generated quiz

As in the case for student A, at the end of the presentation, the student is given the option to complete a content related AI-generated quiz, to confirm their understanding of the topic. The multiple choice quiz below is created by the AI algorithm. The answers are supplied after the student’s attempt to answer the questions.

Question 1:

What is the primary function of myelin in the human brain? Select one answer.
a) To provide structural support to neurons.
b) To transmit neurotransmitters between neurons.
c) To insulate axons and increase the speed of electrical signal transmission.
d) To regulate blood flow to the brain.

Answer:

c) To insulate axons and increase the speed of electrical signal transmission.

Explanation:

Myelin acts as an insulating layer around the axons of neurons, significantly speeding up the conduction of nerve impulses. This allows for faster communication between different parts of the brain.

Question 2:

Which cells in the central nervous system are responsible for producing myelin?
a) Astrocytes.
b) Microglia.
c) Oligodendrocytes.
d) Schwann cells.

Answer:

c) Oligodendrocytes.

Explanation:

Oligodendrocytes are a type of glial cell that produce and maintain the myelin sheath around axons in the central nervous system (brain and spinal cord). Schwann cells perform a similar function in the peripheral nervous system.

Scenario 3 – Student C is studying Year 12 Chemistry

Background

Student C's academic journey, marked by successful completion of Year 11 Chemistry (71% [*Tag: ER_che_71*]) and Science (66% [*Tag: ER_sci_66*]), led to their enrolment in Year 12, continuing both subjects.

Learning profile

The NSLE's response to student B is multifaceted, encompassing the Year 11 results, the self-assessment Questionnaire data [Table 12.4] and ongoing dynamic information.

Table 12.4. Student C's self-assessment responses: random example.

Chemistry	
Questionnaire forms	**Random generated selections**
Cognitive profiling form	bbbcdabdcdcd545145513153421
Cognitive task performance record	14245
VARK questionnaire	acaadbbbacdacabd
Gad-7 form	bdcecce
Student behaviour observation form	ynnnnynnnyyyynnnynynn
Mayer Salovey Caroso form	aaaaabbabbaababaaaaaaaabbabaaabbbabbbbba
Emotional intelligence questionnaire	bdcbadbcabdbadd
Cognitive processing	34213213223243322424

Learning profile analysis

Student C presents a fascinating profile, as summarised in *Appendix O*. They demonstrate a notable strength in attention to detail and possess a keen ability to recognise numerical patterns. However, their profile also indicates challenges with short-term memory and navigating complex problem-solving tasks. Interestingly, there appears to be a discrepancy between their high self-reported cognitive abilities and a lower level of confidence when faced with tasks. This could potentially suggest underlying anxiety or perhaps a misinterpretation of their actual skill level in certain areas. This student expresses a strong preference for multimodal learning, which can often be an advantage, their difficulties with focus and task completion suggest a need for carefully structured interventions to maximize the benefits of this preference. We also see a contrast between their reported fluctuating anxiety and challenges in self-assessment and resilience, and their seemingly strong interpersonal skills. The Cognitive Processes Assessment provides further insight, revealing strengths in auditory processing and critical thinking alongside weaknesses in executive functions and emotional regulation. To effectively support student C's learning and overall well-being, I believe in a comprehensive approach involving targeted interventions to address these cognitive and affective inconsistencies .

Revision media selection

As students A and B, student C also has the option to review the teacher's notes, listen to a podcast or a view the video recording of the lesson material. They opted to review the podcast for this revision session. This decision confirms their learning profile's identified preference for auditory processing and critical thinking.

The student – AI interaction

Student C reviews the classroom lesson on the introduction to the collision theory in chemistry. The flow diagram, as presented in Appendix T, demonstrates the simulated interaction between the AI algorithm and student C. The student wants to revise the reasons for reactions to occur and why particles must collide with sufficient energy and the correct orientation.

AI generated quiz

At the end of the presentation, this student is also presented with the option to complete a content related AI-generated quiz, to confirm their understanding of the topic. The multiple choice quiz is created by the AI algorithm. The answers are supplied after the student’s attempt to answer the questions.

Question 1:

According to collision theory, what are the two primary requirements for a chemical reaction to occur between reacting particles?

a) High pressure and low temperature.
b) Sufficient kinetic energy and proper orientation.
c) Low concentration and the presence of a catalyst.
d) Large surface area and a high pH.

Answer:

b) Sufficient kinetic energy and proper orientation.

Explanation:

Collision theory states that reactant particles must collide with enough energy (activation energy) to break existing bonds and with the correct orientation for new bonds to form.

Question 2:

What term describes the minimum amount of energy required for a collision between reactant particles to result in a chemical reaction?
a) Potential energy.
b) Kinetic energy.
c) Activation energy.
d) Thermal energy.

Answer:

c) Activation energy.

Explanation:

Activation energy is the energy barrier that must be overcome for a reaction to proceed. Only collisions with kinetic energy equal to or greater than the activation energy can lead to a reaction.

Scenario 4 – Student D is studying Year 12 Geography

Background

Student D's academic journey, marked by successful completion of Year 11 Biology (56% [*Tag: ER_bio_56*]) and Science (45% [*Tag: ER_sci_45*]), led to their enrolment in Year 12, continuing both subjects.

Learning profile

The NSLE's response to Student D is multifaceted, encompassing the Year 11 results, the self-assessment questionnaire data [Table 12.5] and ongoing dynamic information.

Table 12.5. Student D's self-assessment responses: random example.

Geography	
Questionnaire forms	**Random generated selections**
Cognitive profiling form	ccaccabdcaaa445241332414224
Cognitive task performance record	31134
VARK questionnaire	abbcccacdcaaaddb
Gad-7 form	eaeedca

Questionnaire forms	Random generated selections
Student behaviour observation form	yynnyyyynnnyynnyynyny
Mayer Salovey Caroso form	bbabbbabbaaabababbaaabaabaabbabaababbbab
Emotional intelligence questionnaire	dcddacacbbcdaad
Cognitive processing	13312144243231332211

Learning profile analysis

Student D's profile [Appendix P] immediately strikes me as one characterised by notable inconsistencies in their self-reported cognitive strengths and weaknesses. This raises a flag regarding the accuracy of their self-assessment and suggests a potential disconnect between how they perceive their abilities and their actual performance on tasks. While their adaptable multimodal learning style could be an asset, it needs to be considered in light of other challenges present in their profile. Of particular concern is the indication of anxiety, which I believe warrants further evaluation to understand its impact on their learning and well-being. Interestingly, Student D demonstrates strengths in areas such as empathy and conflict management. However, this contrasts with reported struggles in self-awareness, emotional regulation, and decision-making. The findings from the Cognitive Processes Assessment corroborate some of these challenges, specifically highlighting difficulties with focus and problem-solving, which appear to be compounded by anxiety and mental fatigue. To effectively support Student D, a comprehensive approach will be necessary. This approach should aim to reconcile their self-perception with their actual performance and provide targeted interventions to address the identified cognitive and emotional challenges.

Revision media selection

As with the previous students, student D has the option to review the teacher's notes, listen to a podcast or watch the video recording of the classroom lesson material. They opted to review the teacher's notes for this revision session. This decision confirms their learning profile's identified as being a multimodal learning style.

The student – AI interaction

Student D reviews the lesson on how the tides in the Bay of Fundy reaches 15m at high tide. The flow diagram [*Appendix U*] demonstrates how the AI algorithm acts as tutor to assist student D in revising the principles for this phenomenon.

AI generated quiz

At the end of the presentation, this student is also given the option to complete a content related AI-generated quiz, to confirm their understanding of the reviewed topic. The multiple choice quiz is created by the AI algorithm. The answers are supplied after the student's attempt to answer the questions.

Question 1:

The Bay of Fundy is known for its exceptionally high tides, reaching up to 15 meters. What is the primary factor that contributes to this phenomenon?

a) Strong prevailing winds pushing water into the bay.

b) The bay's unique shape and resonance with the ocean's natural oscillation.

c) The presence of underwater volcanoes that displace large volumes of water.

d) High levels of salinity increasing the water's density.

Answer:

b) The bay's unique shape and resonance with the ocean's natural oscillation.

Explanation:

The Bay of Fundy's shape, length, and depth create a natural resonance with the ocean's tides. The time it takes for a tidal wave to travel the length of the bay and back closely matches the ocean's tidal period, amplifying the tides through constructive interference.

Question 2:

The phenomenon of the Bay of Fundy's extreme tides being amplified due to the bay's natural oscillation is most closely related to what physical concept?

a) Diffraction.

b) Refraction.

c) Resonance.

d) Convection.

Answer:

c) Resonance.

Explanation:

Resonance occurs when a system is driven at its natural frequency, causing an increase in amplitude. In this case, the Bay of Fundy's natural oscillation period matches the ocean's tidal period, causing the tidal range to be greatly amplified.

Scenario 5 – Student E is studying Year 12 Economics

Background

Student E's academic journey, marked by successful completion of Year 11 Statistics (56% [*Tag: ER_sta_56*]) and Economics (45% [*Tag: ER_eco_45*]), led to their enrolment in Year 12, continuing both subjects.

Learning profile

The NSLE's response to Student E is multifaceted, encompassing the Year 11 results, the self-assessment questionnaire data [Table 12.6] and ongoing dynamic information.

Table 12.6. Student E's self-assessment responses: random example.

Economy	
Questionnaire forms	**Random generated selections**
Cognitive profiling form	bcbcaaaabadc555511224345322
Cognitive task performance record	13152
VARK questionnaire	accabadbddbbdcac
Gad-7 form	baaecca
Student behaviour observation form	ynnnnnyynynnnnnyynnyy
Mayer Salovey Caroso form	bbbbaabaaaabbbbaaaaaaaabbbababaabbaaabba
Emotional intelligence questionnaire	dbddddbbccddcbd
Cognitive processing	114434232243443334221

Learning profile analysis

Student E's profile [Appendix Q] presents a particularly interesting picture, marked by discrepancies between their self-reported weaknesses and the strengths I've observed. This pattern immediately suggests potential challenges in self-awareness and metacognitive abilities. For instance, while they demonstrate notable strengths in attention and visual processing, they perceive their memory and problem-solving skills as weak areas. There seems to be a disparity between their low confidence in decision-making and their perception of strong planning skills, indicating a possible miscalibration in their self-assessment. Their multimodal learning style, which favours a range of modalities excluding visual and kinesthetic approaches, could be an asset. However, they appear to struggle with maintaining focus and completing tasks in a logical sequence. Affectively, their mixed anxiety profile warrants a more in-depth professional evaluation to understand the underlying dynamics.

Interestingly, despite showing potential for leadership, Student E expresses uncertainty in key areas of emotional intelligence. The Cognitive Processes Assessment further illuminates the situation, revealing strong processing skills alongside deficits in executive functions, memory, and problem-solving. These cognitive challenges appear to be compounded by reported anxiety and mood swings. To effectively support Student E's academic progress and overall well-being, I believe a comprehensive intervention strategy. This intervention should aim to address these cognitive and affective inconsistencies and work towards improving their self-awareness.

Revision media selection

Student E also has the option to review the teacher's notes, listen to a podcast or watch the classroom lesson video. They opted to review the teacher's notes and to listen to the podcast for this revision session. This decision confirms their learning profile's identified as being a multimodal learning style, favouring various modalities except visual and kinesthetic.

The student – AI interaction

Student E reviews the lesson on some basic terminology and definitions in Economics. The flow diagram, as detailed in Appendix V, simulates a tutoring session where the AI algorithm guides student E through the revision material.

AI generated quiz

The following quiz is generated by the AI algorithm, using the lesson content, as well as the content of the interaction with the student. The answers are supplied after the student's attempt to answer the questions.

Question 1:

What do you think is the fundamental problem that necessitates maki
choices in
economics?
a) Unlimited supply.
b) Limited demand.
c) Scarcity.
d) Opportunity cost.

Answer:

c) Scarcity.

Explanation:

Scarcity is "limited resources versus unlimited wants," which is the core issue driving economic decisions.

Question 2:

If a person decides to use their limited income to buy a new video game instead of going to a concert, what economic concept does the value of the concert represent?
a) Supply.
b) Demand.
c) Choice.
d) Opportunity cost.

Answer:
d) Opportunity cost.

Explanation:
Opportunity cost is seen as the "value of the next best alternative." In this case, the concert is the next best alternative that was forgone.

12.5 Pilot study analysis

The following analyses undertakes an examination of the AI algorithms' decision-making processes in the five above scenarios, detailing the interactions observed within the context of student learning. Each analysis will demonstrate the influence of the student's learning profile as the primary driver of these interactions.

Scenario 1 – Student A is studying Year 12 Mathematics

Student A's case presents a particularly illuminating example of a divergence between a student's self-evaluation and other performance indicators. A Year 11 student demonstrating proficiency in Mathematics (83%) and Physics (76%), yet their learning profile reveals a more complex picture. Through a multi-faceted self-assessment questionnaire approach, incorporating AI-assisted cognitive profiling that analysed their performance records, learning style questionnaires, and emotional intelligence measures, several potential areas warranting attention emerged. These included a possible deficit in memory recall, a discrepancy between their self-reported abilities and their actual performance, a preference for auditory, visual, and kinesthetic learning modalities, and a predisposition towards heightened anxiety. The self-assessment questionnaire also underscored a need for targeted support in both emotional intelligence and processing skills. Employing AI algorithms enabled the identification of key patterns and correlations within this rich dataset, revealing an issue: self-assessment bias. It appears that Student A's perception of their own abilities may not align with more objective measures of their performance.
As research by *Oliveira et al. 2023* suggests, this type of misaligned self-assessment can have several detrimental consequences. It can impede the development of effective learning strategies, discourage help-seeking behaviour, compromise the setting of realistic goals, and negatively impact their overall emotional well-being. To address this, I believe in a holistic and data-driven approach. My recommendations would include a professional evaluation of their performance records, the implementation of targeted support strategies tailored to their identified needs, the alignment of instructional strategies with their preferred learning modalities, and

specific interventions aimed at improving the accuracy of their self-assessment. Technology offers promising avenues for intervention. For instance, AI-driven personalised learning platforms that can adapt quiz difficulty based on performance, as explored by [*Kanchon et al. 2024*], could provide valuable tools for offering appropriately challenging material and fostering more accurate self-evaluation. AI-powered emotional intelligence analysis could also refine our support strategies by identifying and addressing any emotional vulnerabilities.

Looking ahead, AI-based predictive analytics might even allow for the anticipation of potential academic challenges and facilitate earlier interventions. AI systems possess the capability to dynamically adjust learning materials to better suit a student's preferred learning style. This case study indicates the critical need to consider both a student's academic achievements and the accuracy of their self-assessment to truly optimise their outcomes. It also necessitates further investigation into several key areas: the efficacy of interventions specifically designed to improve self-assessment accuracy, the long-term impact of misaligned self-assessment on a student's educational journey, and the potential role of AI-driven technologies in supporting more accurate self-evaluation.

Scenario 2 – Student B is studying Year 12 Biology

Student B's situation presents a distinct set of challenges and learning circumstances, truly highlighting the variability we observe in student needs and the critical importance of adopting genuinely tailored educational approaches. Here we have a student who completed Year 11 Biology with 56% and Science with 45% and is continuing with both subjects into Year 12. To gain a comprehensive understanding of Student B's learning profile, I utilised a range of instruments, including AI-assisted cognitive profiling, their performance records, learning style questionnaires, and emotional intelligence measures. This self-assessment questionnaire process, which exploits AI algorithms to analyse these complex datasets, revealed several key factors. Similar to Student A, there are potential memory weaknesses and a discrepancy between their self-reported abilities and their actual performance. Their preferred learning modalities appear to be auditory and read/write. There appears to be an indication of a potential for frequent anxiety, alongside a need for support in self-reflection, targeted academic support, and specific interventions.

This multifaceted profile suggests that Student B, much like Student A, may also exhibit self-assessment biases. AI-driven pattern recognition within the assessment data helps to highlight these discrepancies and potential areas of concern. Interestingly, Student B's choice to review teacher's notes aligns well with their preference for auditory and read/write methods, underscoring the value of encouraging revision strategies that match individual learning profiles. The AI-generated quiz, focusing on the function of myelin, serves as a good example of how intelligent technology can be employed to create targeted learning tools, as explored in the work of Kanchon et al. 2024. AI-powered learning style adaptation could further boost this by automatically generating study materials in their preferred auditory and read/write formats. This case truly highlights the necessity of employing AI assisted self-assessment questionnaire methods to accurately identify the unique needs of each student and to tailor our educational interventions accordingly. Looking ahead, AI-driven predictive analytics could also be invaluable in anticipating potential academic difficulties, allowing for proactive intervention. AI-based emotional analysis could be used to help us monitor and mitigate Student B's reported anxiety.

Scenario 3 – Student C is studying Year 12 Chemistry

Reflecting on Student C's learning journey offers further compelling evidence for the necessity of individualized educational strategies. Having achieved passing grades in Year 11 Chemistry (71%) and Science (66%), they have chosen to pursue both subjects at the Year 12 level. To develop a comprehensive understanding of their learning profile, I employed AI assisted learning style questionnaires and AI-analysed emotional intelligence assessments, revealing several aspects. The self-assessment questionnaires indicated potential memory limitations and a notable difference between their perceived abilities and demonstrated performance. A strong inclination towards note-taking as a primary learning method was also identified, alongside a tendency towards increased anxiety levels. This profile suggests areas requiring focused observation and targeted support.
Similar to previous instances, AI-driven pattern recognition within the assessment data illuminated these inconsistencies, suggesting possible self-assessment biases. AI-based cognitive profiling likely also contributed to the identification of potential memory weaknesses. It is interesting to note that Student C's decision to review the podcast aligns with their identified preference for auditory processing and critical thinking. The AI-generated quiz, centred on collision theory, effectively illustrates the potential of AI algorithms [*Kanchon et al. 2024*] to develop subject-specific learning resources. Looking forward, AI-driven content generation holds considerable promise for creating personalised note-taking materials tailored to their preferred learning style. AI-based emotional analysis could offer valuable insights into monitoring and addressing Student C's potential anxiety, providing a proactive approach to anticipating future academic obstacles.

Scenario 4 – Student D is studying Year 12 Geography

Student D's situation offers another unique lens through which to view the necessity of genuinely individualized approaches in education. Having successfully completed Year 11 Biology (56%) and Science (45%), they are now continuing with both subjects in Year 12. To build a comprehensive picture of their learning profile, I employed a variety of instruments, including AI-assisted cognitive profiling, which revealed several relevant factors. These self-assessment questionnaires indicated creative thinking abilities, a notable discrepancy between their self-reported abilities and their actual performance, a preference for both auditory and visual learning, and a potential tendency towards frequent worry. The profile also highlights a reliance on visual aids and a need for targeted support in specific areas. AI algorithms played a role in identifying these patterns and discrepancies within the assessment data.
This multifaceted profile suggests, consistent with the previous cases we have examined, the likelihood of self-assessment biases influencing Student D's perceptions. AI-driven analysis was particularly helpful in pinpointing the differences between their reported and actual performance levels. Interestingly, Student D's

choice to review teacher's notes suggests a preference for a multimodal learning approach. The AI-generated quiz, focusing on the Bay of Fundy tides, effectively illustrates the capacity of intelligent technology [*Kanchon et al. 2024*] to create subject-specific learning tools that are both engaging and relevant. Looking ahead, AI-powered content generation could be used to create dynamic visual aids tailored to their visual learning preference. AI-based emotional analysis could be valuable in monitoring and addressing Student D's potential anxiety and offer insights into potential future academic challenges.

Scenario 5 – Student E is studying Year 12 Economics

The case of Student E presents a further compelling example of the varied learning profiles encountered within educational settings, truly highlighting the requirement for instruction tailored to the individual. Having successfully completed Year 11 Statistics (56%) and Economics (45%), they are now proceeding with both subjects in Year 12. To achieve a thorough understanding of their learning profile, I employed a range of instruments, including AI-assisted cognitive profiling, which revealed several characteristics. These self-assessment questionnaires indicated a clear necessity for targeted support, a difference between their self-reported abilities and their actual performance, a preference for auditory learning, and a potential inclination towards frequent worry. Notably, their learning style is multimodal but excludes visual and kinesthetic modalities. AI-driven pattern recognition was pertinent in identifying these discrepancies and their specific learning preferences.
This multifaceted profile, consistent with patterns observed in other students, suggests the possibility of self-assessment biases influencing their perceptions. AI analysis of the assessment data proved particularly useful in pinpointing the differences between their reported and actual performance levels. Student E's decision to review teacher's notes and listen to the podcast aligns well with their identified preference for auditory learning. The AI-generated quiz, focusing on basic terminology and definitions, effectively demonstrates the capacity of algorithm technology [*Kanchon et al. 2024*] to create subject-specific learning tools that are both accessible and targeted. Considering future directions, AI-powered content generation could be particularly valuable in creating personalised audio resources and interactive auditory learning materials tailored to their preferred learning style. AI-based emotional analysis could offer valuable insights into monitoring and addressing Student E's potential anxiety, providing a proactive approach to anticipating future academic challenges.

Simulation of random responses for baseline correlation

To examine the inherent properties of the self-assessment questionnaires and to establish a baseline for comparison against the empirical data I will collect following the implementation of the NSLE, I conducted a simulation study involving 50 virtual students using randomized synthetic data. For each of the eight self-assessment questionnaires, I generated a dataset where responses to individual questions were assigned randomly, following a uniform distribution across the available multiple-choice options (either 4 or 5 choices). This randomization procedure was implemented using Javascript, ensuring the independence of each question's responses from one another, their freedom from any underlying cognitive or educational influences, and their complete reproducibility [*Appendix K*]. The primary aim of this simulation, is to thoroughly test the analytical procedures intended for use with real student data. This allowed for verification of the soundness and appropriate application of these procedures to the format of the questionnaires. This randomly generated dataset is suitable for various statistical analyses, including the Chi-Square test (applied to the randomly generated categorical variables [*Appendix W*]), the Student's t-test (for the randomly generated numerical variables [*Appendix X*]), and correlation analyses, specifically Spearman rank and Pearson correlations [*Appendix Y*]. Given my objective to illustrate the methodology and explore the linear relationships between individual questionnaire items, I elected to employ the Pearson correlation test. By generating the responses using a random generator code, I established a null model for my research. Within this null model, any correlations observed between questions would be purely attributable to chance.

This provides a critical baseline for future comparison with the correlations observed in actual student response data once the NSLE is deployed. Any deviations from the correlations seen in this random data would strongly suggest the presence of meaningful relationships between questions in the real data, potentially indicative of underlying cognitive processes or content dependencies. Considering that the questionnaires vary in length (from 7 to 40 questions), the simulation also permitted an investigation into the potential for spurious correlations arising simply from the sheer number of pairwise comparisons. By analysing the distribution of correlation coefficients within these randomized datasets, I could determine the expected range of correlations due to chance and establish appropriate thresholds for statistical significance. This randomized data served as a controlled environment in which to test the soundness of the correlation analysis methods I plan to use. By applying the same analytical procedures to both the randomized data and, subsequently, the empirical data, I could assess the sensitivity of my results to random noise and identify any potential biases in the analysis. The results of this simulation study, as a preliminary but vital step in my research, provide context for interpreting the correlations [*Fig. 12.16*] that I will observe in the actual student data once the NSLE is implemented. By comparing the magnitude and distribution of correlations in the empirical data with those in this randomized data, I can make more informed inferences about the substantive meaning of the relationships between the questions.

The generation of the random data and the subsequent correlation analyses were managed and determined using spreadsheets. This allowed for straightforward visual inspection and the possibility of performing numerous repetitions of the randomization procedure to add to the statistical power of the analysis, all in preparation for the NSLE's future use. The outcome of the Pearson correlations for the VARK [Fig. 12.16] self-assessment questionnaire below demonstrates the correlations between the individual questions. The results for all eight self-assessment questionnaires are presented in Appendix Z.

	Q3_1	Q3_2	Q3_3	Q3_4	Q3_5	Q3_6	Q3_7	Q3_8	Q3_9	Q3_10	Q3_11	Q3_12	Q3_13	Q3_14	Q3_15
Q3_1	1.00	-0.07	-0.24	0.07	0.13	0.00	0.05	0.08	0.15	0.19	0.05	-0.20	-0.12	0.00	-0.23
Q3_2		1.00	0.26	-0.07	-0.01	-0.09	-0.20	0.00	0.01	0.20	0.11	0.10	-0.05	-0.13	0.00
Q3_3			1.00	-0.21	0.02	0.21	-0.11	0.39	0.16	-0.19	-0.20	-0.18	-0.04	-0.02	-0.09
Q3_4				1.00	0.28	-0.05	-0.02	0.09	-0.17	-0.16	0.18	0.09	0.30	0.05	-0.17
Q3_5					1.00	0.11	-0.29	0.31	0.10	-0.06	-0.14	0.08	0.37	0.23	-0.12
Q3_6						1.00	-0.09	0.16	-0.02	-0.21	-0.30	0.06	0.03	0.12	-0.16
Q3_7							1.00	-0.14	-0.07	0.18	-0.14	-0.06	-0.27	0.19	-0.02
Q3_8								1.00	0.18	-0.05	-0.02	0.03	0.11	-0.02	-0.15
Q3_9									1.00	-0.13	-0.04	0.03	0.07	0.05	-0.16
Q3_10										1.00	0.04	-0.03	-0.11	-0.04	0.10
Q3_11											1.00	0.31	0.10	-0.08	-0.16
Q3_12												1.00	-0.14	0.31	-0.20
Q3_13													1.00	-0.18	0.15
Q3_14														1.00	-0.21
Q3_15															1.00
Q3_16															

Figure 12.16. Analysis of Correlation Coefficient Distribution from randomised VARK questionnaire responses [*Appendix C*].

Interpreting the correlation results of the dataset above is valid for all datasets in *Appendix Z*. The correlation between the questions is explained below.

(a) The correlation function returns a value between -1 and +1.
(b) +1: Perfect positive correlation
(as one variable increases, the other increases perfectly).
(c) -1: Perfect negative correlation
(as one variable increases, the other decreases perfectly).
(d) 0: No linear correlation.
(e) Values closer to +1 or -1 indicate stronger correlations.
(f) Values closer to 0 indicate weaker correlations.

This simulation study, employing randomized response data, has proven to be a valuable methodological tool. It has allowed me to establish a baseline, assess potential biases inherent in the questionnaires, and lay a solid foundation for interpreting the correlation analyses I will conduct on the actual student data. I believe this approach significantly strengthens the rigour of the subsequent analysis and will contribute to a more nuanced understanding of the intrinsic properties of the self-assessment questionnaires themselves.

12.6 Programming Algorithms

I'll now focus on the core algorithms powering the NSLE's intelligent tutoring system, mentioned earlier in chapter 9.1. Here, I'll examine their design, purpose, goals, and evaluation methods. My primary focus will be on how these algorithms personalise each student's learning experience. Following this, I'll discuss initial results, potential future applications, and broader implications for the NSLE.

12.6.1 Dynamic algorithm design

A key difference between the NSLE and static learning environments lies in its use of dynamic algorithms to understand each student's learning process. For the NSLE to work, specific algorithms are coded in Python. The NSLE’s architecture is adaptable, allowing changes to existing algorithms, creation of new ones, or addition of bespoke algorithms as needed. A central innovation is the algorithm's role in prioritising the individual student profile when curating revision materials. When a student asks for content, the system analyses their learning needs, profile details, and current progress [*Section 12.6.2*], rather than just retrieving generic resources. This dynamic adaptation, I believe, empowers learners to take more responsibility for their education. It cultivates engagement, boosts motivation, and strengthens knowledge acquisition and retention. By detailing the design of these algorithms, this section shows how the NSLE transforms educational data into actionable insights for both students and educators. It offers a view into the system's core function and its ongoing efforts to refine the learning experience. To clarify how these algorithms operate, I will now demonstrate their function and efficacy using the first of five scenarios discussed earlier [*Section 12.4*].

Important factors to consider

The NSLE's operation depends on its system architecture, memory, processing power, and how often algorithms run. While the algorithms I use in my demonstrations are simple, they show their application and achieve success here. For algorithms handling individual files, performance might slow when managing data for more than a few hundred students per algorithm file. I expect a full system implementation would use a database or a more efficient data storage method to handle larger student numbers.

12.6.2 Algorithms : Creating dynamic student profile and datasets

To show how the algorithms in this section work, I will use data from Student A, who studies Year 12 Mathematics, from the pilot studies in *section 12.4*. Within the NSLE, the following algorithms demonstrate the collection and updating of student self-assessment questionnaire data. Managing this core personal information is important, as it directly influences the learning material the algorithms provide. These algorithms are programmed using Python 3.12 for demonstration and reproducibility purposes. My algorithms consolidate all student and learning material data from different sources into a standard JSON file. This file, a text-based format, serves as the central data source, enabling seamless interaction for all NSLE algorithms.

(a) ***sa_write.py***

The data for this algorithm's [*Appendix AA*] variables comes from student self-assessment questionnaire summaries. I ensured that each variable represents a student's choice and is assigned a value of '1' or '0' based on their selection. These variable-value pairs are saved in a standard *sa_data.json* file, which Python can easily access and read. This file acts as the central data source for the other algorithms.

(b) ***sa_read.py***

This algorithm was specifically coded [Appendix AB] to test the variables and their assigned values generated by the "*sa_write.py*" algorithm. The goal is to determine if the "*sa_update.py*" algorithm has modified the original variables within the "sa_*write.py*" file. This testing algorithm is ensuring the integrity of the data when the files are executed and their actions are reproduced.

(c) ***sa_update.py***

This algorithm [*Appendix AC*] enables users to modify variable values in response to changes arising after questionnaire completion. It is recommended that educators manage these updates to ensure accuracy and facilitate discussion with students regarding any necessary changes.

(d) ***sa_session1.py***

The algorithm [*Appendix AD*] interacts directly with the student. After welcoming them and providing initial advice tailored to their preferences, it directs them to the NSLE user interface to continue.

(e) ***sa_data.json***

The profile data accumulated from the student's questionnaires are saved in this standard type JSON file, which is accessible to all algorithms.

You revise now Integration and Areas.

All variables from sa_data.json:	
student_id: S1001	*SA_v: 1*
full_name: EV	*SA_h: 0*
age: 18	*SA_kin: 0*
major: Mathematics	*SA_n: 0*
Year 11 result: 0.83	*VR / AR: 1*
SA_ct: 1	*SA_anx: 1*
SA_attn: 0	*SA_w: 1*
SA_ml: 0	*SA_conman: 1*
SA_ps: 0	*SA_ts_chalem: 1*
SA_r_ctpr: 1	*SA_senpro: 1*
SA_a: 1	*SA_int_ar: 1*

(f) ***sa_matr_update.py***

The purpose of this algorithm [Appendix AE] is to store and manage data related to student A's learning preferences and available learning materials. It acts as a simple database for this learning preference and material matching system. The algorithm reads the values for the variables from the above mentioned sa_data.json file and make learning material recommendations for the student. The data is saved in a standard format, in sa_matr_data.json file.

(g) ***sa_matr_learning_material_selection.py***

This algorithm [Appendix AF] creates a data storage file called sa_matr_data.json to hold information about student learning profiles and learning materials. The script reads the data, saved in the sa_matr_update.py file, mentioned above. It loads the profile data and determine suitable learning materials for a student based on their preferences.

(h) ***sa_matr_data.json***

The file recommends specific learning materials, based on certain learning style preferences, teacher's notes [SA_n], videos [SA_v], podcasts [SA_a], hands-on activities [SA_h] or kinaesthetic activity [SA_kin]. The final result below is an example of the content, displayed after executing the latest sa_matr_update.py file.

For EV, the following learning materials are recommended:
- Calculus Explained Visually
- Interactive Algebra Practice
- Abstract Math Concepts (Text-based)
- Geometry VR Experience
- Statistics Problem Solving
- Mathematical Proofs (Auditory)
SA_n is 0, so the book list is not displayed.
Based on SA_v = 1, here is a list of videos:
- Visual Introduction to Calculus
- The Beauty of Fractals
- Understanding Quantum Mechanics
- History of Mathematics
Based on SA_a = 1, here is a list of auditory materials:
- Mathematics Lectures Podcast
- Audiobook: A History of Pi
- Learning Algebra Through Sound
- Theorems Explained (Audio)
SA_h is 0, so the hands-on activities list is not displayed.
SA_kin is 0, so the kinaesthetic activities list is not displayed.
Analysis date saved to sa_matr_data.json: 2025-04-28T00:20:17.653415

As I demonstrated with the algorithms above, questionnaire information is converted and stored in easily accessible JSON files. Other algorithms might also access these variables to assist in their decision-making processes. To strengthen maintainability, I strongly recommend the regular backing up of these files. Additionally, I propose a file structure of one algorithm file per class per subject, given that the student population is not anticipated to exceed a few hundred per class. This would allow maintenance personnel to easily identify and access the relevant file, if needed. Control over the variables can be achieved through the single algorithm above, namely *sa_update.py*. Although the algorithms detailed above presently manage only one student, they are designed for straightforward expansion to accommodate more students within a class.

12.6.3 Algorithm: Student progress tracking and prediction

I simulated a Python programming lesson for a class, covering syntax, loops, and functions. To support individual learning, I developed *person_learn_1.py* [*Appendix*

AG]. This algorithm monitors student progress, tracking coding speed, error rates, and exercise success. It also draws on curriculum standards, textbook notes, and teacher notes to understand the learning context and predict student performance. I envision this algorithm as a core NSLE component, adapting to each student's path. Thinking about neural networks, I designed the algorithm to predict knowledge retention and learning speed. It does this by combining current performance data with the system's tagged educational resources. This allows it to adjust content complexity and introduction timing, aligning with curriculum objectives. In practice, the system delivers content that grows with student abilities, intelligently offering targeted help from our tagged resource pool. The NSLE becomes a dynamic guide, shaping each person's learning journey. For students progressing quickly, the system provides more challenging problems and richer learning materials from our semantically tagged data. For those learning at a comfortable pace, they receive appropriate problems and focused resources, often with direct links to relevant textbook and teacher notes. My goal for this algorithm is for it to act like a personalised tutor, offering the right support and challenge for every individual learning style, while adhering to curriculum standards and effective teaching practices.

Result and analysis

This output provides a step-by-step simulation, offering a look at this personalised learning experience. The NSLE monitors a simulated student's engagement and success as they interact with Python topics and resources. The reappearance of topics like 'Basics' and 'Loops' in the lesson_plan shows the system's ability to revisit modules, either for reinforcement or based on evolving predictions. Changes in *knowledge_retention* and *learning_rate* values across these revisits highlight how the simulated learning adapts to student performance. This output lesson plan gives a detailed view of how the NSLE operates in a simulated environment. It shows its capacity to monitor performance, anticipate learning outcomes, and adaptively choose learning resources, providing data to analyse the effectiveness and dynamism of our adaptive learning algorithms. I will now walk you through these simulation results, breaking down each step to illustrate how the NSLE adjusts learning materials based on the simulated student's journey. We will see how it uses completion times, error rates, and exercise scores to estimate knowledge retention and learning speed, and then selects appropriate learning materials.

Lesson Plan Breakdown:

"Adaptive Lesson Plan Simulation"
Description: This simulation demonstrates how the Neuro-Synaptic Learning Environment (NSLE) adapts learning resources based on a simulated student's progress through a series of topics. This is a simplified version.

topic: Basics	resource_title: Basic Python Syntax

completion_times	error_rates	exercise_scores	knowledge_retention	learning_rate
10.7	0.2	99.47	0.99	0.1
Analysis: For the topic of 'Basics', the system presented the resource 'Basic Python Syntax'. The student's activity resulted in a code completion time of 10.70 minutes, an error rate of 0.20, and an exercise score of 99.47. The predicted knowledge retention is 0.99, and the learning rate is 0.10.				

topic: Loops		resource_title: Loops in Python		
completion_times	error_rates	exercise_scores	knowledge_retention	learning_rate
7.46	0.02	74.76	0.75	0.1
Analysis: For the topic of 'Loops', the system presented the resource 'Loops in Python'. The student's activity resulted in a code completion time of 7.46 minutes, an error rate of 0.02, and an exercise score of 74.67. The predicted knowledge retention is 0.75, and the learning rate is 0.10.				

topic: Functions		resource_title: Advanced Functions		
completion_times	error_rates	exercise_scores	knowledge_retention	learning_rate
14.82	0.23	91.4	0.91	0.1
Analysis: For the topic of 'Functions', the system presented the resource 'Advanced Functions'. The student's activity resulted in a code completion time of 14.82 minutes, an error rate of 0.23, and an exercise score of 91.40. The predicted knowledge retention is 0.91, and the learning rate is 0.10.				

topic: Basics		resource_title: Basic Python Syntax		
completion_times	error_rates	exercise_scores	knowledge_retention	learning_rate
6.23	0.19	91.39	0.91	0.1
Analysis: For the topic of 'Basics', the system presented the resource 'Basic Python Syntax'. The student's activity resulted in a code completion time of 6.23 minutes, an error rate of 0.19, and an exercise score of 91.39. The predicted knowledge retention is 0.91, and the learning rate is 0.10.				

topic: Loops		resource_title: Loops in Python		
completion_times	error_rates	exercise_scores	knowledge_retention	learning_rate
9.51	0.28	78.44	0.78	0.1
Analysis: For the topic of 'Loops', the system presented the resource 'Loops in Python'. The student's activity resulted in a code completion time of 9.51 minutes, an error rate of 0.28, and an exercise score of 78.44. The predicted knowledge retention is 0.78, and the learning rate is 0.10.				

Below, 5 graphs illustrate the results derived from the tabulated data for the *person_learn_1.py* algorithm.

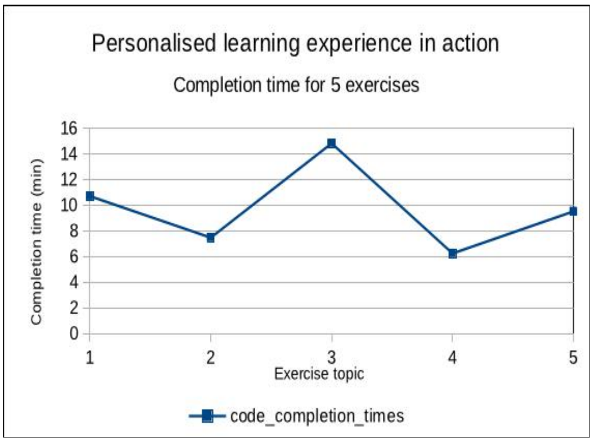

Figure 12.17. Student completion times for five exercises.

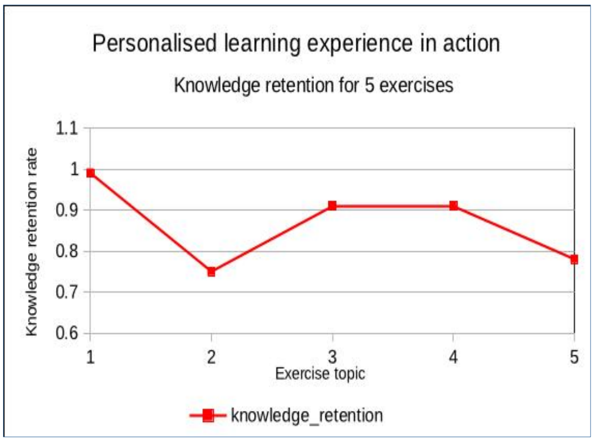

Figure 12.18. Student knowledge retention for five exercises.

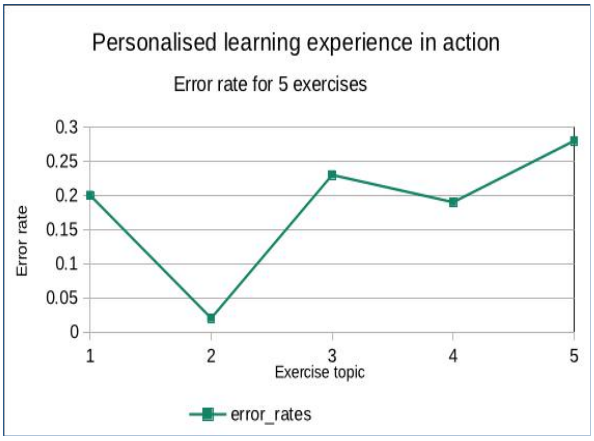

Figure 12.19. Student error rate for five exercises.

Figure 12.20. Student learning rate for five exercises.

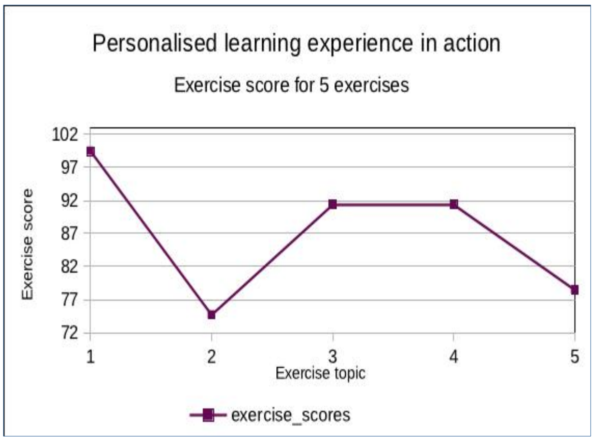

Figure 12.21. Student exercise score for five exercises.

This simulation shows how the NSLE personalises learning. By comparing these graphs, we see the algorithm in action. It intelligently selects exercises to revisit based on completion time, error rate, and scores. Topics 1 and 4 are the same, as are topics 2 and 5. This student completed topics 2 and 4 in the shortest time, 7.46 and 6.23 minutes respectively. The highest error rate, 0.28, occurred during revisited exercise 5. This student's learning rate is constant for these topics; therefore, the algorithms would likely provide more challenging work during their next revision session, as their knowledge retention and learning rate appear consistent. The positive correlation between completed exercises and increasing accuracy of both predictions and results is significant.

12.6.4 Possible changes to the algorithm

I will now demonstrate the process for re-evaluating and potentially enhancing an algorithm. The existing algorithm's approach requires revision to foster a more intuitive understanding of adaptive learning simulation. My proposal involves refining the *person_learn_1.py* algorithm and naming the updated version *person_learn_2.py*, as detailed in *Appendix AH*. The revised output format, presented below, aims to improve clarity and ease of reference. This output demonstrates the benefits of regular code updates. This latest algorithm iteration uses classes for organization and code reusability. It incorporates a realistic simulation of student activity by introducing randomness. Knowledge and learning prediction employ a simplified moving average model, with potential for future integration of more complex neural network models. The system adjusts content by selecting resources based on student performance. It also generates lesson plans illustrating student progress. I envision that all resources and student progress will be tagged in the future to enable an effective referencing system, ultimately benefiting our students. The summaries below, from the enhanced algorithm's *person_learn_2.py* data, and the subsequent graphs, show the detail with which this version analyses content.

<table>
<tr><td colspan="2">topic: Basics</td><td colspan="3">resource_title: Simple Variables</td></tr>
<tr><td>completion_times</td><td>error_rates</td><td>exercise_scores</td><td>knowledge_retention</td><td>learning_rate</td></tr>
<tr><td>15.412155376409
17.912348290727
13.737671397841
10.954566635486
7.2491144864507</td><td>0.110906978352751
0.035221445018190
0.240386345629084
0.152206590959486
0.198707717496539</td><td>78.2711273241634
84.4518275412022
65.7082950972797
65.7823074017261
90.5632805517126</td><td>0.8</td><td>0.1</td></tr>
<tr><td colspan="5">Analysis: For the topic of 'Basics', the system presented the resource 'Basic Python Syntax'. The simulated student's first activity resulted in a code completion time of 15.41 minutes, an error rate of 0.11, and an exercise score of 78.27. At this stage, the predicted knowledge retention is the initial value of 0.80, and the learning rate is 0.10.</td></tr>
</table>

<table>
<tr><td colspan="2">topic: Loops</td><td colspan="3">resource_title: Loops in Python</td></tr>
<tr><td>completion_times</td><td>error_rates</td><td>exercise_scores</td><td>knowledge_retention</td><td>learning_rate</td></tr>
<tr><td>15.412155376409
17.912348290727
13.737671397841
10.954566635486
7.2491144864507</td><td>0.110906978352751
0.035221445018190
0.240386345629084
0.152206590959486
0.198707717496539</td><td>78.2711273241634
84.4518275412022
65.7082950972797
65.7823074017261
90.5632805517126</td><td>0.8</td><td>0.1</td></tr>
<tr><td colspan="5">Analysis: Moving to the 'Loops' topic, the system provided 'Loops in Python'. The student's second simulated activity yielded a completion time of 17.91 minutes, an error rate of 0.04, and an exercise score of 84.45. The knowledge retention and learning rate predictions remain at their initial values as there haven't been enough exercise scores to calculate a moving average.</td></tr>
</table>

<table>
<tr><td colspan="2">topic: Functions</td><td colspan="3">resource_title: Advanced Functions</td></tr>
<tr><td>completion_times</td><td>error_rates</td><td>exercise_scores</td><td>knowledge_retention</td><td>learning_rate</td></tr>
<tr><td>15.412155376409
17.912348290727
13.737671397841
10.954566635486
7.2491144864507</td><td>0.110906978352751
0.035221445018190
0.240386345629084
0.152206590959486
0.198707717496539</td><td>78.2711273241634
84.4518275412022
65.7082950972797
65.7823074017261
90.5632805517126</td><td>0.76</td><td>-0.63</td></tr>
<tr><td colspan="5">Analysis: For the 'Functions' topic, the resource 'Advanced Functions' was selected. The third simulated activity resulted in a completion time of 13.74 minutes, an error rate of 0.24, and an exercise score of 65.71. Still with fewer than three exercise scores, the knowledge retention and learning rate remain at their initial values.</td></tr>
</table>

topic: Basics		resource_title: Simple Variables		
completion_times	error_rates	exercise_scores	knowledge_retention	learning_rate
15.412155376409 17.912348290727 13.737671397841 10.954566635486 7.2491144864507	0.110906978352751 0.035221445018190 0.240386345629084 0.152206590959486 0.198707717496539	78.2711273241634 84.4518275412022 65.708295097279 65.7823074017261 90.563280551712	0.72	-0.93
Analysis: Revisiting the 'Basics' topic, the system presented 'Basic Python Syntax' again. The fourth simulated activity showed a completion time of 10.95 minutes, an error rate of 0.15, and an exercise score of 65.78. Now, with three previous scores, the predicted knowledge retention has been updated to approximately 0.72, and the learning rate to approximately -0.93, reflecting the recent performance.				

topic: Loops		resource_title: Loops in Python		
completion_times	error_rates	exercise_scores	knowledge_retention	learning_rate
15.412155376409 17.912348290727 13.737671397841 10.954566635486 7.2491144864507	0.110906978352751 0.035221445018190 0.240386345629084 0.152206590959486 0.198707717496539	78.2711273241634 84.4518275412022 65.7082950972797 65.7823074017261 90.5632805517126	0.74	1.24
Analysis: Finally, for the second encounter with the 'Loops' topic, the system selected 'Loops in Python'. The fifth simulated activity resulted in a completion time of 7.25 minutes, an error rate of 0.20, and an exercise score of 90.56. The predicted knowledge retention has been updated to approximately 0.74, and the learning rate to approximately 1.24, indicating a recent change in performance.				

Below, 5 graphs illustrate the results derived from the tabulated data for the person_learn_2.py algorithm.

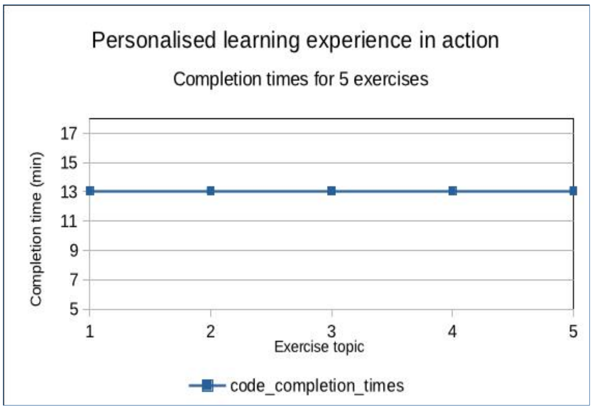

Figure 12.22. Student completion times for five exercises, as generated by the updated algorithm.

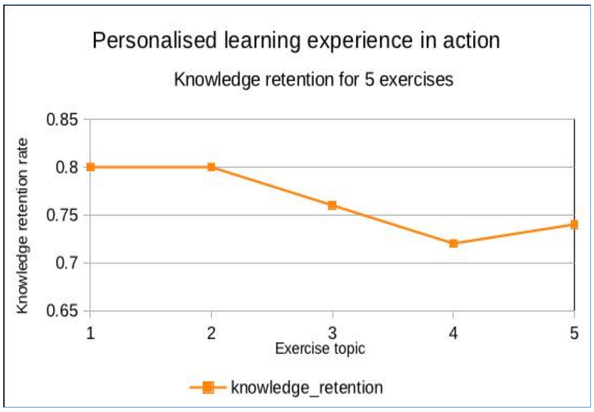

Figure 12.23. Student knowledge retention for five exercises, as generated by the updated algorithm.

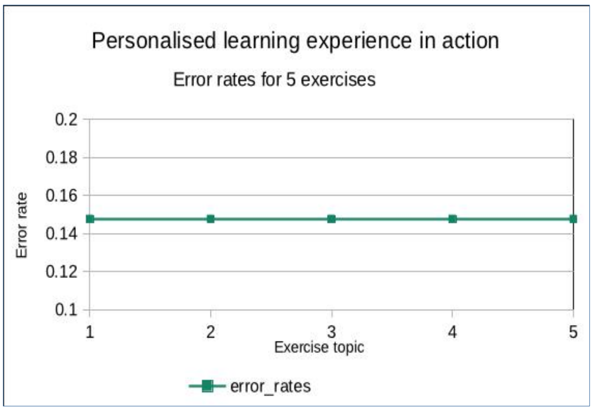

Figure 12.24. Student error rates for five exercises, as generated by the updated algorithm.

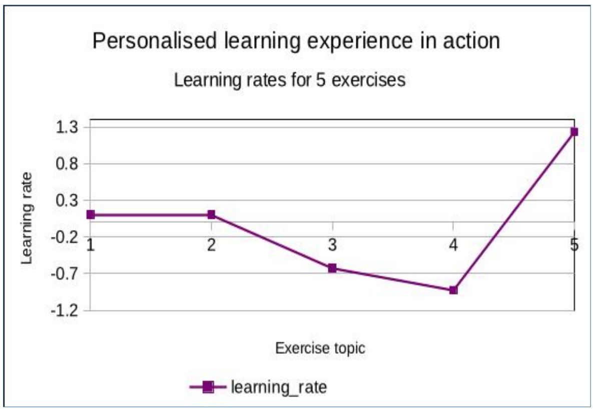

Figure 12.25. Student learning rates for five exercises, as generated by the updated algorithm.

Figure 12.26. Student exercise scores for five exercises, as generated by the updated algorithm.

Comparing the algorithms

To understand why it is so important to revisit algorithms and update the codes regularly, I will now discuss and demonstrate the differences between these 2 algorithms and why the results of the updated code [person_learn_2.py] is different and more effective than the original [person_learn_1.py] .

Object-Oriented Design

Initially, my approach involved using dictionaries to manage student data and learning resources. While functional, this was essentially a procedural approach contained within a class structure. Recognizing the benefits of object-oriented programming [*OOP*], I enhanced the original algorithm code by introducing the dedicated classes, *StudentData* and *LearningResource*. This fundamental shift to OOP allows me to model the core entities of the system, students and resources, in a much more intuitive way. By bundling the data and the operations that act upon it, I've achieved greater organisation, which ultimately makes the codebase more comprehensible and easier to maintain moving forward.

Encapsulation

My initial design with student data within the NSLE class as a dictionary, lacked explicit control over data access and modification. The dedicated StudentData class, mentioned above, encapsulates all student-related information, allowing access to this data only through the StudentData class's methods. This principle of encapsulation is important as it helps me prevent unintended data corruption and provides the flexibility to modify the internal structure of the data in the future without impacting other components of the system.

Code Organisation and Readability

To improve the original structure, where the logic for managing both student data and learning resources was closely integrated within the NSLE class, I've significantly modularized the code. Now, the NSLE class primarily focuses on orchestrating the overall learning process, while the *StudentData* and *LearningResource* classes each handle their specific areas of responsibility. This improved organisation makes the codebase considerably easier for me to read, understand, and navigate, which is invaluable both for debugging, reproducibility and for facilitating future development efforts.

Maintainability and Scalability

Previously, adding new student attributes or resource properties would have required modifications directly within the NSLE class, which could have increased its complexity over time. However, with the enhanced object-oriented design, incorporating new attributes or properties is now a much simpler process. I can directly modify the *StudentData* or *LearningResource* classes as needed. This key advantage of the OOP approach significantly improves the maintainability and scalability of the code. It allows me to extend the system's functionality more easily without the risk of introducing unforeseen issues or making the codebase difficult to manage.

Data Handling

Originally, I relied on a basic dictionary to store student data, which I recognized would become increasingly cumbersome as the system's complexity grew. With the enhanced design, the StudentData class is now structured to hold lists of completion times, error rates, and exercise scores. This allows me to perform much more sophisticated calculations, such as implementing a moving average to better understand knowledge retention. This improved approach to data handling is a significant advantage, enabling more complex and ultimately more accurate modelling of individual student learning.

Clarity and Explicitness

My initial implementation of dictionaries to store data, which I realized could be less transparent regarding the expected data structure. By moving to classes, I've established a clear blueprint for the data organisation. While not explicitly shown in this snippet, the use of type hints could be easily incorporated in the future to further enhance this clarity. The significant advantage here is that these classes make the code more self-documenting. This reduces the likelihood of errors and will make it much easier for other developers, or even my future self, to understand the codebase at a glance.

The results of the 2 algorithms are tabulated and compared below. We can see the differences in the final values in the tables below.

Table 12.7. Summary of results for person_learn_1.py

The algorithm results for the 5 exercises [person_learn_1.py]					
Topic	Completion Time (m)	Error Rate	Exercise Score	Knowledge Retention	Learning Rate
Basics	10.7	0.2	99.47	0.99	0.1
Loops	7.46	0.02	74.76	0.75	0.1
Functions	14.82	0.23	91.4	0.91	0.1
Basics	6.23	0.19	91.39	0.91	0.1
Loops	9.51	0.28	78.44	0.78	0.1

Table 12.8. Summary of results for person_learn_2.py

The revisited algorithm results for the 5 exercises [person_learn_2.py]					
Topic	Completion Time (m)	Error Rate	Exercise Score	Knowledge Retention	Learning Rate
Basics	13.05	0.15	76.96	0.8	0.1
Loops	13.05	0.15	76.96	0.8	0.1
Functions	13.05	0.15	76.96	0.76	-0.63
Basics	13.05	0.15	76.96	0.72	-0.93
Loops	13.05	0.15	76.96	0.74	1.24

Comparing the results from *person_learn_1.py* [*Table 12.7*] and the revisited algorithm in *person_learn_2.p*y [*Table 12.8*] reveals a striking contrast. While the original algorithm yielded varied performance metrics, the enhanced version presents a uniformity in *Completion Time*, *Error Rate*, and *Exercise Score*. This similarities raises questions about the nature and impact of the algorithmic revisions of those aspects. The negative learning rates in *Table 12.8* underscores a fundamental shift in how learning outcomes are being measured, demonstrate a shift in the approach of the two algorithms.

12.6.5 Dynamic content adjustment and visualisation

A core focus of this research involves the NSLE's ability to dynamically adjust content and visualize a student's learning. To show this, I developed a simulation with five students interacting with a lesson across five subjects: Mathematics, Biology, Chemistry, Geography, and Economics. This refers to the pilot studies in *section 12.4*. My aim is to demonstrate the NSLE's adaptability to both individual learners and subject matter. Upon execution, the algorithm first presents the generated lesson plans for each student, showing material difficulty. It then displays two graphs *[Fig. 12.22 – 12.31*]. The first, *visualise_difficulty_adjustment*, shows a suitable difficulty for the student's subsequent lessons. The second, *visualise_student_progress*, tracks the student's learning journey lesson by lesson. Selecting more lessons, I suggest, will allow for a more detailed visual representation and improve the algorithm's effectiveness. By comparing these graphs, the relationship between learning material difficulty and student progress becomes clear. The *5_students_5_subjects.py* algorithm demonstrates how the AI [Appendix AI] simulates these learning paths.

Lesson Plan for Student 1 (Mathematics)

Difficulty: Calculus (5), Calculus (5), Calculus (5), Calculus (5), Calculus (5)

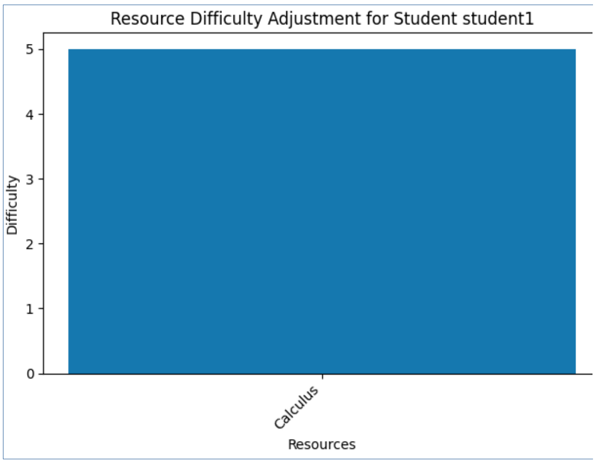

Figure 12.27. Visualization of difficulty adjustment for Student 1.

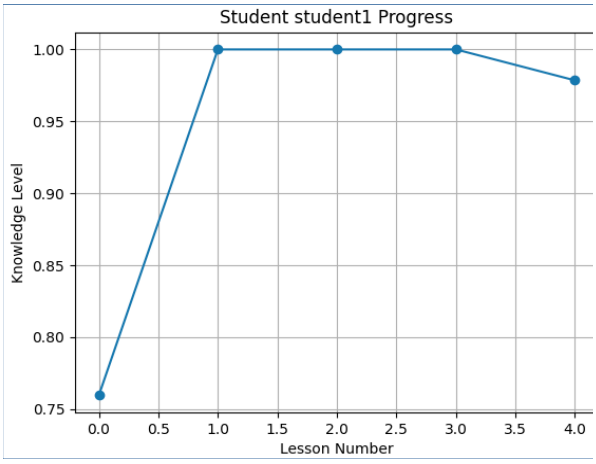

Figure 12.28. Demonstration of Student 1's learning progress.

Lesson Plan for Student 2 (Biology)

Difficulty: Cell structure (4), Genetics (6), Genetics (6), Genetics (6), Genetics (6)

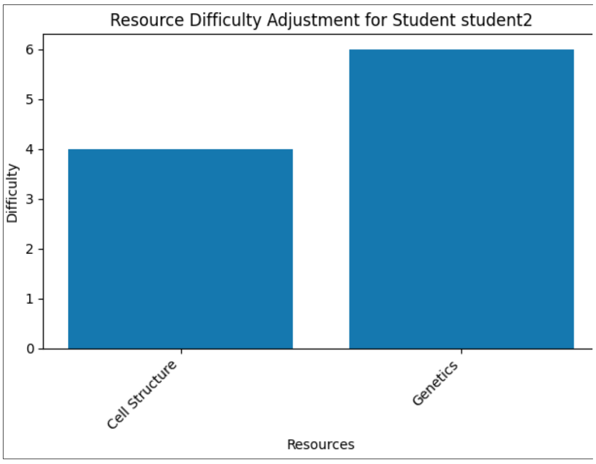

Figure 12.29. Visualization of difficulty adjustment for Student 2.

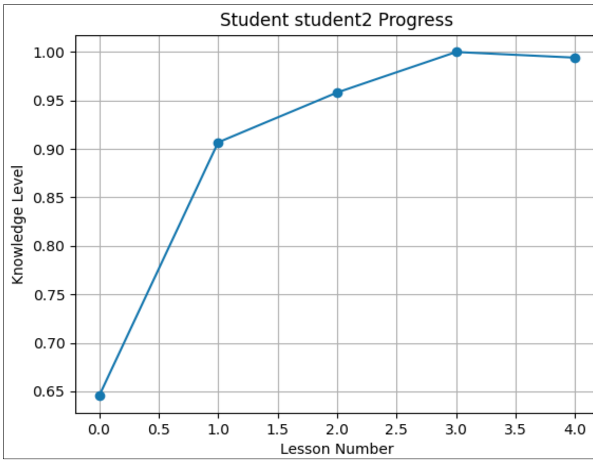

Figure 12.30. Demonstration of Student 2's learning progress.

Lesson Plan for Student 3 (Chemistry)

Difficulty: Chemical bonds (3), Organic chemistry (7), Chemical bonds (3), Chemical bonds (3), Organic chemistry (7)

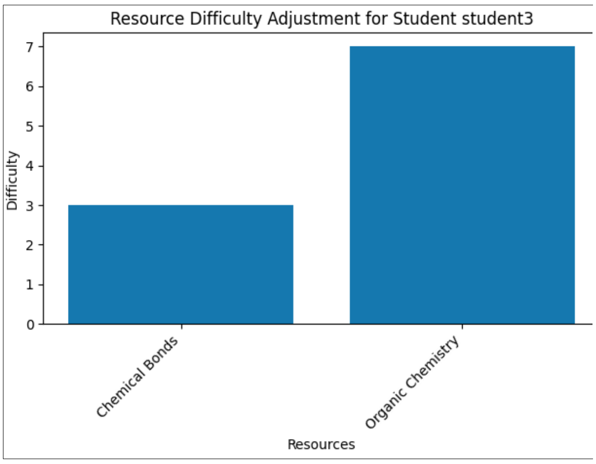

Figure 12.31. Visualization of difficulty adjustment for Student 3.

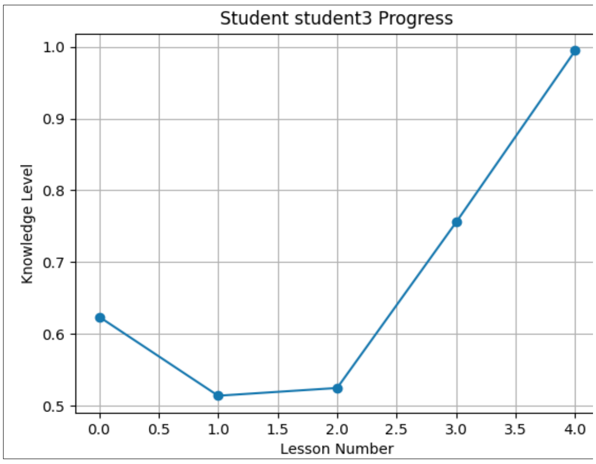

Figure 12.32. Demonstration of Student 3's learning progress.

Lesson Plan for Student 4 (Geography)

Difficulty: Human geography (4), World geography (2), World geography (2), Human geography (4), Human geography (4)

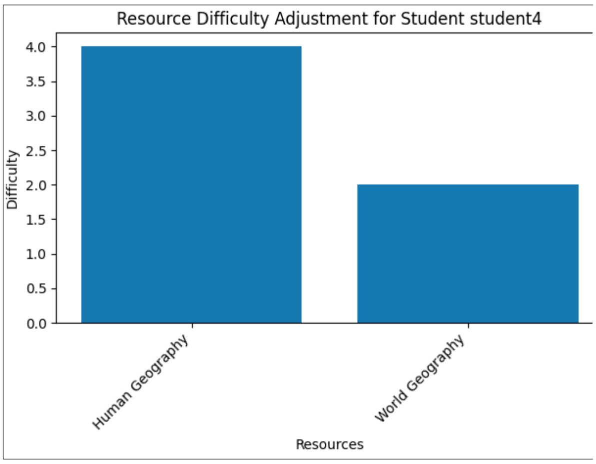

Figure 12.33. Visualization of difficulty adjustment for Student 4.

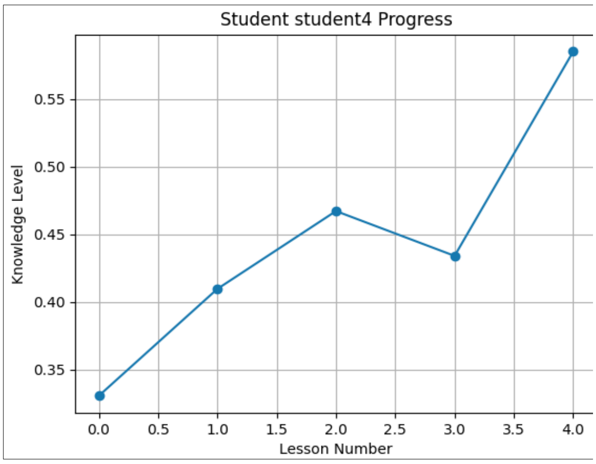

Figure 12.34. Demonstration of Student 4's learning progress.

Lesson Plan for Student 5 (Economics)

Difficulty: Economic systems (5), Microeconomics (6), Microeconomics (6), Microeconomics (6), Microeconomics (6)

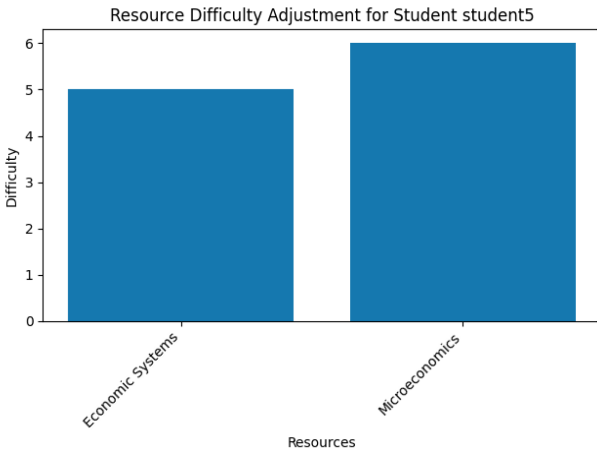

Figure 12.35. Visualization of difficulty adjustment for Student 5.

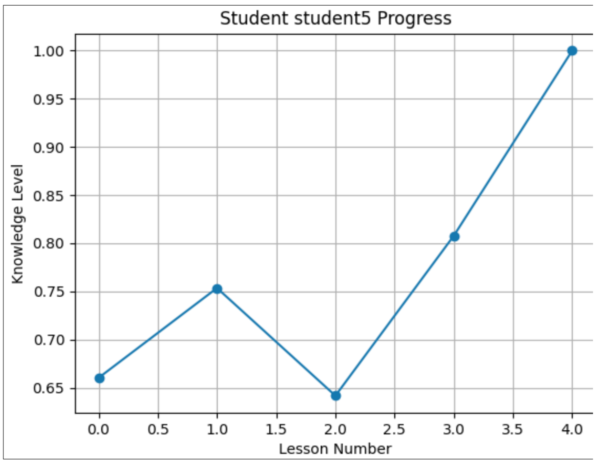

Figure 12.36. Demonstration of Student 5's learning progress.

12.6.6 Implementation Details

The initial evaluation of the NSLE algorithms shows promise, but a full understanding requires rigorous testing with real-world data. This next phase is important for analysing performance in complex environments and addressing unexpected outcomes from real-world datasets. This assessment will examine the algorithm's strengths and weaknesses in practical scenarios, moving beyond our initial controlled tests. The algorithm's performance, as tested, depends on data quality, feature selection, and algorithm design, all aspects I considered. Any findings that differ from our expectations, such as in real-world implementation, will require investigation. The NSLE algorithm's strengths, particularly in personalization, adapting to individual learner needs, and potential for improved learning outcomes, have been highlighted. Conversely, I recognize weaknesses, which may include computational complexity and the volume and nature of data needed for performance. Trade-offs in design, like balancing accuracy and efficiency or deep personalization and broad generalisation, were also factored. We've explored the practical implications for educators, students, and institutions considering the NSLE's adoption. The theoretical implications for understanding learning processes and personalised education are also discussed. Based on identified limitations and insights gained, I propose future research directions to extend the algorithm's capabilities and address challenges, with further real-world data testing as a key next step. Finally, we've considered the ethical implications of using such algorithms in education, particularly regarding data privacy, potential biases, and ensuring equitable access for all learners, considerations I find paramount. Throughout this discussion, I link back to the initial research questions in *chapter 1.5*, keeping our focus on original aims. This discussion demonstrates the significance of our research, reinforcing its credibility and the NSLE algorithm's potential impact in personalised learning.

12.6.8 Experimental setup

I suggest that the evaluation of all NSLE algorithms follows a structured experimental process, centred on reproducibility and validation. Initially, the focus group and I determined the variables most important for selecting student learning material. Our detailed experimental procedure is in Appendix AJ. Currently, before full NSLE implementation, only reproducibility is ensured through controlled random variables. Full algorithm experimentation, with more statistical tests and variables, will yield optimal results once the system is in place.

12.6.9 Algorithm execution and future evaluation

(a) **Rigorous Post-Implementation Testing: My Approach**

Once the NSLE is implemented, I believe it's absolutely crucial to embark on a rigorous and comprehensive testing period. This post-implementation phase isn't just a formality; it's genuinely critical for me to ensure the system's robustness, accuracy, and reliability in what will effectively be real-world educational scenarios. My approach involves using simulated numerical values for tagged variables within the

learning material. This allows me to conduct controlled and repeatable evaluations of the system's core functionalities, which is essential for systematic research. My primary goal during this testing is to meticulously assess the algorithms' ability to accurately identify and effectively address individual student knowledge gaps. Throughout this crucial period, I'll be applying the metrics I've discussed in this section to empirically demonstrate the AI algorithms' effectiveness. Their performance will be objectively assessed through a comprehensive suite of test metrics, which I've carefully chosen to gauge their efficacy and enable meaningful comparative analysis. These metrics specifically focus on personalization effectiveness, system efficiency, and resource use. I selected them based on established practices in both educational technology and machine learning, drawing insights from work such as Nafea. 2018, which allows for direct comparisons with existing benchmarks.
To give you a concrete example of how this testing will unfold, I've focused on a key metric for evaluating the system's personalization capabilities: the Normalised Discounted Cumulative Gain (NDCG). This metric is specifically designed to assess the relevance and ranking of personalised learning materials, which is central to the NSLE's function. To illustrate its application and the system's expected behavior, I conducted a simulated test. Using data from an earlier hypothetical student, 'Student A,' who is studying A-level Mathematics, I processed a specific set of learning materials through the NSLE system. The resulting NDCG score for Student A was 0.89. For me, this high value is really encouraging because it demonstrates that, in this simulated scenario, the system's underlying calculations effectively identified and prioritised highly relevant learning content for Student A. This aligns precisely with what I would consider optimal performance for a well-functioning personalization algorithm, and it clearly shows the NDCG calculations working exactly as they should. Finally, *Appendix AK* provides a detailed rationale for each metric's selection, outlining its calculation and relevance to my research. I've also included the Python code there to replicate the NDCG calculations for future application, ensuring the transparency and replicability of these critical evaluations.

(b) **Results presentation**

While the NDCG offers a valuable framework for evaluating AI algorithms, I recognize the practical realities of my research. A representative assessment of the algorithms' efficacy depends on the full implementation of the NSLE, populated with a substantial corpus of tagged learning materials. Only with this robust dataset can we conduct meaningful testing and generate reliable performance metrics. This comprehensive implementation will allow us to move beyond theoretical evaluations and gain an accurate understanding of algorithm performance in a real-world learning context.

The NSLE focus group

The NSLE focus group received instructional material [Appendix AJ] guiding them through activities designed to evaluate the algorithms in this chapter. This document references every algorithm in the appendices and includes the full code for each. Through collaborative testing with the focus group, the algorithm tests showed a high reproducible success rate. As expected, when variables updated dynamically to simulate real-world NSLE implementation, the algorithms consistently executed correctly across all trials, with output accurately reflecting the updated information.

(c) **Comparison**

Given that the NSLE algorithms represent a novel development, direct, immediate comparisons with existing systems that utilise identical methodologies and data aren't currently feasible. However, in this section, I wanted to establish a framework for future benchmarking and analysis. This will enable an evaluation of the NSLE as similar systems emerge in the field. To prepare for these future analyses, I provided a clear rationale for my selection of relevant baseline algorithms. These encompass both state-of-the-art and more traditional approaches to personalised learning. These baselines will serve as fundamental points of comparison in future studies.

12.6.10 Discussion

The initial evaluation of the NSLE algorithms shows promise, but a full understanding requires rigorous testing with real-world data. This next phase is important for analysing performance in complex environments and addressing unexpected outcomes from real-world datasets. This assessment will examine the algorithm's strengths and weaknesses in practical scenarios, moving beyond our initial controlled tests. The algorithm's performance, as tested, depends on data quality, feature selection, and algorithm design, all aspects I considered. Any findings that differ from our expectations, such as in real-world implementation, will require investigation. The NSLE algorithm's strengths, particularly in personalization, adapting to individual learner needs, and potential for improved learning outcomes, have been highlighted. Conversely, I recognize weaknesses, which may include computational complexity and the volume and nature of data needed for performance. Trade-offs in design, like balancing accuracy and efficiency or deep personalization and broad generalisation, were also factored.

We've explored the practical implications for educators, students, and institutions considering the NSLE's adoption. The theoretical implications for understanding learning processes and personalised education are also discussed. Based on identified limitations and insights gained, I propose future research directions to extend the algorithm's capabilities and address challenges, with further real-world data testing as a key next step. Finally, we've considered the ethical implications of using such algorithms in education, particularly regarding data privacy, potential biases, and ensuring equitable access for all learners, considerations I find paramount. Throughout this discussion, I link back to the initial research questions in *chapter 1.5*, keeping our focus on original aims. This discussion demonstrates the significance of our research, reinforcing its credibility and the NSLE algorithm's potential impact in personalised learning.

12.6.11 Error analysis

Here, I analyse potential errors from our initial NSLE algorithm evaluation, examining error types and causes to inform future refinements. A primary source of these errors appears in data tagging. Ensuring correct tagging of learning material and student data remains an area requiring attention due to human involvement. The selection of variables for tagging to provide correct learning material is important, and without careful management, bias here could lead to errors. These specific errors did not surface during focus group testing, where we used pre-determined tagged data. We also examined constraints from the algorithm's design, issues from feature engineering, and sensitivities in parameter tuning [*person_learn_1.py* ; *person_learn_2.py*]. These could all cause errors in future applications. To understand these errors, we used qualitative methods, including simulated pilot studies [*Section 12.4*] of student interactions with the NSLE. This allowed for a more in-depth look at the context of these occurrences. Finally, I recommend using specific error metrics to monitor, test, and evaluate the algorithm's real-world performance. This will help identify and address any appearance of these errors.

Limitations

While the NSLE algorithm shows promise for personalised learning, it has limitations. Acknowledging these maintains intellectual honesty and builds a foundation for future research. The algorithm's performance depends on data availability and quality, as discussed in the error analysis [*Section 12.6.11*]. Future research should address data scarcity or bias. My evaluation occurred in a simulated environment; future studies should test its performance across more learning domains and real-world settings. The NSLE algorithm's complexity might challenge real-time deployment. Future research should focus on optimising its efficiency and exploring hardware acceleration for practical use. The current NSLE setup prioritises core functionality; future research should enhance student experience and engagement. The study's timeframe was limited. To understand the NSLE's long-term effects on learning and retention, longitudinal studies tracking student progress are necessary.

Future research should also address ethical implications of AI in education, including bias, data privacy, and equitable access. An important area for future investigation is the NSLE's impact on student cognitive load. Research should explore how the system affects cognitive processing and how to optimise it to minimize overload. By acknowledging these limitations, I aim to show intellectual honesty and open avenues for future research. This will ensure the NSLE algorithm continues to evolve and contribute to personalised learning in education. The next step is real-world testing of the NSLE algorithm with students in educational settings.

12.6.12 Conclusion

Summarize the key contributions

This dissertation details the development, application, and evaluation of the NSLE algorithms. Drawing on a comprehensive dataset, I've shown how the algorithms dynamically adapt to individual student learning profiles [*Section 12.4*]. Based on neuro-synaptic modelling, the NSLE algorithm emulates human brain learning within AI education. Evaluation, after implementation, will quantified the algorithm's performance [Appendix AK], demonstrating its effectiveness in enhancing student learning. It is necessary to analyse the algorithm's strengths, weaknesses, and limitations to inform future improvements. An error analysis will also contribute to further system refinements. Beyond the technical aspects, I've addressed the ethical considerations of implementing AI in education.

Future work

My dissertation on the NSLE aims for clear and concise communication, making its concepts accessible to a broad academic audience. I've presented this research using precise language and logical progression, avoiding jargon, and using examples to improve clarity. I've also prevented redundancy through careful phrasing, visual aids, and succinct summaries. Upholding scholarly rigour has been key. This includes accurate citations, a transparent methodology, and a thorough analysis of both existing literature and my own findings. To make this work accessible to those less familiar with the NSLE's technical aspects, I define terms on first appearance, explain methodologies, and provide background context. I hope that by maintaining clarity, conciseness, and rigour, this dissertation contributes to the advancement of personalised learning in education.

12.6.13 Key considerations throughout.

My dissertation on the Neuro-Synaptic Learning Environment [*NSLE*] aims for clear and concise communication, making its concepts accessible to a broad academic audience. I've presented this research using precise language and logical progression, avoiding jargon, and using examples to improve clarity. I've also prevented redundancy through careful phrasing, visual aids, and succinct summaries. Upholding scholarly rigour has been key. This includes accurate citations, a transparent methodology, and a thorough analysis of both existing literature and my own findings. To make this work accessible to those less familiar with the NSLE's technical aspects, I define terms on first appearance, explain methodologies, and provide background context. I hope that by maintaining clarity, conciseness, and rigour, this dissertation contributes to the advancement of personalised learning in education.

Reproducibility

Throughout this dissertation, clarity and accessibility have guided my work on the NSLE. This principle has shaped how I present every element, from notation to structure. I established a consistent system for all coding notations, material tags, and algorithms from the outset. Each symbol and term is defined upon its first appearance, with any deviations explained. I also used a core vocabulary, defining key concepts at their introduction to avoid confusion. Beyond language and code, I focused on overall presentation. Every section, figure, table, and citation follows a uniform style, enhancing readability. For example, all figures and tables are formatted identically, and my citations follow the Harvard system. To maintain these standards, I regularly used automated checks and manual reviews to correct inconsistencies. This focus on consistency, alongside providing sufficient detail for reproducibility, goes beyond presentation; it aims to make the research unambiguous. I included specific generated data to test every algorithm, demonstrating consistent, reproducible results. I hope this approach allows readers to focus on the research and provides a foundation for others to build upon and verify my work.

12.7 NSLE algorithmic contributions

My research focuses on the Neuro-Synaptic Learning Environment (NSLE). This chapter explains the algorithms that run it. I have included Python and HTML5 code, along with examples, to show these concepts in action; I believe this work supports the research direction. My goal for the NSLE is to personalise learning in AI education, and these algorithms are a first step in that effort.

CHAPTER 13
FUTURE DIRECTIONS AND RESEARCH OPPORTUNITIES

13.1 A comprehensive roadmap

It's fascinating to witness the transformative influence of digital learning platforms and the wealth of data they generate. My research examines this dynamic landscape, revealing the potential of learning analytics and AI to reshape how we approach education. Through this dissertation, I've developed a comprehensive roadmap intended to support educators, policymakers, and fellow researchers in effectively harnessing these technologies to better understand and support our students. At the heart of this work lies the Neuro-Synaptic Learning Environment [*NSLE*] framework, born from investigation and practical application, offering tangible pathways toward improved academic outcomes. However, my research also acknowledges the complexities inherent in applying these powerful tools. While their potential is undeniable, thoughtful and informed implementation remains paramount. Going beyond theoretical constructs, this dissertation grapples with the critical imperatives of data privacy and ethical considerations. Technological advancements in education are guided by principles of responsibility and equity. My aim is to contribute an actionable perspective, moving beyond abstract discussions to lay a foundation for meaningful progress in real-world educational settings.

The very nature of learning analytics and AI-powered educational ecosystems, so clearly exemplified by the NSLE, demands collaborative expertise from a variety of fields. The insights of experienced educators, the understanding of psychologists, and the skills of technologists are valuable. Likewise, policymakers play a vital role in establishing ethical boundaries and ensuring fair access. It's through continued interdisciplinary collaboration, inquiry, and careful ethical reflection that we can truly unlock the full potential of AI and learning analytics in education. Building on the development and evaluation of the NSLE, my research envisions a future where data-driven insights and AI-personalised learning empower each and every student. Achieving this vision, however, hinges on thoughtfully addressing technical integration, pedagogical alignment, data governance, and the ethical implications that arise. Future research should focus on refining AI-driven learning algorithms, examining the impact of seamless technological integration in learning environments, and developing frameworks for ethical and equitable implementation. A central finding of my work illustrates the transformative role that learning analytics now plays in contemporary education. This dissertation offers a practical guide for educators, policymakers, and researchers seeking to strategically employ educational data to create more engaging and effective learning experiences for our students. This framework aims to facilitate continuous improvement in student learning outcomes and the efficacy of educational interventions.

I do recognise the profound impact of digital learning platforms and the exponential growth of educational data. Learning analytics has become an indispensable tool, offering unprecedented insights into the nuances of student learning and enabling more tailored support, as demonstrated through the lens of the NSLE. My work has explored both the theoretical underpinnings and the practical applications of learning analytics, advocating for its careful and considered adoption. By embracing data-driven insights and personalised approaches, we can strive toward a more equitable educational future where every student has the opportunity to reach their full potential. The strategic application of learning analytics represents a fundamental shift toward a more responsive and more effective educational paradigm.

13.2 AI-powered mentorship

While the promise of AI-powered mentorship in education is considerable, especially within the NSLE fuelled by intelligent algorithms, its successful integration relies heavily on mentors who can effectively guide both educators and policymakers. Further investigation justifies to determine the practical feasibility and impact of these AI systems across a variety of educational contexts. Mentors possessing expertise in both AI and pedagogy are vital to bridge the divide between technological innovation and real-world application. They must demonstrate to educators how AI can personalise learning experiences, offer objective, real-time feedback, and provide support for the implementation and ongoing maintenance of the NSLE. Empirical studies are necessary to quantify the tangible career outcomes resulting from these AI mentorship programs, requiring the development of metrics and long-term studies. Mentors must guide policymakers in comprehending the ethical and societal implications of AI in education. This involves illustrating how AI algorithms can be designed to minimize bias and foster workplace diversity and inclusion, thereby ensuring equitable support for all learners. Research should examine the effectiveness of AI mentorship in cultivating inclusive environments, specifically addressing how mentors can facilitate discussions and the development of policies around these critical issues. Mentors with specific industry knowledge and experience are indispensable for developing and evaluating AI mentorship platforms tailored to unique professional and educational requirements. These mentors can help connect academic theory with practical industry application, ensuring that AI functionalities are relevant and effective in preparing learners for their future careers. Mentors with a strong understanding of resource management are needed to tackle the practical challenges that non-profit organisations face when implementing AI mentorship, particularly concerning data acquisition and management. These mentors can offer guidance on overcoming obstacles and ensuring fair access in environments with limited resources.

Mentors must emphasise the indispensable role of human involvement in conjunction with AI. Research should explore effective models of collaboration between AI and human mentors or educators to optimise student support and address individual needs that extend beyond the capabilities of AI alone. These mentors will be instrumental in determining the ideal balance between AI-driven guidance and human oversight, ensuring responsible and significant integration. By focusing on the education and empowerment of educators and policymakers through targeted mentorship, we can effectively address these research gaps. This will lead to a more comprehensive understanding of AI mentorship's benefits, limitations, and practical implementation strategies, advancing personalised guidance and support within the NSLE and across the broader educational and professional landscape.

13.3 Educator engagement and satisfaction

A critical area demanding our attention is educator engagement and satisfaction with innovative learning systems. The successful adoption and long-term viability of AI-powered educational ecosystems, such as the NSLE, fundamentally depend on the perceptions and experiences of teachers on the ground. Moving forward, empirical investigation in several key areas should be a priority for researchers. Quantifying the level of educator enthusiasm for, and perceived support surrounding, new learning systems is key. Employing mixed-methods approaches, which combine the breadth of surveys with the depth of interviews, can uncover both the general sentiment and the more nuanced perspectives regarding what helps or hinders adoption.

Equally important is evaluating the effectiveness of professional development initiatives designed to equip teachers with the skills needed to integrate AI-powered tools seamlessly into their practice. Research should explore various training methods, their duration, intensity, and the provision of ongoing support. Longitudinal studies will be invaluable in tracking skill acquisition, retention, and the evolving attitudes of teachers toward these technologies. Critically, we must assess the impact of these efforts on the actual transfer of knowledge and skills into classroom applications. Research should examine how smoothly teachers incorporate AI tools into their lesson plans, adapt their teaching methodologies, and utilise the insights provided by these systems to reinforce student learning. Observational studies and analyses of teaching practice can yield particularly valuable data in this regard.

The impact of these systems on teacher job satisfaction and retention needs careful consideration. Investigating potential increases in workload, feelings of being deskilled, or perceptions of efficiency is vital. Understanding the factors that influence teacher satisfaction in the context of AI integration is necessary for developing supportive strategies and ensuring a positive experience for educators. An investigation into teacher engagement, professional development, the translation of skills into practice, and job satisfaction will provide a comprehensive understanding of the human factors that influence the implementation of AI-powered learning systems. This knowledge will play am important role in informing policy decisions and ensuring the sustainable and beneficial integration of AI in education.

13.4 Translation of innovative AI solutions

The successful transition of innovative AI solutions, such as the NSLE, into practical educational settings hinges on their smooth integration with existing technologies, policies, and established teaching practices. Future research must systematically investigate this integration process, and several key questions immediately come to mind. Initially, it's important to explore the technical hurdles and opportunities involved in connecting AI platforms with the legacy systems already in place, our Learning Management Systems [*LMS*], Student Information Systems [*SIS*], and various digital resources. Research in this area should examine data compatibility issues, the interoperability of different systems, and the development of effective Application Programming Interfaces [*APIs*].

Beyond the technical aspects, the pedagogical implications of integrating AI into our curricula and teaching methodologies demand careful consideration. We need to understand how educators can effectively use AI tools without disrupting their established workflows or compromising sound pedagogical principles. Research could explore collaborative teaching models involving AI, the adaptation of existing lesson plans to incorporate AI, and the subsequent impact on student engagement and learning. Organisational and policy considerations also require thorough examination.

This includes a realistic assessment of the financial implications, the development and implementation of data privacy and security policies, and the provision of necessary training and ongoing support for educators. Research should also address the scalability and accessibility of these integrated systems across educational contexts and to meet the varied needs of all learners.
Finally, empirical studies evaluate the actual effectiveness and broader impact of different integration strategies in real-world classrooms. Case studies, gathering feedback directly from educators and students, and conducting quantitative data analysis can provide invaluable insights into best practices and inform the direction of future development efforts. By systematically addressing these technical, pedagogical, organisational, and policy challenges, I am confident that this research has the potential to significantly contribute to the practical advancement and sustainable adoption of AI in education, leading to more effective and equitable learning experiences.

13.5 Multifaceted ethical challenges

As the integration of AI into our educational systems accelerates, addressing the critical ethical considerations and the imperative of bias mitigation becomes ever more pressing. Ensuring the equitable and responsible deployment of these powerful technologies is paramount for the future of learning. Future research must prioritise an exploration of the multifaceted ethical challenges that arise. In-depth investigations into data privacy and security are imperative. This includes a thorough examination of how educational data is collected, stored, analysed, and used, alongside the development of frameworks for safeguarding this sensitive information and ensuring compliance with relevant regulations. It would also be insightful to explore the perceptions of data privacy held by students, educators, and parents themselves.
Identifying and actively mitigating bias within AI algorithms is another area of inquiry. We urgently need methodologies for effectively detecting and addressing potential discrimination against learners based on factors such as socio-economic background, gender, ethnicity, or learning style. This necessitates a critical examination of the training data used to develop these algorithms and the creation of fairness-aware algorithms from the outset. Transparency and accountability in AI-powered education also demand research attention. Investigating how the decision-making processes of AI can be made transparent and understandable to both educators and learners is vital for fostering trust in these systems. Research should explore the development of clear accountability mechanisms to address errors or any negative consequences that may arise from AI implementation.
The potential impact of AI on the role of human educators also requires careful consideration. Research should explore how AI can effectively augment and support teachers in their work without leading to deskilling or eroding human elements such as empathy and personal connection. Developing effective models of collaboration between human educators and AI tools is a key area for future study. Finally, future research should also consider the broader societal and philosophical implications of introducing AI into education. This includes reflecting on the potential effects on student agency, the development of critical thinking skills, and even our fundamental educational goals. The development of comprehensive ethical guidelines specifically

tailored to the unique context of AI in education is a vital undertaking. A thorough investigation of these ethical considerations and the associated challenges will significantly contribute to the creation of responsible and equitable AI-powered learning environments that truly benefit all learners and uphold the core principles of education.

13.6 Interactive learning experiences that promote learning

My research journey within AI-powered education, particularly through the lens of the NSLE, has led me to consider how we can truly optimise student engagement and knowledge acquisition. It strikes me that the design and implementation of genuinely interactive learning experiences within these systems holds immense potential, and this should be a central focus of future inquiry. Moving forward, several key areas warrant our immediate attention. Firstly, we need in-depth studies to pinpoint the specific design principles that make AI-powered interactive learning truly effective. This involves carefully examining various interactive elements, such as simulations, gamification techniques, and adaptive feedback mechanisms, and determining the optimal levels of interactivity across different subjects and for learner profiles. Secondly, empirically evaluating the impact of AI-driven interactive learning on student motivation and overall engagement is key. Quantitative studies can provide valuable data on time spent on task and levels of participation, while qualitative research can offer deeper insights into students' perceptions and their lived experiences within these interactive environments.
The exciting prospect of integrating neuro-synaptic principles directly within the design of AI-powered interactive learning demands investigation. Research should explore how AI algorithms can dynamically adjust the level of challenge and the nature of feedback provided to optimally support neuroplasticity in learners. The role of carefully tailored repetition, guided by AI insights, also warrants examination. The effectiveness of immersive modalities like virtual reality [*VR*], augmented reality [*AR*], extended reality [*XR*] and mixed reality [*MR*] [*Chapter 8.4*], in actively promoting learning and the practical application of knowledge within simulated scenarios needs careful scrutiny. Studies can compare learning outcomes and engagement levels across different modalities, shedding light on their unique strengths. The role of AI in providing truly personalised guidance and support within these interactive learning experiences also warrants investigation. Research should explore how AI tutors can intelligently analyse student interactions to provide tailored feedback and helpful hints in real-time. Additionally, the integration of emotional intelligence within AI to foster more empathetic and supportive interactions holds considerable promise. Finally, ensuring the seamless integration of AI-powered interactive learning with our existing curricula and established teaching practices is vital for widespread adoption and sustained impact. Studies should explore effective strategies for incorporating these new modalities and examine the professional development needs of educators to facilitate this integration successfully. An investigation into the design, implementation, and impact of AI-powered interactive learning experiences has the potential to significantly contribute to the development of educational environments that are not only engaging and effective but also deeply personalised to the unique needs of each learner.

13.7 Personalised learning pathways

One of the most compelling aspects of the NSLE is its potential to influence education through the creation and implementation of truly personalised learning pathways. My research centres on how we can best utilise AI-driven customization to optimise the unique learning journey of each student. To realize this vision, comprehensive research can determine the most effective methodologies for crafting and adapting these personalised pathways based on student data. This includes carefully investigating how various data points can be meaningfully integrated and weighted, as well as exploring the efficacy of different AI algorithms in dynamically adjusting these pathways in response to individual student progress and needs. Of course, empirically evaluating the actual impact of these personalised learning pathways on student outcomes is usefull.

Well-designed comparative studies, pitting personalised approaches against more traditional methods, and longitudinal studies, examining the long-term effects, will be vital in assessing their true effectiveness. The role of AI-powered feedback in guiding students through these personalised pathways warrants close investigation. We need to explore how AI tutors can provide timely, relevant, and, importantly, adaptive feedback that truly supports student learning. Questions around the optimal timing, modality (e.g. text, audio, visual), and content of such feedback are also key areas for future research. Beyond the immediate impact on students, we must also examine the challenges and opportunities associated with scaling personalised learning pathways across educational settings. This includes tackling practical issues such as efficient data management, ensuring algorithmic fairness to prevent unintended biases, addressing the scalability of these complex systems, and achieving seamless integration with the existing technological infrastructure within our schools.

Finally, understanding the student experience and their perceptions of these personalised learning pathways is paramount. Research should explore their levels of engagement, the perceived relevance of the learning content, and their overall sense of effectiveness. Also, the inherent ethical considerations and the potential for unintended consequences necessitate ongoing and thoughtful research. Investigation into the design, implementation, and impact of AI-powered personalised learning pathways has the potential to contribute substantially to the creation of educational experiences that are not only adaptive and effective but also fundamentally equitable, catering to the unique strengths and needs of every learner.

13.8 Integration with existing educational systems

A primary focus of my ongoing research, and indeed a step toward realizing the full potential of the NSLE, is its effective integration with the educational systems and infrastructure already in place. To truly facilitate its practical adoption and widespread implementation, we must thoroughly explore the technical and logistical challenges of connecting the NSLE with current Learning Management Systems , Student Information Systems, and related educational technologies. This includes a detailed examination of data compatibility issues, the interoperability of different platforms, and the development of Application Programming Interfaces, carefully considering the pros and cons of modular integration versus a more comprehensive system replacement.

We need to carefully examine the infrastructural requirements for deploying the NSLE across different educational settings, taking into account the variations in technological access and internet connectivity that exist. Our focus here should be on identifying cost-effective and scalable solutions that can bridge the digital divide. The impact of NSLE integration on existing workflows and the evolving roles of educators also demands investigation. Specifically, we need to understand how teachers can seamlessly incorporate the NSLE into their daily practice without disrupting effective pedagogy, and what kind of professional development and ongoing support will be necessary. The financial and resource implications of this integration are also paramount and require thorough examination. This includes a detailed analysis of development costs, procurement strategies, data storage requirements, and ongoing maintenance expenses, with a keen eye toward sustainable funding models. Additionally, the security and privacy considerations associated with integrating the NSLE with existing data systems are critical and necessitate research into data encryption methods, access control protocols, and compliance with relevant data protection regulations. The user experience and the level of acceptance of the integrated NSLE by students, educators, and administrators will determine its success.

Studies should explore the usability of the system, its perceived effectiveness in enhancing learning, and its overall value from the perspective of all stakeholders. Employing user-centred design principles will be key to optimising the integration process and ensuring a positive experience. Looking beyond the immediate challenges of integration, future research must also validate the NSLE framework across a wide range of educational contexts and with learner populations. This will require real-world implementations and longitudinal studies to accurately assess its long-term impact on student learning outcomes and teacher effectiveness. The exciting potential of integrating multimodal data, including physiological, behavioural, and even emotional data, to create richer student profiles and further personalise learning pathways is another area ripe for investigation, demanding the application of advanced analytical techniques.

The possibilities presented by Natural Language Processing and generative AI for creating personalised learning content and providing adaptive feedback are also compelling and warrant thorough exploration. Specifically, the development of AI tutors capable of engaging in meaningful dialogue with students and delivering truly tailored content holds immense promise. Given the NSLE’s very neuro-inspired design, a detailed investigation into emulating specific functions of the human brain within AI algorithms to optimise the learning process itself is another fascinating avenue for future inquiry. Finally, the practicalities of large-scale implementation and seamless integration with existing systems require attention, with a focus on developing user-friendly tools and effective strategies for widespread adoption. This concluding chapter, therefore, serves not as an end, but rather as a launchpad for future inquiry. By diligently pursuing these research directions, AI-powered personalised learning, particularly as embodied by the NSLE, can continue to evolve and transform education for all learners.

CHAPTER 14
CONCLUSIONS

14.1 The NSLE and its implications

Throughout this dissertation, I've detailed the conceptualisation, development, and initial evaluation of the Neuro-Synaptic Learning Environment, a novel educational framework born from my deep interest in revolutionising learning through the powerful synergy of artificial intelligence, machine learning, and gamification. My direct experiences as an educator, coupled with witnessing firsthand the inherent limitations of traditional teaching methodologies, served as the primary motivation for this research. I set out to demonstrate how the intelligent application of AI can be strategically harnessed to significantly optimise the learning process for students, support teachers in new ways, and provide valuable insights for policymakers. The central aim of this work has been to address some of the most pressing challenges in education today, including the ever-present constraints of time, the pervasive issue of distractions in the learning environment, and the often-lamented lack of truly personalised support for each student. To tackle these issues, I've developed an intelligent tutoring system at the heart of the NSLE, one capable of providing genuinely individualised feedback and dynamically adapting learning pathways to meet each learner's unique needs. The NSLE, as I envision it, represents a holistic ecosystem designed to foster dynamic, personalised learning experiences and provide truly adaptive assessment strategies.

14.2 NSLE: Functionality and theoretical basis

At its core, the NSLE operates through an intelligent AI engine that analyses student data. My aim here is to identify each student's unique learning style and, based on that understanding, to craft truly tailored and individualised learning trajectories. Beyond this, the AI tutors embedded within the NSLE have the capability to recommend different types of user friendly study material as well as immersive virtual and augmented reality simulations. What's particularly exciting is that the effectiveness of these recommendations is continuously refined by sophisticated machine learning algorithms, which learn and adapt based on real-time student progress and engagement. The intentional incorporation of gamification within the NSLE also plays a role. It's designed to significantly boost student motivation and provide immediate, actionable feedback, collectively striving to move beyond the inherent limitations I've observed in conventional educational practices.
Throughout this research, I've been deeply informed by established learning theories, including constructivism, cognitivism, and connectivism, recognising the vital interconnectedness of teachers, students, and educational content within a truly adaptive learning system. One aspect of the NSLE's development involved the creation of what I term the Holistic Learning Analytics (HLA) framework. This core component is specifically designed to integrate neuro-synaptic networks with sophisticated algorithms. The HLA framework systematically gathers and analyses a rich array of data, not only on student performance and learning behaviours but even on potential environmental influences. By employing descriptive statistics, advanced machine learning algorithms, and insightful data visualisation techniques, my goal is to identify meaningful patterns within this data and use these insights to directly inform more effective pedagogical decisions.

14.3 NSLE: Algorithms, validation, and ethical implications

Building on the foundational aspects of the NSLE, this dissertation has also detailed the iterative development process behind its core graph algorithms. This involved everything from the construction of concept graphs using the power of natural language processing and the principles of graph theory, to the sophisticated methods I've developed for identifying individual knowledge gaps through machine learning, and the adaptive learning path optimisation techniques I've implemented. The pilot studies I conducted, while necessarily based on simulated data to establish baseline correlations, have nonetheless offered a valuable proof of concept. They clearly illustrate the exciting potential of AI to significantly increase educational outcomes by intelligently adapting to individual learning profiles. For instance, the AI's demonstrated ability to automatically generate personalised quizzes and recommend specific revision materials based on a student's self-assessment and identified learning style strongly showcases the NSLE's inherent adaptive capabilities. However, throughout this research, I've also been keenly aware of the inherent challenges and ethical considerations that inevitably arise with the integration of AI in education. Issues such as the paramount importance of data privacy, the need for transparency in algorithmic decision-making, questions of accountability, and the potential for bias within AI algorithms have been addressed as top-priority concerns. These require our careful and ongoing attention as we continue the development and real-world implementation of the NSLE.

14.4 NSLE: Limitations and future research

Throughout this work, I've consistently emphasised the enduring importance of human oversight and the vital continued role of educators in validating learning content and addressing the complex and nuanced needs of individual students. The significance of this study, as I see it, lies in its potential to pave the way for a more efficient and remarkably effective education system, one that truly caters to the unique landscape of individual minds and, most importantly, fosters a genuine and lifelong love of learning. Indeed, the development of the NSLE’s algorithms represents what I believe is a novel and promising approach to personalising learning within such an interconnected ecosystem. Nevertheless, I do acknowledge certain inherent limitations of this initial research. The evaluation I conducted at this stage relied on simulated data, and therefore, real-world testing is undoubtedly a necessary next step to fully validate the NSLE’s efficacy and impact within practical educational settings.
The current evaluation did not explicitly measure cognitive load, a critical area that certainly warrants thorough investigation in future research to further optimise the learning experience and prevent cognitive overload. Therefore, I view this dissertation as laying a foundational framework for future advancements in the exciting field of AI-driven personalised learning. Several compelling potential directions for future research have clearly emerged from this work. These include the immediate need for real-world implementation and comprehensive testing of the NSLE across educational contexts and a wide range of subject areas. In addition, future studies should specifically investigate the impact of the NSLE on learners' cognitive load and explore further refinements to the underlying artificial intelligence algorithms to significantly increase their adaptability and overall effectiveness. Looking ahead, I also see deeper exploration into the integration of neuroscience principles to optimise the NSLE’s impact on neuroplasticity as a particularly promising and potentially transformative avenue for future research. Finally, addressing the critical ethical implications of AI in education, ensuring fairness and actively mitigating potential biases, and fostering interdisciplinary collaborations between AI experts, experienced educators, and

cognitive scientists will be important for the responsible and truly influential advancement of this rapidly evolving field.

14.5 Conclusion: The NSLE's potential

Realizing the NSLE's global potential

In this dissertation, I believe I've compellingly demonstrated the foundational strengths of the NSLE as a paradigm-shifting approach to personalised education with profound global applicability. However, as I see it, the path to its full transformative impact isn't without significant hurdles, and this research has critically illuminated these challenges as relevant to any context.

Foremost among these is the imperative for rigorous real-world evaluation and data validation. While simulations offer initial insights, the true efficacy and long-term impact of the NSLE, including its influence on cognitive load, can only be definitively established through extensive practical deployment across varied learning contexts globally. This must always acknowledge the unique circumstances and existing infrastructure of each individual institution, wherever they might be. This empirical validation is inextricably linked to the critical task of identifying and mitigating algorithmic bias, a persistent challenge that demands proactive design and continuous monitoring to ensure equitable learning experiences for all, regardless of their background or location.

The successful transition of the NSLE from theory to widespread practice also confronts substantial operational and ethical considerations that resonate across borders. Protecting the privacy and security of sensitive student data is non-negotiable; this requires robust protocols and a commitment to transparent data governance to build and maintain trust in diverse regulatory environments. The seamless integration of the NSLE into existing educational systems and practices presents complex technical and infrastructural demands worldwide. This highlights the need for adaptable solutions that complement, rather than disrupt, established pedagogical approaches. I believe the NSLE must reinforce, not replace, the irreplaceable role of human educators and the development of essential human skills like critical thinking and creativity. This necessitates comprehensive teacher training that's tailored to local needs and capacities to ensure effective and responsible AI integration.

I feel the NSLE holds immense potential to reshape educational landscapes, offering unprecedented personalization and adaptive support for learners everywhere. Yet, this potential can only be fully realized by directly confronting and systematically addressing the challenges of real-world validation, ethical AI development, data security, practical integration, and human-AI synergy. This dissertation provides a robust analytical framework for understanding these critical considerations, serving as a vital guide for future research and development aimed at ensuring the NSLE truly delivers on its promise of a more effective, equitable, and human-centred future for global education.

APPENDIX A

The Cognitive profiling self-assessment questionnaire.

Cognitive profiling self-assessment questionnaire

Answer the following questions as accurate as possible.
Export the form as a pdf and return it to me via email.
The information on this form will only be used for statistical research purposes.

Demographic information

Name: Age: Gender:

Education level: Occupation:

Cognitive abilities - attention

Selective attention

Can you focus on a conversation in a noisy room?
Can you easily ignore distractions while studying?

○ Always ○ Often ○ Rarely ○ Never

Sustained attention

How often do you get distracted or lose track of your thoughts while studying?

○ Always ○ Often ○ Rarely ○ Never

Divided attention

Can you effectively multitask while answering phone calls or listen to music while studying or work,?

○ Always ○ Often ○ Rarely ○ Never

Cognitive abilities - memory

Short term memory

Can you easily remember phone numbers or do you often forget where you placed your keys?

○ Always ○ Often ○ Rarely ○ Never

Long term memory

How easily do you recall past events, names, and facts? Do you remembering important dates?

○ Very difficult ○ Challenging ○ Easy ○ Very easy

Working memory

Can you hold information in your mind while performing other tasks?
Can you follow multi-step instructions or remember a list of items?

○ Very difficult ○ Challenging ○ Easy ○ Very easy

Cognitive abilities - memory tasks

Verbal memory task

Read the words: apple, tree, book, car, house. Close your eyes and try to recall the words. How many words could you recall? Do you find it easy or difficult to memorize lists of words?

◯ Very difficult ◯ Challenging ◯ Easy ◯ Very easy

Working memory task

Look at a picture of a bicycle. After a few seconds, remove the picture. How easily can you recall the details of the bicycle?

◯ Most details ◯ Some details ◯ Few details ◯ Very few details

Working memory task

How easily can you repeat the numbers (e.g., 7, 2, 9, 5) in reverse order? Do you find it challenging to hold and manipulate information in your mind?

◯ Most details ◯ Some details ◯ Few details ◯ Very few details

Cognitive abilities - problem-solving tasks

Logical reasoning

What is the next number in the sequence: 2, 7, 12, 17, __. How easily can you identify patterns and rules in number sequences?

◯ Very difficult ◯ Challenging ◯ Easy ◯ Very easy

Analytical thinking

Do you break a complex problem or situation down the problem into smaller steps? Do you analyze different perspectives and consider potential solutions?

◯ Always ◯ Often ◯ Rarely ◯ Never

Creative thinking

Do you enjoy brainstorming and exploring different possibilities? Can you think "outside the box" to find solutions to problems?

◯ Always ◯ Often ◯ Rarely ◯ Never

Observation exercise

This part of the form will be scored by an observer.

Cognitive task

	Low 1	2	3	4	High 5
Attention task	○	○	○	○	○
Visual search task	○	○	○	○	○
Stroop task	○	○	○	○	○
Flanker task	○	○	○	○	○

Processing speed - reaction

	Slow 1	2	3	4	Fast 5
Reaction time	○	○	○	○	○
Information processing speed	○	○	○	○	○

Processing speed - tasks

	Low 1	2	3	4	High 5
Simple reaction task	○	○	○	○	○
Choice reaction task	○	○	○	○	○
Information speed task	○	○	○	○	○

Problem solving - puzzles

	Slow 1	2	3	4	Fast 5
Logic puzzles	○	○	○	○	○
Brain teasers	○	○	○	○	○
Creative exercises	○	○	○	○	○

Problem solving - reasoning

	Slow 1	2	3	4	Fast 5
Logical reasoning	○	○	○	○	○
Analytical thinking	○	○	○	○	○
Creative thinking	○	○	○	○	○

Cognitive profile

Cognitive profile summary

Overall cognitive ability	
Strengths	
Weaknesses	
Recommendation	
Comments	

APPENDIX B

The Cognitive Task Performance Record.

Cognitive Task Peformance Record

Answer the following questions as accurate as possible.
Export the form as a pdf and return it to me via email.
The information on this form will only be used for statistical research purposes.

Demographic information

Name: Age: Gender:

Education level: Occupation:

Task information

Complete the following details.

Task name :
Task description:
Task instruction:

Performance data

Enter the details of the task.

Task completion time: Accuracy:

Errors:

Strategy used:

Self reported confidence: Low 1 2 3 4 5 High

Additional notes

Rating scale

	Poor 1	2	3	4	5 Excellent
Problem-solving ability	○	○	○	○	○
Decisio-making ability	○	○	○	○	○
Planning ability	○	○	○	○	○
Overall cognitive ability	○	○	○	○	○

Additional questions

APPENDIX C

The VARK self-assessment questionnaire.

The VARK self-assessment questionnaire

Answer the following questions as accurate as possible.
Export the form as a pdf and return it to me via email.
The information on this form will only be used for statistical research purposes.

Demographic information

Name: ______ Age: ______ Gender: ______

Education level: ______ Occupation: ______

Question 1

A website has a video showing how to make a special graph or chart. There is a person speaking, some lists and words describing what to do and some diagrams. I would learn most from:

- ○ reading the words
- ○ seeing the diagrams
- ○ watching the actions
- ○ listening

Question 2

When I am learning, I:

- ○ read books, articles and handouts
- ○ see patterns in things
- ○ use examples and applications
- ○ like to talk things through

Question 3

I want to learn to do something new on a computer. I would:

- ○ read the written instructions that came with it
- ○ follow the diagrams in a book
- ○ talk with people who know the program
- ○ start it and learn by trial and error

Question 4

I want to find out more about a tour that I am going on. I would:

- ○ look at details about the highlights and activities
- ○ read about the tour on the itinerary
- ○ use a map and see where the places are
- ○ talk with the tour organiser

Question 5

I have finished a competition or test and I would like some feedback:

- ◯ using examples from what I have done
- ◯ using a written description of my results
- ◯ from somebody who talks it through with me
- ◯ using graphs showing how my performance has improved

Question 6

I prefer a presenter or a teacher who uses:

- ◯ handouts, books, or readings
- ◯ question and answer
- ◯ talk, group discussion, or guest speakers
- ◯ diagrams, charts, maps or demonstrations

Question 7

I am having trouble assembling a wooden table that came in parts. I would:

- ◯ watch a video of a person assembling a similar table
- ◯ study diagrams showing each stage of the assembly
- ◯ read the instructions that came with the table
- ◯ ask for advice from someone who assembles furniture

Question 8

I have been advised by the doctor that I have a medical problem and I have some questions about it. I would:

- ◯ use a 3D model to see what is wrong.
- ◯ look at a diagram showing what was wrong
- ◯ read an article that explains the problem
- ◯ have a detailed discussion with my doctor

Question 9

I want to learn how to take better photos. I would:

- ◯ use examples of good and poor photos showing how to improv
- ◯ use diagrams showing the camera and what each part does
- ◯ ask questions and talk about the camera and its features
- ◯ use the written instructions about what to do

Question 10

I want to find out about a house or an apartment. Before visiting it I would want:

- ◯ a plan showing the rooms and a map of the area to view
- ◯ a video of the property
- ◯ a printed description of the rooms and features
- ◯ a discussion with the owner

Question 11

I want to learn how to play a new board game or card game. I would:

- ◯ use the diagrams that explain the moves and strategies
- ◯ read the instructions
- ◯ watch others play the game before joining in
- ◯ listen to somebody explaining it and ask questions

Question 12

When finding my way, I:

- ◯ rely on verbal instructions from GPS or from someone with me
- ◯ rely on paper maps or GPS maps
- ◯ head in the general direction to see if I can find my destination
- ◯ like to read instructions from GPS or written instructions

Question 13

When learning from the Internet I like:

- ◯ videos showing how to do things
- ◯ podcasts and videos where I can listen to experts
- ◯ interesting design and visual features
- ◯ detailed articles

Question 14

When choosing a career or area of study, these are important for me:

- ◯ working with designs, maps or charts
- ◯ using words well in written communications
- ◯ applying my knowledge in real situations
- ◯ communicating with others through discussion

Question 15

I want to learn about a new project. I would ask for:

- ◯ an opportunity to discuss the project
- ◯ diagrams to show the project stages, benefits and costs
- ◯ examples where the project has been used successfully
- ◯ a written report describing the main features of the project

Question 16

I want to save more money and to decide between a range of options. I would:

- ◯ read a print brochure that describes the options in detail
- ◯ talk with an expert about the options
- ◯ use graphs showing different options for time periods
- ◯ consider examples of each option using my financial informatioı

Summary notes

APPENDIX D

The GAD-7 self-assessment questionnaire.

Generalized Anxiety Disorder 7-item questionnaire

Answer the following questions as accurate as possible.
Export the form as a pdf and return it to me via email.
The information on this form will only be used for statistical research purposes.

Demographic information

Name: ______ Age: ______ Gender: ______

Education level: ______ Occupation: ______

1. How often do you feel nervous, anxious, or on edge?

○ Never ○ Rarely ○ Sometimes ○ Often ○ Very Often

2. How often do you feel unable to stop worrying?

○ Never ○ Rarely ○ Sometimes ○ Often ○ Very Often

3. Are you worrying too much about different things?

○ Never ○ Rarely ○ Sometimes ○ Often ○ Very Often

4. Do you find it diffucult to relax or to sit still?

○ Never ○ Rarely ○ Sometimes ○ Often ○ Very Often

5. Do you find you get easily annoyed or irritable?

○ Never ○ Rarely ○ Sometimes ○ Often ○ Very Often

6. Do you find you are feeling on edge or restless?

○ Never ○ Rarely ○ Sometimes ○ Often ○ Very Often

7. Do you have difficulty concentrating or makind decisions?

○ Never ○ Rarely ○ Sometimes ○ Often ○ Very Often

Additional notes

______

APPENDIX E

The Student Learning Behaviour and Preference Observation form.

Student Learning Behavior and Preference Observation Form

Answer the following questions as accurate as possible.
Export the form as a pdf and return it to me via email.
The information on this form will only be used for statistical research purposes.

Demographic information

Name: ______ Age: ______ Gender: ______

Education level: ______ Occupation: ______

Learning behaviors

Behaviour	Yes	No
Actively participates in discussions and activities	○	○
Maintains focus and attention	○	○
Shows interest and curiosity	○	○
Approaches tasks systematically and logically	○	○
Persists in the face of challenges	○	○
Uses effective problem-solving strategies	○	○
Works well in groups	○	○
Respects others' ideas and contributions	○	○
Communicates effectively with peers	○	○
Monitors own understanding and progress	○	○
Adjusts learning strategies as needed	○	○
Reflects on learning experiences	○	○

Learning Preferences

Behaviour	Yes	No
Prefers visual aids	○	○
Prefers visual aids (e.g., diagrams, charts, images)	○	○
Benefits from visual demonstrations	○	○
Prefers verbal explanations and discussions	○	○
Benefits from lectures and listening activities	○	○
Prefers hands-on activities and experiences	○	○
Benefits from physical movement and exploration	○	○
Prefers reading and writing tasks	○	○
Benefits from taking notes and writing summaries	○	○

Further information

______

APPENDIX F

The Mayer-Salovey-Caruso Emotional Intelligence Test.

Mayer-Salovey-Caruso Emotional Intelligence Test

Answer the following questions as accurate as possible.
Export the form as a pdf and return it to me via email.
The information on this form will only be used for statistical research purposes.

Demographic information

Name: ______ Age: ______ Gender: ______

Education level: ______ Occupation: ______

Self-awareness and emotional intelligence

1. My emotions generally have:
   - ○ a strong impact on the way I behave.
   - ○ little or no impact on the way I behave.

2. I am generally guided by
   - ○ my goals and values.
   - ○ others goals and values

3. When I am under pressure, I generally have
   - ○ changed behaviours from normal.
   - ○ behaviours that remain unchanged.

4. I generally learn most
   - ○ by actively doing activities.
   - ○ from reflecting on past experiences.

5. I generally
   - ○ have a good sense of humour about myself.
   - ○ take myself seriously.

6. I present myself
   - ○ with self-assurance and having "presence".
   - ○ with some confidence and cautiousness

7.

Where there are uncertainties and pressures, I am always

- ○ decisive and make sound decisions.
- ○ cautious about making the right decision.

8.

I always voice views that

- ○ are unpopular and go out on a limb for what is right.
- ○ most others agree with and support.

9.

I always like to

- ○ take on new challenges.
- ○ maintain the status quo.

10.

I generally

- ○ inspire confidence in others.
- ○ rely on others confidence.

Social awareness and relationship management

11.

I generally

- ○ allow my emotions and moods to impact on my behaviours.
- ○ keep my disruptive emotions and impulses under control.

12.

When I am under pressure

- ○ I get easily distracted in other things.
- ○ I think clearly and stay focused.

13.

I always

- ○ do as I say I will do.
- ○ do only what I have to do.

14.

Trust by others

- ○ is automatically given to me.
- ○ is built through reliability and authenticity.

15.
I am always

- ○ flexible in how I see events.
- ○ able to see events for what they are.

16.
During changing situations, I always

- ○ work hard to try and keep up with the demands.
- ○ smoothly handle multiple demands and shifting priorities.

17.
I always

- ○ set myself challenging goals.
- ○ complete the goals that are set for me.

18.
When obstacles and setbacks occur in pursuing my goals, I always

- ○ read just the goals and/or expectations.
- ○ persist in seeking the goals despite what has happened.

19.
Generally, I

- ○ pursue goals beyond what is required or expected of me.
- ○ pursue goals only as far as is required of me.

20.
When I Identify opportunities, I am always

- ○ uncertain about whether to pursue the opportunity.
- ○ proactive in pursuing the opportunity.

Self-management and goal achievement

21.
Group differences are always

- ○ causing difficulties and unrest.
- ○ understood and valued.

22.
When I see bias and intolerance I always

- ○ challenge the initiating people.
- ○ turn a blind eye and ignore it.

23.
I always help out based on

- ○ the tasks others need help with.
- ○ understanding others needs and feelings.

24.
I always

- ○ listen to the important words being said.
- ○ listen well and am attentive to emotional cues.

25.
Others perspectives are always

- ○ understood and sensitivity shown.
- ○ clouding the issues and getting us off track.

26.
I always find social networks in the organisation

- ○ get in the way of delivering performance.
- ○ help create better decision networks.

27.
I always use

- ○ informal key power relationships to get what I need.
- ○ formal decision networks to get what I need.

28.
I always

- ○ give customers what they ask for.
- ○ understand customers needs and match products/services

29.
I always

- ○ act as a trusted advisor to the customer.
- ○ tell the customer what they want to hear.

30.
Increasing customers satisfaction and loyalty

- ○ is always part of the way I work.
- ○ is not important in achieving the sale.

Leadership and decision-making

31. The vision and mission are always

- ○ given to staff so they know where we are going.
- ○ used to inspire groups and individuals.

32. I always

- ○ let people know of the behaviours expected.
- ○ model the behaviours expected of others.

33. I always give assignments to people who

- ○ can get the job done and do it well.
- ○ will grow and develop as a result of the challenge.

34. Winning people over is something

- ○ that I find difficult to do.
- ○ I am very good at.

35. I always communicate in a way

- ○ that everyone understands what I am saying.
- ○ that seeks mutual understanding and full information sharing.

36. I always

- ○ go along with the changes being driven by others.
- ○ recognise the need for changes and remove barriers.

37. I always handle difficult people

- ○ in a straight forward and direct manner.
- ○ with diplomacy and tact.

38. I always seek out relationships that

- ○ are mutually beneficial.
- ○ will help me achieve my end goal.

39.

I generally have a

- ○ stronger focus on tasks rather than relationships.
- ○ balanced focus on tasks and relationships.

40.

When I work with teams, I always

- ○ make it clear what I expect members to do.
- ○ draw all members into enthusiastic participation.

Further information

APPENDIX G

The Emotional Intelligence self-assessment questionnaire.

Emotional Intelligence self-assessment questionnaire

Answer the following questions as accurate as possible.
Export the form as a pdf and return it to me via email.
The information on this form will only be used for statistical research purposes.

Demographic information

Name: ______ Age: ______ Gender: ______

Education level: ______ Occupation: ______

Self - awareness

Question 1

How well do you understand your own emotions?

○ Extremely Confident ○ Confident ○ Uncertain ○ Very Uncertain

Question 2

How accurate are you in assessing your strengths and weaknesses?

○ Extremely Confident ○ Confident ○ Uncertain ○ Very Uncertain

Question 3

How well do you recognize your impact on others?

○ Extremely Confident ○ Confident ○ Uncertain ○ Very Uncertain

Self - regulation

Question 4

How well do you manage your emotions, especially in stressful situations?

○ Extremely Confident ○ Confident ○ Uncertain ○ Very Uncertain

Question 5

How well do you control impulsive behavior?

○ Extremely Confident ○ Confident ○ Uncertain ○ Very Uncertain

Question 6

How effectively do you bounce back from setbacks?

○ Extremely Confident ○ Confident ○ Uncertain ○ Very Uncertain

Social skills

Question 7

How well do you communicate your thoughts and feelings effectively?

○ Extremely Confident ○ Confident ○ Uncertain ○ Very Uncertain

Question 8

How well do you build and maintain positive relationships?

○ Extremely Confident ○ Confident ○ Uncertain ○ Very Uncertain

Question 9

How well do you resolve conflicts and negotiate effectively?

○ Extremely Confident ○ Confident ○ Uncertain ○ Very Uncertain

Empathy

Question 10

How well do you understand and share the feelings of others?

○ Extremely Confident ○ Confident ○ Uncertain ○ Very Uncertain

Question 11

How well do you take the perspective of others?

○ Extremely Confident ○ Confident ○ Uncertain ○ Very Uncertain

Question 12

How well do you respond to the emotional needs of others?

○ Extremely Confident ○ Confident ○ Uncertain ○ Very Uncertain

Motivation

Question 13

How motivated are you to achieve your goals?

○ Extremely Confident ○ Confident ○ Uncertain ○ Very Uncertain

Question 14

How well do you delay gratification?

○ Extremely Confident ○ Confident ○ Uncertain ○ Very Uncertain

Question 15

How well do you maintain a positive attitude in the face of challenges?

○ Extremely Confident ○ Confident ○ Uncertain ○ Very Uncertain

APPENDIX H

Cognitive Processes self-assessment questionnaire

Cognitive Processes self-assessment questionnaire

Answer the following questions as accurate as possible.
Export the form as a pdf and return it to me via email.
The information on this form will only be used for statistical research purposes.

Demographic information

Name: ______ Age: ______ Gender: ______

Education level: ______ Occupation: ______

Cognitive functions

Selective attention

1. How would you rate your ability to focus and concentrate?

○ Excellent ○ Good ○ Fair ○ Poor

Sustained attention

2. How often do you experience mental fatigue or brain fog?

○ Rarely ○ Occasionally ○ Frequently ○ Almost always

Divided attention

3. How would you rate your ability to learn new information?

○ Excellent ○ Good ○ Fair ○ Poor

Short term memory

4. How often do you experience difficulty remembering recent events or conversations?

○ Rarely ○ Occasionally ○ Frequently ○ Almost always

Long term memory

5. How would you rate your ability to make quick decisions?

○ Excellent ○ Good ○ Fair ○ Poor

Emotional Processing

Working memory

6. How would you rate your emotional regulation skills?

○ Excellent ○ Good ○ Fair ○ Poor

Verbal memory task

7. How often do you experience anxiety or stress?

○ Rarely ○ Occasionally ○ Frequently ○ Almost always

Working memory task

8. How would you rate your ability to empathize with others?

○ Excellent ○ Good ○ Fair ○ Poor

Working memory task

9. How often do you experience mood swings or irritability?

○ Rarely ○ Occasionally ○ Frequently ○ Almost always

Logical reasoning

10. How would you rate your ability to manage conflict or disagreements?

○ Excellent ○ Good ○ Fair ○ Poor

Sensory Processing

Analytical thinking

11. How would you rate your ability to process visual information?

○ Excellent ○ Good ○ Fair ○ Poor

Creative thinking

12. How often do you experience difficulty with spatial awareness or navigation?

○ Rarely ○ Occasionally ○ Frequently ○ Almost always

Creative thinking

13. How would you rate your ability to process auditory information?

○ Excellent ○ Good ○ Fair ○ Poor

Creative thinking

14. How often do you experience difficulty with speech or language processing?

○ Rarely ○ Occasionally ○ Frequently ○ Almost always

Creative thinking

15. How would you rate your ability to process tactile information?

○ Excellent ○ Good ○ Fair ○ Poor

Executive Functions

Creative thinking

16. How would you rate your ability to plan and organize tasks?

○ Excellent ○ Good ○ Fair ○ Poor

Creative thinking

17. How often do you experience difficulty with time management or prioritization?

○ Rarely ○ Occasionally ○ Frequently ○ Almost always

Creative thinking

18. How would you rate your ability to problem-solve and think critically?

○ Excellent ○ Good ○ Fair ○ Poor

Creative thinking

19. How often do you experience difficulty with decision-making or problem-solving?

○ Rarely ○ Occasionally ○ Frequently ○ Almost always

Creative thinking

20. How would you rate your ability to adapt to new situations or changes?

○ Excellent ○ Good ○ Fair ○ Poor

Scoring:
For each question, assign a score of 1-4 based on the response: a=4, b=3, c=2, d=1. Calculate the total score by adding up the scores for all 20 questions. Interpret the results based on the following ranges:

80-100: Excellent cognitive function and brain activity.
60-79: Good cognitive function and brain activity, with some areas for improvement.
40-59: Fair cognitive function and brain activity, with significant areas for improvement.
0-39: Poor cognitive function and brain activity, with significant deficits.

APPENDIX I

This letter serves to formally request from the UK Department of Education for consideration for a research collaboration involving me as Ph.D candidate at Selinus University.

SELINUS UNIVERSITY
OF SCIENCES AND LITERATURE

To whom it may concern,

It is attested that the student:

JAN HENDRIK VAN NIEKERK

Enrollment number: UNISE0835EG   Date of enrollment: 06-12-2024

Is enrolled in the faculty of **Arts & Humanities** of Selinus University and is about to pursue a **Doctor of Philosophy (Ph.D.) in Education**.

This letter formalizes the process of gathering the information and data necessary to the student's research through questionnaires and interviews. Since the research work will be implemented in the student's Ph.D. thesis, you are kindly requested to provide all the information needed. We ensure that there will be no misuse of the information collected and its source will be kept concealed.

The student will carry out the research work with constant commitment, in order to defend his final thesis that is about: *Neuro-synaptic Learning Environments: A Holistic AI-Powered Education Ecosystem.*

Selinus University of Sciences and Literature,
Ragusa, 21st January 2025
Dr. Adriana Nifosì - Chief Academic Secretary

MEMENTO AUDERE SEMPER

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Uniselinus Educational Group Srl: Via Roma, 200 - 97100 Ragusa - IT
info@selinusuniversity.it - www.uniselinus.education
Accredited by
WorldCertificationInstitute GlobalAuthorityon OccupationalCertification
California University FCE FOR DIPLOMA USA EQUIVALENT
Quality Assurance in Higher Education
American Association for Higher Education and Accreditation

APPENDIX J

This letter is the response from the UK Department of Education for consideration for a research collaboration in schools of the UK.

From: ACCOUNT, Unmonitored Unmonitored.ACCOUNT@education.gov.uk
Subject: Department for Education: 2025-0003490 CRM:0463664
Date: 7 February 2025 at 10:31
To: Jan van Niekerk janvanniekerk@gmail.com

UA

Dear Mr van Niekerk

I am writing on behalf of the Secretary of State for Education to thank you for your email of 30 January about carrying out research in schools in the Thanet area.

You may be interested to know that schools are autonomous institutions and responsible for the management of their own affairs including data protection and for complying with any relevant legislation.

With this in mind you may wish to approach schools directly to secure their participation. A useful resource is Get information about schools, which allows you to search for contact details for all schools in England, and is available here:

https://get-information-schools.service.gov.uk/.

Thank you once again for writing and may I take this opportunity to wish you well with your research.

Your correspondence has been allocated reference number 2025-0003490. If you need to respond to us, please visit https://www.education.gov.uk/contactus and quote your reference number.

Yours sincerely

M DHOKIA
Ministerial and Public Communications Division
Web: https://www.education.gov.uk
X (formerly Twitter): https://www.x.com/educationgovuk
Facebook: https://www.facebook.com/educationgovuk

As part of our commitment to improving the service we provide to our customers, we are interested in hearing your views and would welcome your comments via our website at: https://form.education.gov.uk/service/TOCMTfeedback.

Thank you for your help.

We are the department for **opportunity**

APPENDIX K

The following Javascript code is used to generate simulated choices for student self-assessment questionnaires [*Appendices A to H*].

```
<!DOCTYPE html>
<html>
<head>
  <title>Random student self-assessment choices</title>
</head>
<body>
  <script>

// Generates a set of random answers for a single student across 12 questions.
// Each question is assigned one of four possible answer options ('a', 'b', 'c', 'd').
// @returns {object} An object where keys are question identifiers (e.g. 'q1', 'q2')
// and values are the randomly selected answer (a string).

    function generateRandomAnswers() {
// Initialize an empty object to store the student's answers.
      const answers = {};
// Loop through each question, from question 1 to 12.
      for (let i = 1; i <= 12; i++) {                                    // Q_12
// Generate a random index between 0 (inclusive) and 4 (exclusive).
// This index will be used to select an answer option from the 'options' array.
        const randomOption = Math.floor(Math.random() * 4);              // Op_4
// The commented-out line below is for 5 options ('a' to 'e').
// const randomOption = Math.floor(Math.random() * 5);                   // Op_5
// Define an array containing the possible answer options for each question.
        const options = ['a', 'b', 'c', 'd'];                            // Op_ad
// The commented-out line below is for 5 options ('a' to 'e').
// const options = ['a', 'b', 'c', 'd', 'e'];                            // Op_ae
// Assign the randomly selected answer option to the current question.
// The key for each answer in the 'answers' object will be in the format 'q' followed by
// the question number (e.g. 'q1').
        answers[`q${i}`] = options[randomOption];
      }
// Return the object containing the randomly generated answers for all 12 questions.
      return answers;
    }
// Initialize an empty array to store the results (sets of answers) for multiple students.
    const allResults = [];
// Loop through each student. In this case, the loop runs only once to simulate one
// student.
// In a real scenario, this loop would iterate for the number of students you want to
// simulate.
    for (let i = 0; i < 1; i++) {
// Call the 'generateRandomAnswers' function to get a set of random answers for the
// current student.
      const studentAnswers = generateRandomAnswers();
// Add the generated answers for the current student to the 'allResults' array.
```

```
    allResults.push(studentAnswers);
  }

// Analyses the results of multiple students to count the frequency of each answer
// option for each question.
// @param {array} results An array of objects, where each object represents a
student's
// answers (as returned by the 'generateRandomAnswers' function).
// @returns {object} An object where keys are question identifiers (e.g. 'q1') and
values
// are objects containing the counts for each answer option (e.g. { a: 2, b: 5, c: 1, d:
3 }).

  function analyzeResults(results) {
// Initialize an empty object to store the frequency count of each answer for each
// question.
    const counts = {};
// Loop through each question (1 to 12) to initialize the 'counts' object.
    for (let i = 1; i <= 12; i++) {                                   // Q_12
// For each question, create an inner object with initial counts of 0 for each possible
// answer option ('a', 'b', 'c', 'd').
      counts[`q${i}`] = { a: 0, b: 0, c: 0, d: 0 };                   // Op_ad0
// The commented-out line below is for 5 options ('a' to 'e').
// counts[`q${i}`] = { a: 0, b: 0, c: 0, d: 0, e: 0};                 // Op_ae0
    }
// Loop through each student's results in the 'results' array.
    for (const result of results) {
// Loop through each question and its corresponding answer in the current student's
// result object.
      for (const question in result) {
// Get the answer given by the student for the current question.
        const answer = result[question];
// Increment the count for the specific answer option for the current question in the
// 'counts' object.
        counts[question][answer]++;
      }
    }
// Return the 'counts' object, which now contains the frequency of each answer
option
// for each question across all students.
    return counts;
  }
// Call the 'analyzeResults' function to process the 'allResults' and get the answer
// frequencies.
  const answerFrequencies = analyzeResults(allResults);
// Output a heading to the HTML document.
  document.write("<p>Answer Frequencies (Results):</p>");
```

```
// Output the 'answerFrequencies' object as a formatted JSON string to the HTML
// document.
// 'JSON.stringify' converts the JavaScript object into a JSON string.
// 'null, 2' ensures the output is nicely formatted with an indentation of 2 spaces for
// readability.
    document.write("<pre>" + JSON.stringify(answerFrequencies, null, 2) + "</pre>");
// Log the 'answerFrequencies' object to the browser's console.
// This is useful for debugging and examining the data directly in the developer tools.
    console.log(answerFrequencies);
  </script>
</body>
</html>
// End of code
```

APPENDIX L

The Cognitive Profiling Form – student choices tagged.

Cognitive profiling form (Proposed tagged information)

This form contains the tagged information for student data.

Demographic information

Name: [ ] Age: CP_age Gender: CP_tp(1,2,3)

Education level: CP_ed (1,2,3,4) Occupation: CP_oc (1,2,3,4,5)

Cognitive abilities - attention

Selective attention

Can you focus on a conversation in a noisy room?
Can you easily ignore distractions while studying?

○ CP_at_ ○ CP_at_ ○ CP_at_ ○ CP_at_

Sustained attention

How often do you get distracted or lose track of your thoughts while studying?

○ CP_su_ ○ CP_su_ ○ CP_su_ ○ CP_su_

Divided attention

Can you effectively multitask while answering phone calls or listen to music while studying or work,?

○ CP_da_ ○ CP_da_ ○ CP_da_ ○ CP_da_

Cognitive abilities - memory

Short term memory

Can you easily remember phone numbers or do you often forget where you placed your keys?

○ CP_stm_1 ○ CP_stm_2 ○ CP_stm_3 ○ CP_stm_4

Long term memory

How easily do you recall past events, names, and facts? Do you remembering important dates?

○ CP_ltm_1 ○ CP_ltm_2 ○ CP_ltm_ ○ CP_ltm_4

Working memory

Can you hold information in your mind while performing other tasks?
Can you follow multi-step instructions or remember a list of items?

○ CP_wm_1 ○ CP_wm_2 ○ CP_wm_3 ○ CP_wm_4

Cognitive abilities - memory tasks

Verbal memory task

Read the words: apple, tree, book, car, house. Close your eyes and try to recall the words. How many words could you recall? Do you find it easy or difficult to memorize lists of words?

○ CP_vmt_1 ○ CP_vmt_2 ○ CP_vmt_3 ○ CP_vmt_4

Working memory task

Look at a picture of a bicycle. After a few seconds, remove the picture. How easily can you recall the details of the bicycle?

○ CP_wmt_1 ○ CP_wmt_2 ○ CP_wmt_3 ○ CP_wmt_4

Working memory task

How easily can you repeat the numbers (e.g., 7, 2, 9, 5) in reverse order? Do you find it challenging to hold and manipulate information in your mind?

○ CP_wmta_1 ○ CP_wmta_2 ○ CP_wmta_ ○ CP_wmta_

Cognitive abilities - problem-solving tasks

Logical reasoning

What is the next number in the sequence: 2, 7, 12, 17, __. How easily can you identify patterns and rules in number sequences?

○ CP_lr_1 ○ CP_lr_2 ○ CP_lr_3 ○ CP_lr_4

Analytical thinking

Do you break a complex problem or situation down the problem into smaller steps? Do you analyze different perspectives and consider potential solutions?

○ CP_at_1 ○ CP_at_2 ○ CP_at_3 ○ CP_at_4

Creative thinking

Do you enjoy brainstorming and exploring different possibilities? Can you think "outside the box" to find solutions to problems?

○ CP_ct_1 ○ CP_ct_2 ○ CP_ct_3 ○ CP_ct_4

Observation exercise

This part of the form will be scored by an observer.

Cognitive task

	Low 1	2	3	4	High 5
Attention task	CP_ob_a1	CP_ob_a2	CP_ob_a3	CP_ob_a4	CP_ob_e5
Visual search task	CP_ob_b1	CP_ob_b2	CP_ob_b3	CP_ob_b4	CP_ob_e5
Stroop task	CP_ob_c1	CP_ob_c2	CP_ob_c3	CP_ob_c4	CP_ob_e5
Flanker task	CP_ob_d1	CP_ob_d2	CP_ob_d3	CP_ob_d4	CP_ob_e5

Processing speed - reaction

	Slow 1	2	3	4	Fast 5
Reaction time	CP_ot_a1	CP_ot_a2	CP_ot_a3	CP_ot_a4	CP_ot_e5
Processing speed	CP_ot_b1	CP_ot_b2	CP_ot_b3	CP_ot_b4	CP_ot_e5

Processing speed - tasks

	Low 1	2	3	4	High 5
Simple reaction	CP_os_a1	CP_os_a2	CP_os_a3	CP_os_a4	CP_os_e5
Choice reaction	CP_os_b1	CP_os_b2	CP_os_b3	CP_os_b4	CP_os_e5
Information speed	CP_os_c1	CP_os_c2	CP_os_c3	CP_os_c4	CP_os_e5

Problem solving - puzzles

	Slow 1	2	3	4	Fast 5
Logic puzzles	CP_op_a1	CP_op_a2	CP_op_a3	CP_op_a4	CP_op_e5
Brain teasers	CP_op_b1	CP_op_b2	CP_op_b3	CP_op_b4	CP_op_e5
Creative exercises	CP_op_c1	CP_op_c2	CP_op_c3	CP_op_c4	CP_op_e5

Problem solving - reasoning

	Slow 1	2	3	4	Fast 5
Logic reasoning	CP_or_a1	CP_or_a2	CP_or_a3	CP_or_a4	CP_or_e5
Analytical thinking	CP_or_b1	CP_or_b2	CP_or_b3	CP_or_b4	CP_or_e5
Creative thinking	CP_or_c1	CP_or_c2	CP_or_c3	CP_or_c4	CP_or_e5

Cognitive profile

Cognitive profile summary

Overall cognitive ability	
Strengths	
Weaknesses	
Recommendation	
Comments	

APPENDIX M

Scenario 1: Student A's self-assessment summary & Tags

The Cognitive Profiling Form [*Appendix A*]

The student has strong creative thinking [*Tag: SA_ct = 1*] but struggles with attention [*Tag: SA_attn = 0*], memory [*Tag: SA_ml = 0*], and problem-solving [*Tag: SA_ps = 0*]. While they process visual information quickly, a discrepancy exists between their self-perception and actual performance, necessitating further investigation of memory and problem-solving strategies.

The Cognitive Task Performance Record Form [*Appendix B*]

The student displays a large gap between high self-perceived cognitive ability and low observed performance, indicating a need for interventions focused on metacognitive awareness and accurate self-assessment. More detailed assessment documentation is recommended [*Tag: SA_r_ctpr = 1*].

The VARK Questionnaire [*Appendix C*]

The student primarily learns through auditory [*Tag: SA_a = 1*] and visual methods [*Tag: SA_v = 1*], excelling in environments with lectures, discussions, and visual aids. Prioritising these methods will maximize their learning potential.

The GAD-7 Questionnaire [*Appendix D*]

The student's GAD-7 results suggest potential anxiety [*Tag: SA_anx = 1*], particularly frequent worry [*Tag: SA_w = 1*], which could negatively impact academic performance. Further professional evaluation is recommended.

The Student Learning Behaviour and Preference Observation form [*Appendix E*]

The student displays good social skills but limited active learning engagement. They prefer visual, auditory, and kinesthetic learning, but struggle with hands-on activities [*Tag: SA_h = 0*], reading, and note-taking. Effective teaching should prioritise visual materials, lectures, and movement, while encouraging active participation.

The Mayer-Salovey-Caruso Emotional Intelligence Test [*Appendix F*]

The student shows strong perceived self-awareness and drive, but struggles with social awareness and conflict management [*Tag: SA_conman = 1*], indicated by difficulty understanding others' emotions and a lack of nuanced self-reflection. Targeted support in these areas is recommended.

The Emotional Intelligence Questionnaire [*Appendix G*]

The student perceives strong social skills in impulse control and relationship building, but reports challenges in emotional regulation [*Tag: SA_chalem = 1*], resilience, empathy, and communication. This suggests a need for targeted support in these areas, despite their confidence in goal achievement.

The Cognitive Processes Assessment [*Appendix H*]

The student's self-assessment reveals fair cognitive function with notable weaknesses in sensory and executive processing [*Tag: SA_senpro = 1*], alongside reported mental fatigue and mood swings. Their overall score indicates a need for targeted interventions and professional evaluation to develop appropriate support strategies.

The tags for Student A. Note the values assigned to the tags. The value “0” means not available, no skill, no abilities, struggling or negative. The value “1” means available, skilled, posses abilities, not struggling or positive.

```
"SA_ct": 1,            # strong creative thinking
"SA_attn": 0,          # struggles with attention
"SA_ml": 0,            # struggles with memory
"SA_ps": 0,            # struggles with problem-solving
"SA_r_ctpr": 1,        # more assessment recommended
"SA_a": 1,             # prefer auditory
"SA_v": 1,             # prefer visual
"SA_h": 0,             # prefer hands-on
"SA_kin": 0,           # prefer kinaesthetic
"SA_n": 0,             # prefer teacher’s notes
"VR / AR": 1,          # virtual / augmented reality available
"SA_anx": 1,           # significant anxiety
"SA_w": 1,             # frequent worry
"SA_conman": 1,        #  conflict management
"SA_ts_chalem": 1,     # challenges in emotional regulation
"SA_senpro": 1,        # sensory and executive processing
"SA_Int_Ar]": 1,       # chapter = Integration, Topic = areas
```

APPENDIX N

Scenario 2: Student B's self-assessment summary & Tags

The Cognitive Profiling Form [*Appendix A*]

This student exhibits a mixed cognitive profile, demonstrating strong analytical and creative thinking skills [*Tag: SA_ct_1*], as evidenced by their proficiency in pattern recognition, logic puzzles, and brain teasers. However, they struggle significantly with working memory, memory recall [*Tag: SA_ml_1*], attention, information processing speed, and visual search tasks, resulting in inconsistent performance and difficulties with multitasking and reaction tasks. Targeted interventions focusing on memory strategies, attention training, and improving processing speed are recommended, while harnessing their inherent strengths in logical and creative problem-solving.

Tag: SA_ct_1: Self-assessment_critical thinking_1
Tag: SA_ml_1: Self-assessment_memory lacking_1

The Cognitive Task Performance Record Form [Appendix B]

This student demonstrates a discrepancy between their perceived overall cognitive ability and their self-reported confidence in specific executive functions, notably decision-making and planning. While they rate their general cognitive and problem-solving skills highly, their perceived abilities in decision-making and planning are significantly lower, suggesting a possible overestimation of their global competence. Despite high self-confidence, targeted interventions focusing on developing these weaker executive function areas are recommended [*Tag: SA_r_ctpr*], and a deeper analysis of task performance and errors would provide a more detailed understanding of their learning profile.

Tag: SA_r_ctpr: Self-assessment_repeat_ Cognitive Task Performance Record

The VARK Questionnaire [*Appendix C*]

This student demonstrates a complex learning profile, primarily favouring aural and read/write methods [*Tag: SA_a_n_1*], showing a preference for listening to explanations, engaging in discussions, and utilising written materials. They also benefit from visual aids like maps and diagrams, particularly for spatial and procedural understanding, and learn effectively through observation. This suggests a learner who thrives with clear, structured verbal and textual information, supplemented by visual and observational learning strategies.

Tag: SA_a_n_1: Self-assessment_ auditory_notes_1

The GAD-7 Questionnaire [*Appendix D*]

This student's GAD-7 responses suggest they experience some anxiety, reporting "sometimes" for most symptoms and "often" for one, while indicating "never" for two others, suggesting the anxiety is not constant [*Tag: SA_f_a_1*]. While demographic data offers context, further observation and interaction, along with the specific GAD-7 questions, are needed to understand the impact of this anxiety on their learning and well-being.

Tag: SA_f_a_1: Self-assessment_ frequent anxiety_1

The Student Learning Behaviour and Preference Observation form [*Appendix E*]

This student is a collaborative and self-aware learner who thrives in varied learning environments. They demonstrate strong group work and communication skills, actively monitor their understanding, and adapt their learning strategies. They prefer a multi-modal approach, benefiting from visual aids, verbal explanations, hands-on activities [*Tag: SA_kl_1*], and note-taking, indicating a preference for processing information through writing.
Tag: SA_kl_1: *Self-assessment_ kinesthetic learning_1*

The Mayer-Salovey-Caruso Emotional Intelligence Test [*Appendix F*]

The student's questionnaire responses suggest a task-oriented learning style with potential deficits in self and social awareness, marked by rigid thinking and a prioritisation of tasks over relationships. They may benefit from strategies promoting self-reflection, empathy, and flexibility [*Tag: SA_s_r_1*]. However, due to flaws in the questionnaire design, these observations are speculative and require confirmation through a more reliable assessment.
Tag: SA_s_r_1: *Self-assessment_ self_reflection_1*

The Emotional Intelligence Questionnaire [*Appendix G*]

This student displays strong self-awareness and resilience, but struggles with emotional regulation, communication, conflict resolution, and delayed gratification. While they excel in building relationships and cognitive empathy, they lack emotional empathy and exhibit fluctuating motivation. Targeted support [*Tag: SA_ts_1*] in these areas would strengthen their emotional intelligence and overall development.
Tag: SA_ts_1: *Self-assessment_ targeted support_1*

The Cognitive Processes Assessment [*Appendix H*]

This student's self-assessment indicates "fair" cognitive function with areas for improvement. While they perceive strengths in focus, learning, and decision-making, they report substantial challenges in emotional regulation, sensory processing, and executive functions like planning and problem-solving. This discrepancy suggests a disconnect between information processing and practical application, necessitating targeted interventions [*Tag: SA_ti_1*] to complement emotional intelligence, sensory integration, and executive functioning for improved learning and well-being.
Tag: SA_ti_1: *Self-assessment_ targeted interventions_1*

APPENDIX O

Scenario 3: Student C's self-assessment summary & Tags

The Cognitive Profiling Form [*Appendix A*]

The student's cognitive profile is a blend of strengths and weaknesses. They excel at attention and numerical pattern recognition, but struggle with short-term memory [*Tag: SA_ml_1*] and complex problem-solving. Observer ratings confirm these disparities. Strategies to improve short-term memory and analytical problem-solving [*Tag: SA_ct_1*], alongside creative development, are needed. In short, focused interventions to address their selective cognitive weaknesses.
Tag: SA_ml_1: *Self-assessment_memory lacking_1* *Tag: SA_ct_1*: Self-assessment_critical thinking_1

The Cognitive Task Performance Record Form [*Appendix B*]

The student's cognitive task performance reveals a mismatch between low self-confidence and high perceived cognitive abilities. Despite rating their performance confidence very low, they assess their problem-solving and planning skills, and overall cognitive ability, as high. However, decision-making is rated lower. This suggests a disconnect between perceived skills and task execution. Further observation [*Tag: SA_r_ctpr*] of task performance, including strategy analysis, completion time, and accuracy, is necessary for a comprehensive understanding. The student's low confidence could stem from various factors, such as test anxiety or task misunderstanding.
Tag: SA_r_ctpr: *Self-assessment_repeat_ Cognitive Task Performance Record*

The VARK Questionnaire [*Appendix C*]

This student exhibits a remarkably multimodal learning profile, demonstrating strong preferences across visual, aural, read/write, and kinesthetic modalities. They excel when information is presented visually, such as through diagrams and graphs, and also benefit from detailed written instructions [*Tag: SA_n_1*]. They appreciate auditory learning, thriving in question-and-answer sessions. Practical application and examples for their learning, emphasising a kinesthetic inclination. Therefore, while the student adapts well to various learning environments, integrating visual, auditory, textual, and practical elements will significantly increase their comprehension and retention.
Tag: SA_n_1: *Self-assessment_ notes_1*

The GAD-7 Questionnaire [*Appendix D*]

The student's GAD-7 responses reveal fluctuating anxiety levels. While some symptoms are infrequent, others occur 'Sometimes' and, 'Very Often.' This pattern, with multiple moderate and significant anxiety indicators [Tag: SA_anx_1], suggests

a noticeable impact on daily life. Therefore, further assessment and potential support are warranted.
Tag: SA_anx_1: *Self-assessment_ anxiety_1*

The Student Learning Behaviour and Preference Observation form [*Appendix E*]

The student actively participates in discussions and demonstrates effective problem-solving, along with self-monitoring and reflective abilities. However, they struggle with focus, consistent interest, systematic task approaches, and collaborative work. They respond well to visual aids, lectures, and physical movement, indicating a preference for multisensory learning [*Tag: SA_msl_1*].
Tag: SA_msl_1: *Self-assessment_ multisensory learning_1*

The Mayer-Salovey-Caruso Emotional Intelligence Test [*Appendix F*]

The student's emotional intelligence profile is mixed. They demonstrate self-awareness, recognising emotional impact and aligning with values. However, they exhibit contradictory social awareness, both voicing opinions and preferring the status quo. They are goal-oriented, yet struggle with social dynamics and uncertainty. While capable of self-management, they rely on formal structures and may struggle with change or novel opportunities. Therefore, further observation [*Tag: SA_fo_1*] would aid their development.
Tag: SA_fo_1: *Self-assessment_ further observation_1*

The Emotional Intelligence Questionnaire [*Appendix G*]

The student's profile highlights notable strengths and developmental needs. They are confident in understanding emotions, managing stress, communicating, and exhibiting empathy. They are extremely confident in impulse control and conflict resolution. However, they express uncertainty in self-assessment, recognising their impact on others, resilience, perspective-taking, delayed gratification, and maintaining a positive attitude. Therefore, while possessing strong interpersonal and emotional management skills, they require support [*Tag: SA_ts_2*] in self-reflection, resilience, and adaptability. Further development in self-awareness and coping strategies would complement their emotional intelligence and learning.
Tag: SA_ts_2: *Self-assessment_ targeted support_2*

The Cognitive Processes Assessment [*Appendix H*]

The student's Cognitive Processes Assessment reveals a mixed cognitive profile. Their strengths include auditory processing and critical thinking, alongside moderate

abilities in focus, decision-making, sensory processing, and empathy. However, they face challenges in learning, emotional regulation, planning, time management, spatial awareness, and decision-making. They report high levels of mental fatigue and speech processing difficulties. Their overall cognitive function is rated as fair, requiring targeted interventions [*Tag: SA_ts_3*] to improve executive functions and learning abilities, while capitalizing on their auditory and critical thinking strengths.
Tag: SA_ts_3: *Self-assessment_ targeted support_3*

APPENDIX P

Scenario 4: Student D's self-assessment summary & Tags

The Cognitive Profiling Form [*Appendix A*]

This student's cognitive profile is markedly inconsistent, raising serious concerns about self-reporting accuracy. Their current self-assessment sharply deviates from previous evaluations, with claimed weaknesses in attention and numerical patterns juxtaposed against reported strengths in complex problem-solving and creative thinking [Tag: SA_cret_1]. Observer ratings further underscore this discrepancy, revealing a mismatch between perceived and observed performance, particularly in information processing speed. These inconsistencies suggest a need for further evaluation to discern genuine cognitive strengths and weaknesses. In short, the data's reliability is questionable, necessitating objective assessments to inform effective learning strategies.
Tag: SA_cret_1: Self-assessment_ creative thinking_1

The Cognitive Task Performance Record Form [*Appendix B*]

The student's cognitive profile displays a separation between perceived specific abilities and overall self-assessment. Despite neutral confidence, they report weak problem-solving and decision-making skills, yet perceive their overall cognitive ability as relatively high. Planning ability is rated neutrally. This suggests a disconnect between perceived specific executive functions and general cognitive capacity. Therefore, detailed task analysis, including strategies, time, and accuracy, for understanding these discrepancies. The student may be underestimating specific skills, warranting further investigation [*Tag: SA_r_ctpr*].
Tag: SA_r_ctpr: Self-assessment_repeat_ Cognitive Task Performance Record

The VARK Questionnaire [*Appendix C*]

The student displays a strong multimodal learning profile, favouring read/write, visual, and aural styles. They learn effectively through written materials, visual aids like diagrams and videos, and auditory methods such as discussions [*Tag: SA_a_v_1*]. They demonstrate a talent for recognising visual patterns. Thus, instructional strategies should combine written, visual, and auditory elements to optimise their learning experience.
Tag: SA_a_v_1: Self-assessment_ auditory_visual_1

The GAD-7 Questionnaire [*Appendix D*]

The student's GAD-7 responses highlight significant anxiety. Three items marked 'Very Often' and one 'Often' indicate substantial anxiety symptoms, despite a few less frequent occurrences. A comprehensive assessment by a mental health professional

is strongly recommended to determine the extent of their anxiety and provide appropriate support [*Tag: SA_f_w_1*].
Tag: SA_f_w_1: Self-assessment_ frequent worry_1

The Student Learning Behaviour and Preference Observation form [*Appendix E*]

The student actively engages in learning, maintaining focus and participating in discussions. They demonstrate resilience and effective problem-solving, collaborating respectfully with peers and exhibiting reflective learning. However, their interest is limited, and they struggle with systematic task approaches, peer communication, self-monitoring, and adapting learning strategies. They respond well to general visual aids [*Tag: SA_visa_1*], verbal explanations, lectures, and physical movement, benefiting from note-taking and summaries, but struggle with graphs, diagrams, demonstrations, hands-on activities, and reading/writing tasks.
Tag: SA_visa_1: Self-assessment_ visual aids_1

The Mayer-Salovey-Caruso Emotional Intelligence Test [*Appendix F*]

The student's learning profile is complex. They perceive minimal emotional impact on personal behaviour, yet acknowledge changes under pressure and value reflection. They exhibit cautious confidence, favouring decisive decisions aligned with norms. Socially, they blend emotional awareness with reliance on established trust, demonstrating goal-oriented persistence. However, they are uncertain about new opportunities and find group differences disruptive. Self-management prioritises task completion over networking. Leadership emphasises inspiration and clear communication, focusing on efficiency and diplomacy. Therefore, this student values stability and efficiency, but may struggle with social complexities and adaptability. Further observation would aid their development [*Tag: SA_ts_1*].
Tag: SA_ts_1: Self-assessment_ targeted support_1

The Emotional Intelligence Questionnaire [*Appendix G*]

The student's profile reveals a striking contrast: strong confidence in impulse control, communication, and goal achievement, alongside uncertainty in key emotional intelligence areas. While they believe in their ability to delay gratification, they struggle with self-awareness, emotional regulation, and empathy. Specifically, they

feel uncertain about understanding their emotions, managing stress, and responding to others' needs. They struggle with self-assessment, resilience, relationship building, and perspective-taking. Therefore, the student, while possessing strong drive and communication skills, requires substantial support [*Tag: SA_ts_2*] in developing self-awareness, emotional regulation, and interpersonal sensitivity for a balanced learning experience.
Tag: SA_ts_2: Self-assessment_ targeted support_2

The Cognitive Processes Assessment [*Appendix H*]

The student's Cognitive Processes Assessment shows a profile of distinct strengths and challenges. They excel in empathy and conflict management, while demonstrating moderate skills in learning, sensory processing, and planning. However, they struggle significantly with focus, emotional regulation, decision-making, adaptability, and problem-solving. They experience frequent anxiety and mental fatigue. Their overall cognitive function is rated as fair, necessitating targeted interventions [*Tag: SA_ts_3*] to improve executive functioning and emotional regulation, while capitalizing on their interpersonal strengths. Addressing anxiety is also key for their well-being and academic success.
Tag: SA_ts_3: Self-assessment_ targeted support_3

APPENDIX Q

Scenario 5: Student E's self-assessment summary & Tags

The Cognitive Profiling Form [*Appendix A*]

The student's cognitive profile shows a gap between self-reported weaknesses and observed strengths. Despite claiming difficulties with memory and problem-solving, their attention and visual processing are rated highly. Conversely, reaction time and information processing are low, and there's a disparity between visual and verbal memory. Thus, further investigation is needed to reconcile these discrepancies and provide targeted support [*Tag: SA_tas_1*]. The difference between self-reports and observations suggests potential issues with self-awareness.
Tag: SA_tas_1: Self-assessment_targeted support g_1

The Cognitive Task Performance Record Form [*Appendix B*]

The student's cognitive profile reveals a striking disparity: despite low confidence and poor decision-making ratings, they believe their planning skills are excellent. However, overall cognitive ability is rated low, suggesting a disconnect between specific executive functions and general competence. They may excel at planning but struggle with execution or other cognitive aspects. The low confidence likely influences their self-perception. Therefore, detailed task analysis needed [Tag: SA_r_ctpr] to understand these discrepancies. The student's perception of their planning abilities may be skewed.
Tag: SA_r_ctpr: Self-assessment_repeat_ Cognitive Task Performance Record

The VARK Questionnaire [*Appendix C*]

The student exhibits a multimodal learning profile, favouring read/write, aural, visual, and kinesthetic styles. They process information well through written materials, verbal interactions, visual aids [*Tag: SA_a_v_1*], and practical examples. Thus, a learning environment integrating these elements would maximize their success.
Tag: SA_a_v_1: Self-assessment_ auditory_visual_1

The GAD-7 Questionnaire [*Appendix D*]

The student's GAD-7 results are mixed. While most items indicate no anxiety, one item marked 'Very Often' suggests intense anxiety related to a specific trigger. Two items marked 'Sometimes' indicate occasional moderate anxiety. Therefore, a professional evaluation is needed to understand the specific nature of their anxiety [*Tag: SA_f_w_1*] and provide appropriate support.
Tag: SA_f_w_1: Self-assessment_ frequent worry_1

The Student Learning Behaviour and Preference Observation form [*Appendix E*]

The student excels in collaborative learning, demonstrating respect for peers and effective group work, alongside self-monitoring abilities. Their preferred learning styles are auditory and textual [*Tag: SA_audl_1*], thriving in lectures and written tasks. However, they struggle with sustained focus, logical task completion, problem-

solving, persistence, peer communication, and adapting learning strategies. Visual and kinesthetic learning are ineffective for them.
Tag: SA_audl_1: Self-assessment_ auditory learning_1

The Mayer-Salovey-Caruso Emotional Intelligence Test [*Appendix F*]

The student's emotional intelligence profile reveals a confident, yet nuanced, individual. They perceive minimal emotional influence on personal behaviour, but acknowledge its role in social contexts. While maintaining focus under pressure, they approach uncertainties cautiously. Demonstrating self-assurance, they tackle challenges and express dissenting opinions, valuing humour and inspiring confidence. Socially, they cultivate trust through reliability and attend to emotional cues, though they find group differences disruptive and are selective in opportunity pursuit. Driven and goal-oriented, they set challenging goals and persevere, albeit relying on formal expectations. In leadership, they excel in communication and development, utilising informal networks and balancing task and relationship focus. However, they prefer straightforward handling of difficult situations and prioritise internal vision over customer satisfaction. Therefore, this driven individual, possessing strong leadership potential, could benefit from increased social flexibility and adaptability to other perspectives [*Tag: SA_ts_1*].
Tag: SA_ts_1: Self-assessment_ targeted support_1

The Emotional Intelligence Questionnaire [*Appendix* G]

The student's profile indicates emotional intelligence challenges. They express high uncertainty in understanding their emotions, managing stress, controlling impulses, demonstrating resilience, and exhibiting empathy. While confident in self-assessment, communication, and relationship building, these strengths are overshadowed by pervasive uncertainty in some areas. Therefore, the student requires substantial support in developing self-awareness, emotional regulation, empathy, and resilience for successful academic and social navigation. Focused interventions [*Tag: SA_ts_2*] on these foundational skills would be highly beneficial.
Tag: SA_ts_2: Self-assessment_ targeted support_2

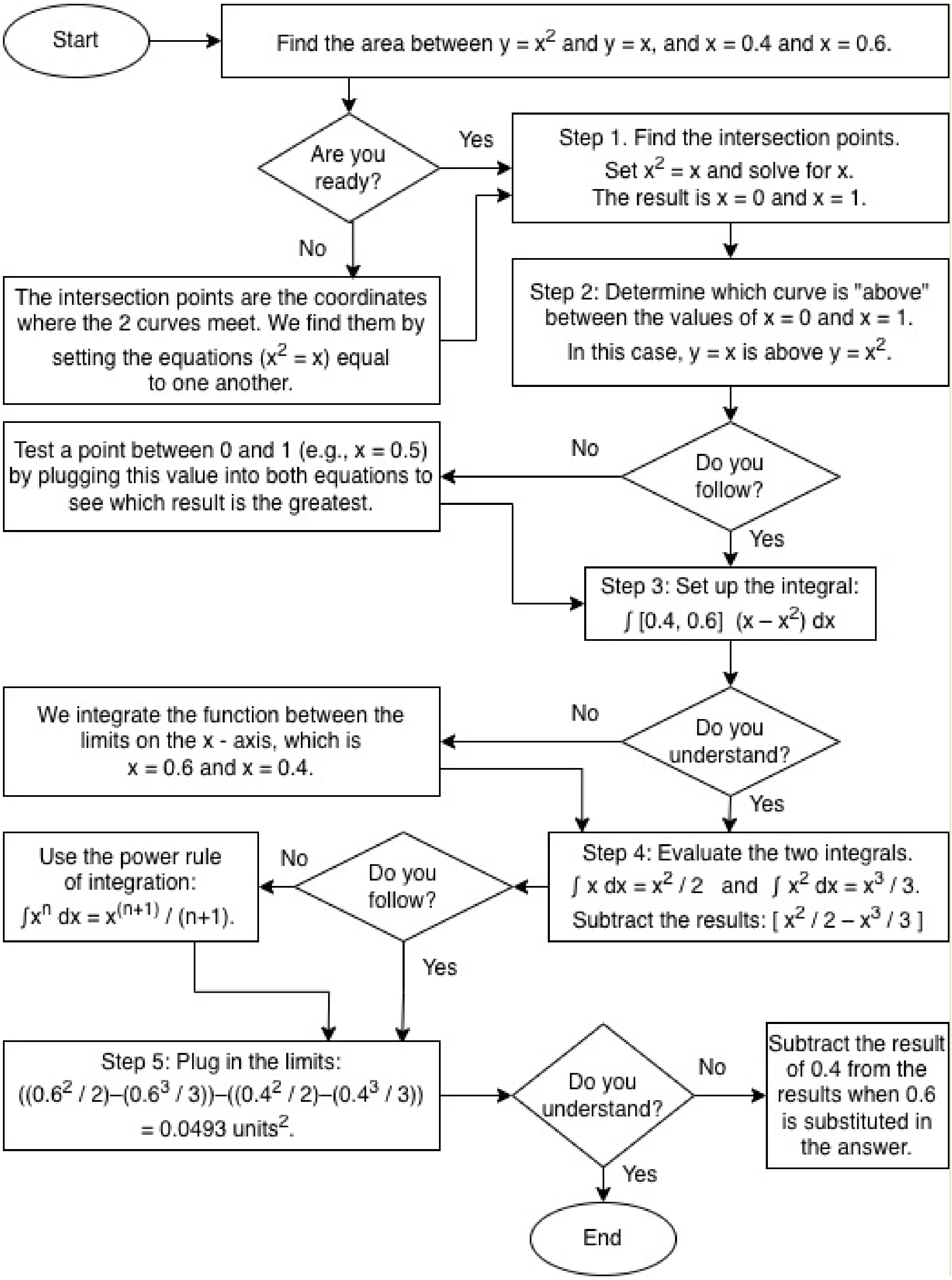
The Cognitive Processes Assessment [*Appendix H*]

The student's Cognitive Processes Assessment reveals a mix of strengths and challenges. While demonstrating strong learning, visual, auditory processing, and emotional regulation, they struggle significantly with focus, adaptability, and time management. They experience challenges in recent memory, speech processing,

problem-solving, and decision-making. Though mental fatigue is infrequent, anxiety and mood swings are moderate. Their overall cognitive function is rated as fair, indicating areas for improvement. Targeted interventions should address executive function deficits [*Tag: SA_ts_3*], while employing their sensory processing and learning strengths. Memory and speech processing also require attention.
Tag: SA_ts_3: *Self-assessment_ targeted support_3*

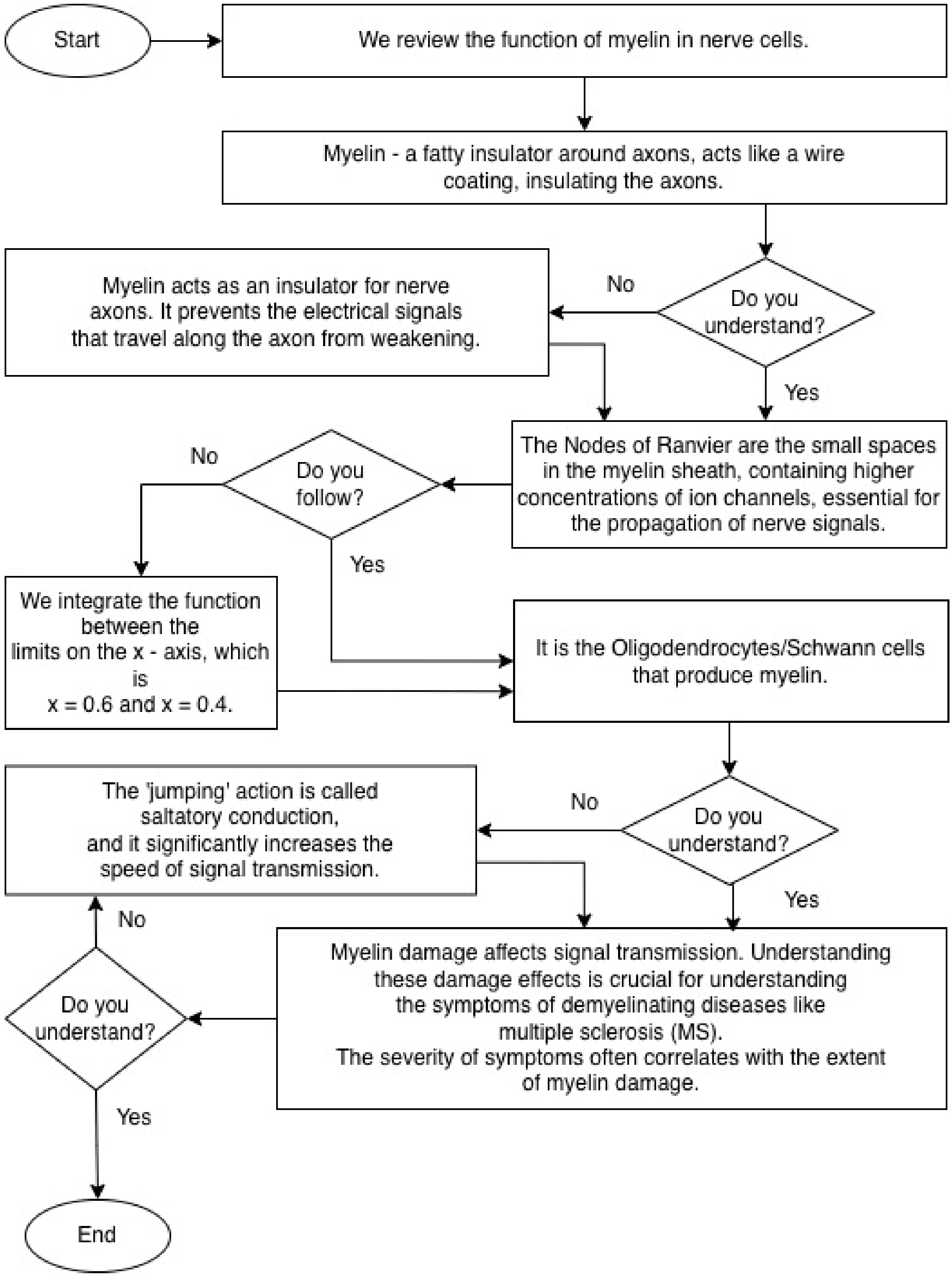
APPENDIX R

Scenario 1: AI - Student interaction flow diagram.



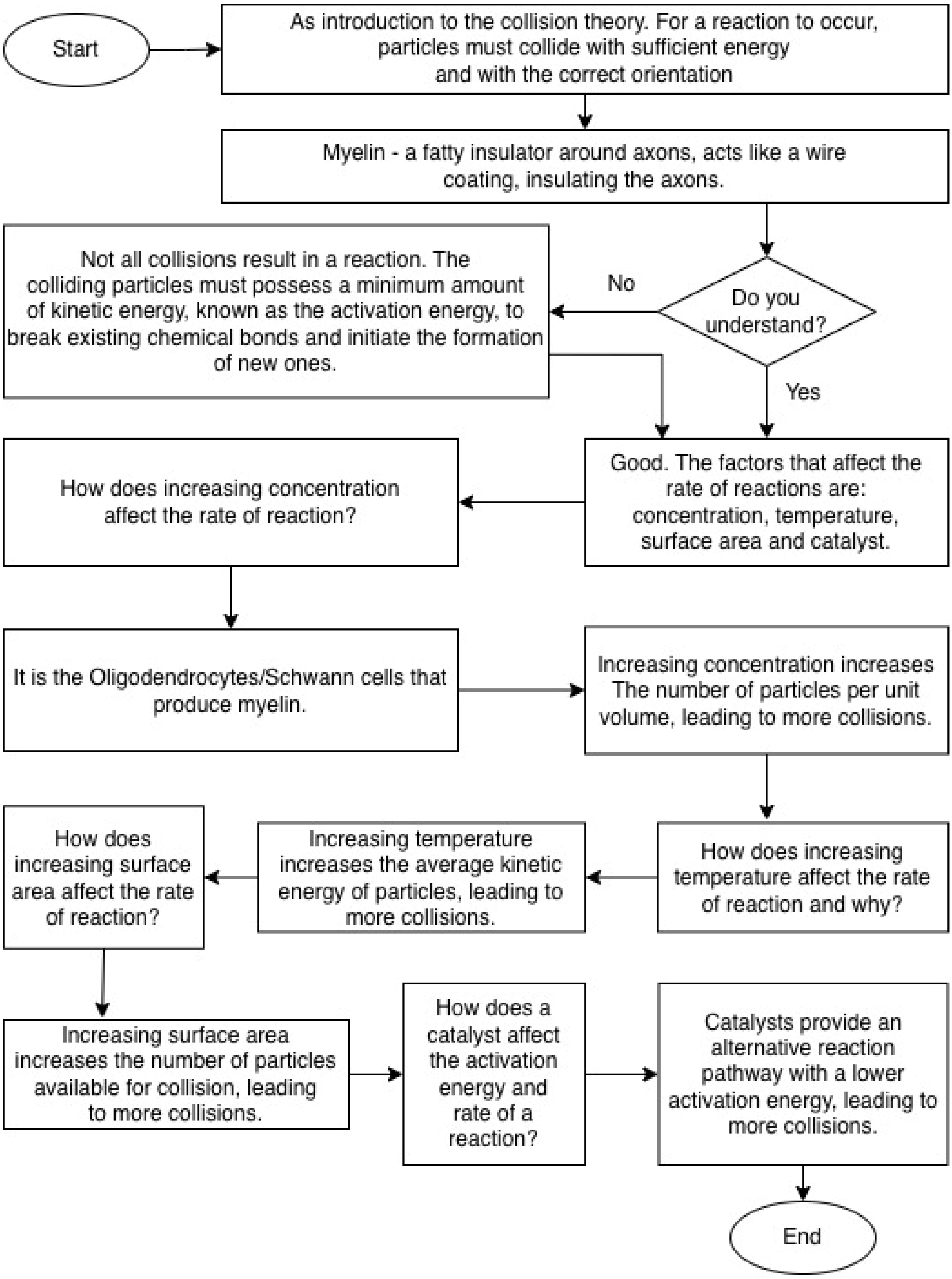
APPENDIX S

Scenario 2: AI - Student interaction flow diagram.



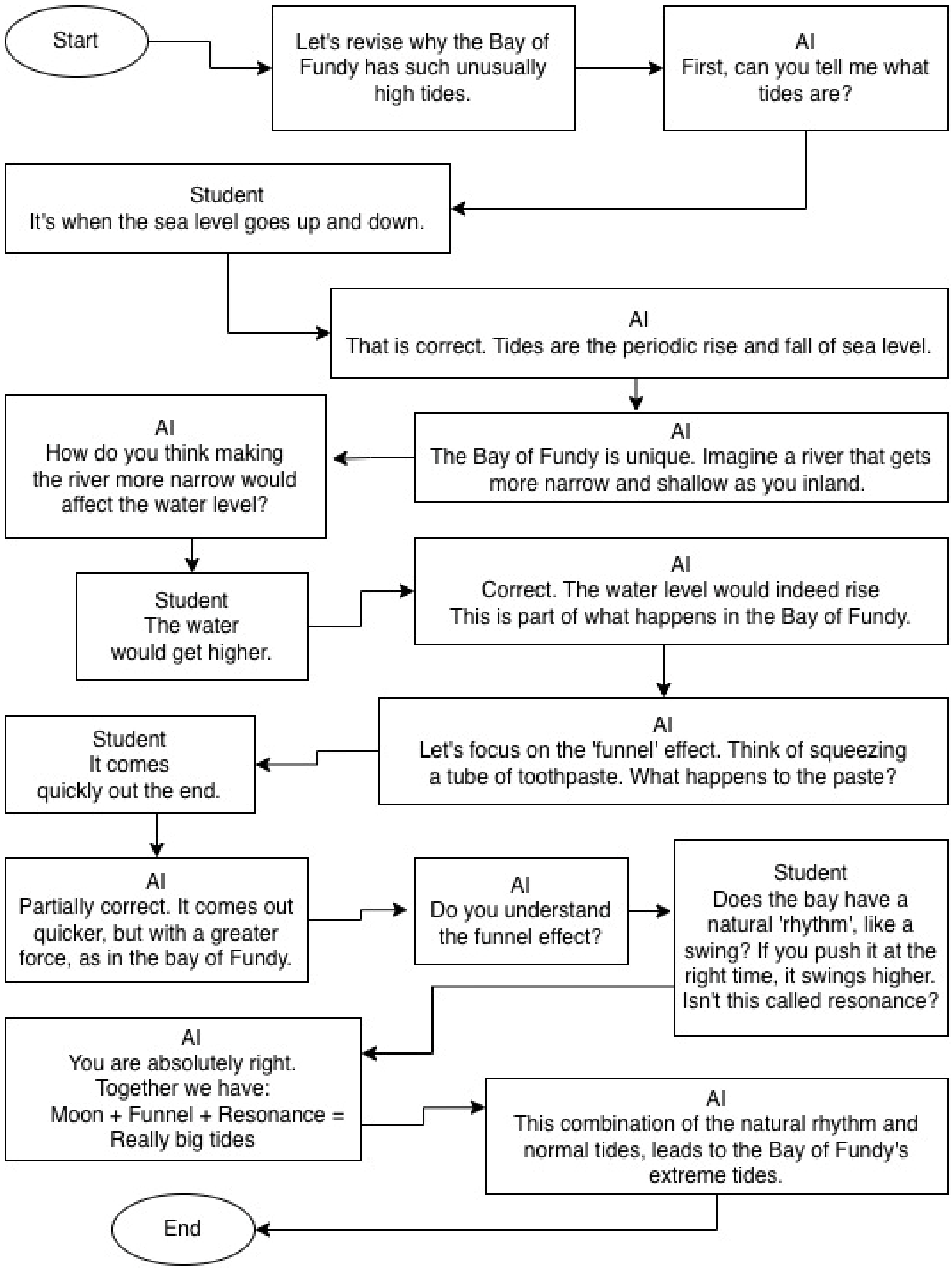
APPENDIX T

Scenario 3: AI - Student interaction flow diagram.



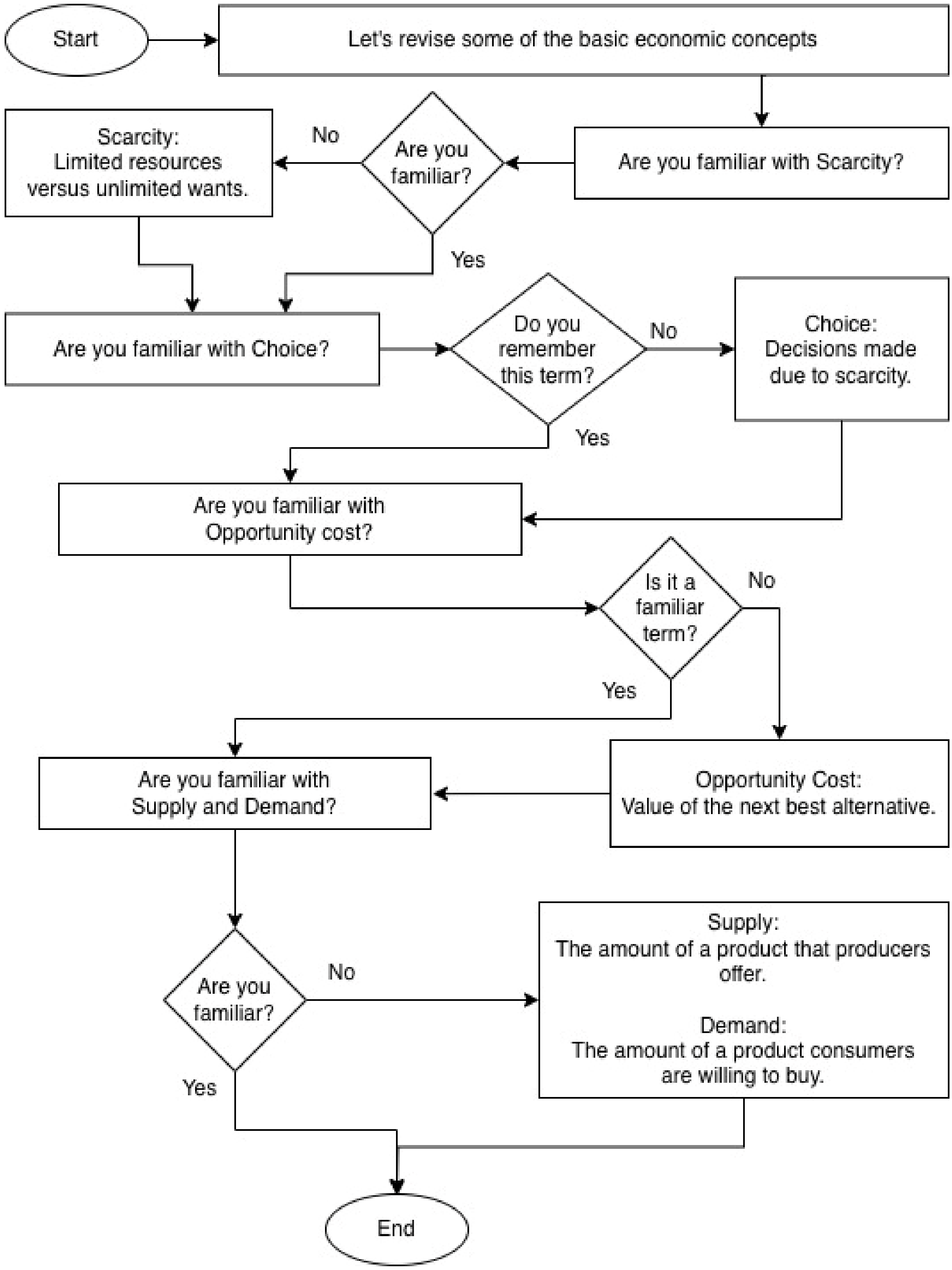
APPENDIX U

Scenario 4: AI - Student interaction flow diagram.



APPENDIX V

Scenario 5: AI - Student interaction flow diagram.



APPENDIX W

An example of the Chi-Square Test (with Randomly Generated Categorical Data)

Generating Random Categorical Data:

Imagine you have you have two questions (e.g. Question A and Question B). For each question, you need to generate categorical responses.

You can use programming languages like Python or R, or even spreadsheet software, to generate random categories.

```
# Python version 3.12 is successfully used to test this code on Mac 10.15.7
from scipy.stats import chi2_contingency
# Sample data (representing counts in a contingency table)
# This represents the observed frequencies in a 2x2 contingency table.
# The rows represent categories (A and B), and the columns represent groups (X
and Y).
observed_data = [
   [10, 20],  # Category A: 10 in Group X, 20 in Group Y
   [15, 5]   # Category B: 15 in Group X, 5 in Group Y
]
# Perform the Chi-Square test
# chi2_contingency() calculates the chi-square statistic, p-value, degrees of freedom,
and
# expected frequencies.
# It takes the observed_data (contingency table) as input.
chi2, p, dof, expected = chi2_contingency(observed_data)
# Print the results and the calculated chi-square statistic, p-value, degrees of
freedom,
# and expected frequencies.
print(f"Chi-square: {chi2}") # Chi-square test statistic
print(f"P-value: {p}") # P-value associated with the chi-square statistic
print(f"Degrees of freedom: {dof}") # Degrees of freedom of the chi-square
distribution
print("Expected frequencies:") # Expected frequencies under the null hypothesis of
# independence
print(expected) # Print the matrix of expected frequencies.
# End of code
```

Outcome:

```
Chi-square: 6.75
P-value: 0.0093747684594349
Degrees of freedom: 1
Expected frequencies:
[[15. 15.]  [10. 10.]]
```

APPENDIX X

An example of the Student's t-test (with Randomly Generated Numerical Data)

Generating Random Numerical Data:
Let's say you have two groups (e.g. Group 1 and Group 2) and want to compare their scores on a test.
Generate random numerical data for each group.
Note that I set the means of both groups to 70, and the standard deviations to 10. This is to show that when random data is generated from similar distributions, there will likely be no statistical difference.
Performing the Independent Samples t-test:
Use the scipy.stats.ttest_ind function in Python or the t.test() function in R.
Example in python:

```
# Python version 3.12 is successfully used to test this code on Mac 10.15.7
import numpy as np
group1_scores = np.random.normal(loc=70, scale=10, size=25) # mean 70, std dev
10
group2_scores = np.random.normal(loc=70, scale=10, size=25) # mean 70, std dev
10
from scipy.stats import ttest_ind
# Perform an independent two-sample t-test.
# ttest_ind() compares the means of two independent samples to determine if there
is a
# statistically significant difference.
# group1_scores and group2_scores are the two samples being compared.
# The function returns the t-statistic and the p-value.
t_stat, p_value = ttest_ind(group1_scores, group2_scores)
# Print the results of the t-test.
# Print the calculated t-statistic and p-value.
print(f"T-statistic: {t_stat}") # The calculated t-statistic
print(f"P-value: {p_value}") # The p-value associated with the t-statistic
# End of code
```

Outcome:
T-statistic: -0.9035406258091964
P-value: 0.3707513898548923

Interpretation:
With randomly generated data, you'll likely get a p-value greater than 0.05, indicating no difference between the means of the two groups.

APPENDIX Y

An example of determining the Pearson correlations.

There are 8 questionnaires, 50 students, between 7 and 40 questions per questionnaire and 4 or 5 options per question.

Spreadsheet 1: Raw Data (Student Responses)
A table where each row is a student, and each column is a question from one of 8 questionnaires.

Student ID (Column A):

This column simply numbers your students from 1 to 50, making it easy to keep track of them.

Example:

A1: Student ID
A2: 1
A3: 2
...
A51: 50

Questionnaire 1 (Columns B-I):

These columns represent the eight questions from your first questionnaire.

Example:

B1: Q1_1 (Question 1 of questionnaire 1)
C1: Q1_2 (Question 2 of questionnaire 1)
D1: Q1_3 (Question 3 of questionnaire 1)
...
I1: Q1_8 (Question 8 of questionnaire 1)
Then you would populate B2 through I51 with the random numbers.

Questionnaire 2 (Columns J-Q):

These columns represent the eight questions from your second questionnaire.

Visual Representation (Simplified):

Student ID	Q1_1	Q1_2	Q1_3	...	Q8_6	Q8_7	Q8_8	…
1	7	3	9	...	2	6	1	…
2	2	8	1	...	5	9	4	…
3	5	6	4	...	8	3	7	…
...	...	...	...	...	...	...	...	…
50	9	1	5	...	1	4	8	…

Example:

J1: Q2_1 (Question 1 of questionnaire 2)
K1: Q2_2 (Question 2 of questionnaire 2) etc.
And so on, until you have all 8 questionnaires, each with 8 columns.

Spreadsheet 2: Descriptive Statistics

This spreadsheet summarizes the data from Spreadsheet 1.

Question/Questionnaire (Column A):

This column lists each question (e.g. Q1_1, Q1_2) and also the overall score for each questionnaire (e.g. Questionnaire 1, questionnaire 2).

To get the questionnaire score, in excel, for student one, you would use =SUM(B2:I2) from the first spreadsheet, and drag that formula down for all of the other students. Then you would use the average of that column to get the average score for the questionnaire.

Mean (Column B):

The average score for each question or questionnaire.

In Excel, you'd use =AVERAGE(range). For example, =AVERAGE(Sheet1!B2:B51) would give you the mean for Q1_1.

Median (Column C):

The middle score.

In Excel, use =MEDIAN(range).

Standard Deviation (Column D):

A measure of how spread out the scores are.

In Excel, use =STDEV.S(range).

And so on, for Variance, Minimum, Maximum, Skewness, and Kurtosis.

Visual Representation (Simplified):

Question/Q'naire	Mean	Median	Std Dev	Var	Min	Max	Skew	Kurtosis
Q1_1	5.3	5	2.9	8.41	1	10	-0.2	2.8
Q1_2	6.1	6	2.2	4.84	2	10	0.1	2.6
Q'naire 1	42.5	43	8.5	72.25	25	60	-0.1	3.0
Q'naire 2	38.2	39	9.0	81.00	20	56	0.0	2.9

Spreadsheet 3: Correlation Matrix

This shows how the questions and questionnaires relate to each other.

You will have the questions and questionnaires as both the row and column headers.

In the cells where the rows and columns intersect, you will put the correlation value of those two variables.

In excel, the formula is =CORREL(array1, array2)

array1 would be for example, sheet1!B2:B51.

array2 would be for example, sheet1!C2:C51.

You will then drag the formula to fill in the rest of the matrix.

The formulas to use to determine the following:

=AVERAGE(B2:B51) (Mean)

=MEDIAN(B2:B51) (Median)

=STDEV.S(B2:B51) (Standard Deviation)

=VAR.S(B2:B51) (Variance)
=MIN(B2:B51) (Minimum)
=MAX(B2:B51) (Maximum)
=SKEW(B2:B51) (Skewness)
=KURT(B2:B51) (Kurtosis)

APPENDIX Z

The Pearson correlation outcomes for the 8 self-assessment questionnaires.

The Cognitive Profiling questionnaire.

1.00	-0.06	0.01	-0.08	-0.05	-0.31	0.14	0.02	-0.10	-0.06	0.11	0.23	0.21	-0.07	0.05	-0.11	-0.05	0.01	0.11	0.29	-0.14	-0.16	-0.11	-0.11	0.02	-0.27	0.16
	1.00	0.14	0.06	-0.17	0.07	-0.22	-0.03	-0.02	-0.02	-0.20	0.09	0.08	0.09	0.09	0.22	0.01	-0.23	-0.19	0.20	-0.33	0.00	-0.24	0.27	0.07	0.09	-0.09
		1.00	-0.04	0.14	0.01	0.15	-0.11	0.13	0.00	0.12	-0.09	0.00	0.04	0.05	-0.16	-0.04	0.10	-0.13	-0.04	-0.19	-0.08	0.20	0.05	0.20	-0.01	-0.18
			1.00	-0.31	0.23	0.06	0.20	0.03	0.07	-0.05	0.14	-0.01	-0.11	-0.12	-0.28	-0.08	-0.19	-0.07	-0.05	-0.18	0.20	-0.05	-0.17	-0.18	-0.33	0.04
				1.00	0.08	0.20	-0.15	0.04	-0.16	0.08	-0.39	0.25	-0.18	0.00	0.01	0.02	0.14	0.15	0.13	0.07	-0.22	0.19	0.14	0.20	0.04	-0.01
					1.00	-0.16	0.14	-0.13	0.10	-0.32	-0.13	-0.08	0.01	0.12	-0.06	-0.22	-0.26	-0.02	-0.07	-0.03	0.21	0.10	-0.27	-0.05	-0.01	0.09
						1.00	-0.02	0.27	-0.05	0.08	0.05	0.10	-0.14	-0.05	-0.15	0.07	0.17	0.13	0.03	0.03	-0.31	0.07	-0.20	-0.18	-0.14	0.08
							1.00	-0.05	0.01	-0.08	0.10	-0.11	0.17	-0.02	0.12	0.01	-0.07	0.07	-0.10	0.23	0.12	0.08	-0.16	0.01	-0.14	-0.16
								1.00	-0.10	0.01	0.13	0.15	-0.44	0.11	-0.23	0.10	0.39	0.03	-0.19	-0.01	-0.32	-0.06	-0.04	-0.23	-0.10	-0.06
									1.00	-0.07	-0.09	0.01	-0.07	-0.15	-0.07	-0.17	0.05	-0.32	-0.06	0.06	-0.08	0.02	0.01	-0.03	0.25	-0.20
										1.00	0.05	-0.04	0.06	0.11	-0.06	0.02	0.23	0.05	0.03	0.01	-0.15	0.18	-0.15	0.16	-0.01	-0.13
											0.04	-0.03	0.07	0.11	-0.07	0.01	0.23	0.04	0.03	0.01	-0.15	0.20	-0.15	0.18	-0.01	-0.14
												1.00	-0.21	-0.13	0.01	-0.04	0.10	0.03	0.36	0.03	-0.05	-0.10	-0.02	-0.04	0.17	-0.24
													1.00	0.11	0.27	0.15	-0.13	0.10	0.10	-0.05	0.34	0.24	0.09	0.21	-0.06	-0.02
														1.00	-0.08	-0.14	-0.13	0.20	-0.13	0.02	0.03	-0.15	-0.23	-0.02	-0.37	0.01
															1.00	-0.04	-0.01	0.24	0.20	0.16	0.10	-0.18	0.28	0.02	0.16	-0.09
																1.00	0.13	0.23	0.13	0.08	-0.08	0.07	0.09	-0.28	-0.07	0.05
																	1.00	0.11	-0.42	0.23	-0.23	0.05	-0.04	-0.16	-0.07	-0.05
																		1.00	0.11	0.08	0.01	-0.09	0.03	-0.12	-0.45	0.38
																			1.00	-0.11	0.00	0.01	0.14	0.05	0.11	0.19
																				1.00	0.18	0.09	-0.01	-0.08	0.09	-0.20
																					1.00	0.07	0.03	0.01	0.08	-0.22
																						1.00	-0.08	0.32	-0.02	0.06
																							1.00	0.22	0.16	0.01
																								1.00	0.15	-0.06
																									1.00	-0.31
																										1.00

The Cognitive Task Performance Record

1.00	-0.33	0.05	0.09	0.08	-0.23
	1.00	0.18	-0.05	-0.09	0.27
		1.00	-0.08	-0.03	0.26
			1.00	0.22	-0.11
				1.00	-0.24
					1.00

The VARK questionnaire

1.00	-0.07	-0.24	0.07	0.13	0.00	0.05	0.08	0.15	0.19	0.05	-0.20	-0.12	0.00	-0.23	0.00
	1.00	0.26	-0.07	-0.01	-0.09	-0.20	0.00	0.01	0.20	0.11	0.10	-0.05	-0.13	0.00	-0.20
		1.00	-0.21	0.02	0.21	-0.11	0.39	0.16	-0.19	-0.20	-0.18	-0.04	-0.02	-0.09	0.01
			1.00	0.28	-0.05	-0.02	0.09	-0.17	-0.16	0.18	0.09	0.30	0.05	-0.17	0.07
				1.00	0.11	-0.29	0.31	0.10	-0.06	-0.14	0.08	0.37	0.23	-0.12	-0.06
					1.00	-0.09	0.16	-0.02	-0.21	-0.30	0.06	0.03	0.12	-0.16	0.15
						1.00	-0.14	-0.07	0.18	-0.14	-0.06	-0.27	0.19	-0.02	0.00
							1.00	0.18	-0.05	-0.02	0.03	0.11	-0.02	-0.15	-0.08
								1.00	-0.13	-0.04	0.03	0.07	0.05	-0.16	0.22
									1.00	0.04	-0.03	-0.11	-0.04	0.10	-0.36
										1.00	0.31	0.10	-0.08	-0.16	0.03
											1.00	-0.14	0.31	-0.20	-0.03
												1.00	-0.18	0.15	0.09
													1.00	-0.21	-0.12
														1.00	0.10
															1.00

The GAD-7 questionnaire

1.00	-0.02	0.29	-0.32	-0.09	-0.07	-0.12
	1.00	-0.02	-0.01	-0.08	-0.03	0.05
		1.00	-0.04	-0.31	-0.13	0.06
			1.00	0.06	0.20	-0.09
				1.00	-0.05	-0.32
					1.00	0.02
						1.00

The Student Learning Behaviour and Preference Observation form

1.00	0.06	-0.12	-0.15	-0.05	-0.13	-0.34	0.03	0.06	-0.14	0.22	-0.29	0.19	-0.14	0.05	0.16	0.05	0.08	0.23	-0.05	0.11
	1.00	0.26	-0.05	-0.17	0.20	0.06	-0.07	0.14	0.25	0.09	-0.23	-0.02	0.07	0.10	0.18	0.02	-0.06	0.00	-0.17	-0.25
		1.00	0.06	-0.13	-0.14	0.13	-0.10	0.07	0.14	-0.22	0.29	0.02	0.05	-0.03	0.00	0.03	-0.10	-0.07	-0.18	-0.07
			1.00	-0.01	-0.09	-0.11	-0.03	-0.22	0.21	-0.19	0.17	0.16	-0.17	-0.06	-0.12	0.18	0.18	-0.04	0.03	0.09
				1.00	0.15	-0.06	0.02	-0.03	-0.08	-0.13	0.35	-0.10	-0.11	0.05	0.18	0.17	0.09	0.04	0.27	0.05
					1.00	0.16	-0.29	-0.18	0.07	0.00	0.07	0.16	-0.14	0.15	-0.19	-0.30	-0.14	-0.10	-0.10	-0.18
						1.00	-0.06	-0.03	-0.05	-0.32	0.08	-0.25	0.00	0.19	0.03	-0.03	0.12	0.08	-0.31	0.09
							1.00	0.11	-0.06	-0.04	-0.03	-0.21	-0.04	-0.02	-0.09	0.18	0.01	0.23	0.15	-0.03
								1.00	0.05	-0.01	-0.13	0.20	0.01	-0.25	0.20	-0.16	-0.18	-0.07	-0.03	-0.11
									1.00	-0.16	-0.09	-0.01	-0.04	-0.11	-0.03	-0.25	0.02	-0.22	-0.04	0.00
										1.00	-0.28	0.13	-0.07	-0.08	0.11	-0.07	-0.05	0.32	-0.02	-0.34
											1.00	0.10	0.04	0.03	-0.11	0.11	-0.09	-0.09	-0.13	0.07
												1.00	-0.03	-0.19	-0.02	-0.08	-0.10	0.08	-0.02	0.02
													1.00	0.06	0.06	0.18	0.18	-0.11	-0.04	-0.01
														1.00	0.01	0.09	-0.08	0.01	-0.21	-0.09
															1.00	-0.06	0.00	0.25	-0.10	0.05
																1.00	0.38	0.04	-0.01	0.08
																	1.00	0.26	0.01	0.04
																		1.00	0.03	-0.23
																			1.00	0.13
																				1.00

The Mayer-Salovey-Caruso Emotional Intelligence Test

1.00	-0.02	0.14	0.02	-0.17	-0.05	-0.05	-0.08	0.03	0.17	0.08	0.17	0.21	0.03	-0.04	-0.04	0.15	0.05	-0.18	0.09	0.06	0.03	-0.07	0.08	0.00	0.01	-0.21	-0.01	-0.14	-0.24	0.28	0.11	0.03	0.04	-0.03	-0.12	0.01	0.08	-0.01	0.04
	1.00	-0.04	0.00	-0.28	0.02	0.41	0.11	-0.13	0.11	-0.16	0.16	-0.12	-0.02	-0.04	-0.28	0.20	0.02	-0.02	-0.13	0.15	0.24	0.06	-0.22	0.04	0.09	0.21	-0.08	-0.04	-0.04	-0.25	-0.06	0.07	0.13	0.08	-0.20	0.26	-0.06	-0.05	-0.13
		1.00	0.27	-0.31	-0.01	-0.08	-0.10	0.09	-0.13	0.01	0.09	-0.07	0.07	0.04	0.00	-0.04	0.10	-0.06	0.01	0.03	-0.14	-0.26	0.07	0.09	0.04	-0.15	-0.08	-0.16	-0.04	-0.15	-0.10	0.11	-0.04	0.23	0.09	0.04	-0.15	0.21	-0.07
			1.00	0.18	-0.16	0.04	-0.02	-0.21	-0.09	-0.26	0.21	0.04	0.24	0.02	-0.03	0.09	0.21	0.22	0.24	0.20	-0.10	-0.23	-0.34	-0.20	0.14	0.03	-0.12	0.31	0.18	0.08	-0.06	0.05	0.11	-0.23	-0.06	0.03	0.08	0.24	0.11
				1.00	-0.07	-0.23	0.00	-0.12	-0.02	-0.28	-0.22	0.17	-0.02	-0.03	0.06	-0.19	0.09	0.29	-0.02	-0.16	0.12	-0.05	-0.11	0.08	-0.11	0.24	-0.05	0.11	0.09	0.12	0.16	-0.25	0.04	-0.05	0.02	0.03	0.02	-0.12	0.09
					1.00	-0.24	0.08	0.13	0.01	0.19	-0.21	0.02	-0.14	0.04	-0.05	0.02	-0.06	-0.07	-0.41	-0.16	0.06	0.15	0.25	-0.11	0.02	-0.05	-0.17	0.14	-0.18	0.00	-0.21	-0.03	-0.06	0.04	0.22	-0.01	-0.05	-0.11	-0.27
						1.00	-0.10	-0.22	0.03	0.05	0.06	-0.13	0.18	0.01	0.06	0.10	-0.01	0.13	0.02	0.19	0.15	-0.01	-0.05	0.03	0.47	0.08	0.27	0.05	-0.04	-0.04	-0.10	-0.09	0.17	-0.20	-0.18	0.00	0.07	0.00	0.13
							1.00	-0.05	0.14	0.22	0.19	0.02	-0.10	-0.20	-0.16	-0.24	0.26	0.19	-0.12	-0.02	-0.18	0.02	-0.23	0.08	0.04	0.25	-0.07	0.16	0.28	-0.27	0.09	-0.14	0.00	0.11	0.11	-0.05	0.16	-0.24	-0.13
								1.00	-0.02	-0.08	-0.08	0.01	-0.37	0.00	0.17	-0.30	0.12	-0.07	-0.21	-0.03	0.00	-0.14	0.29	-0.21	-0.07	-0.17	-0.12	0.24	-0.02	-0.06	-0.09	-0.03	-0.29	-0.19	0.16	-0.23	-0.05	0.03	-0.32
									1.00	0.03	0.19	0.33	-0.04	0.03	-0.19	0.15	-0.17	0.11	-0.03	0.06	0.22	-0.03	-0.08	0.10	0.10	-0.15	0.11	-0.06	-0.32	-0.06	0.01	0.21	-0.03	0.01	-0.04	0.19	0.12	-0.10	0.05
										1.00	0.00	0.09	0.05	0.08	0.31	0.01	-0.13	-0.33	-0.14	-0.20	-0.07	0.18	-0.12	0.13	0.18	0.00	0.04	-0.05	0.18	0.02	0.04	-0.02	0.02	0.04	0.11	-0.15	-0.05	-0.08	-0.04
											1.00	-0.30	-0.02	-0.27	-0.30	0.29	-0.22	0.10	0.14	0.10	-0.02	0.08	-0.28	-0.01	-0.01	-0.11	-0.05	0.18	0.05	0.08	-0.05	0.00	-0.14	-0.04	-0.30	0.18	-0.04	0.12	0.12
												1.00	0.20	0.20	0.08	-0.01	0.11	0.04	0.15	0.13	0.24	0.03	-0.08	0.00	0.06	0.14	0.06	-0.18	-0.27	0.01	0.22	0.00	0.11	0.02	0.09	0.01	-0.04	-0.15	0.12
													1.00	-0.06	0.09	0.10	-0.09	0.09	0.41	0.02	0.11	-0.09	-0.16	0.10	0.18	0.09	0.00	-0.16	-0.17	0.03	-0.19	0.22	0.27	-0.31	0.16	-0.17	-0.09	-0.14	0.39
														1.00	-0.05	-0.16	-0.07	-0.16	-0.30	0.17	-0.09	-0.09	0.08	0.00	0.07	-0.04	0.13	0.02	-0.11	-0.08	-0.06	0.06	0.05	0.10	-0.04	0.04	-0.02	-0.02	-0.06
															1.00	-0.02	-0.15	-0.03	0.08	-0.04	0.12	-0.12	-0.08	-0.18	0.08	-0.14	0.08	-0.06	0.31	0.15	0.08	-0.03	-0.01	-0.02	0.19	-0.06	-0.13	-0.01	-0.15
																1.00	-0.26	0.03	0.11	0.17	0.29	0.24	-0.30	-0.06	-0.04	-0.20	0.03	-0.01	-0.08	0.22	-0.09	-0.05	-0.12	-0.01	-0.11	0.26	0.00	0.00	0.14
																	1.00	-0.08	-0.10	0.06	-0.15	0.09	0.10	0.04	0.13	0.10	0.08	0.11	0.13	-0.14	0.08	-0.05	0.06	-0.07	0.04	-0.16	0.01	0.01	0.16
																		1.00	0.08	-0.02	0.11	-0.12	0.08	-0.14	0.17	0.01	-0.09	0.27	0.04	0.01	0.10	-0.04	0.26	0.02	-0.14	-0.07	0.13	0.11	-0.06
																			1.00	0.08	0.09	-0.01	-0.17	-0.05	-0.09	0.01	0.02	-0.01	-0.01	0.16	0.11	0.05	0.02	-0.13	0.10	-0.04	0.20	0.16	0.38
																				1.00	0.02	-0.17	-0.07	0.18	0.25	-0.04	0.33	-0.01	0.10	-0.02	0.04	-0.21	-0.11	-0.12	-0.27	0.19	0.05	0.07	0.19
																					1.00	0.24	-0.21	-0.11	-0.21	-0.08	-0.09	-0.11	-0.21	-0.05	0.01	0.02	0.03	0.02	-0.02	0.28	0.10	-0.03	-0.05
																						1.00	-0.08	-0.02	-0.31	-0.08	-0.18	0.07	0.24	-0.08	0.21	0.00	-0.08	0.16	0.10	0.07	0.18	-0.07	0.18
																							1.00	0.01	0.10	-0.19	-0.01	0.06	-0.27	0.07	-0.04	0.11	0.00	0.01	-0.08	-0.02	-0.03	0.06	-0.08
																								1.00	0.20	0.09	0.34	-0.19	0.00	-0.01	0.08	-0.13	0.21	0.06	-0.25	0.16	0.00	0.06	0.30
																									1.00	0.14	0.28	0.11	-0.17	0.21	0.09	-0.15	0.16	-0.29	-0.24	-0.07	0.07	0.09	0.07
																										1.00	0.12	-0.02	0.06	-0.12	0.08	-0.19	-0.10	0.01	0.20	-0.04	0.10	-0.29	0.33
																											1.00	-0.06	-0.03	-0.01	0.01	-0.06	-0.09	-0.10	-0.20	-0.05	0.03	0.04	0.32
																												1.00	0.41	0.15	-0.06	-0.09	-0.20	-0.25	0.01	-0.11	0.25	0.12	-0.08
																													1.00	-0.03	0.08	-0.09	0.00	-0.05	0.01	-0.01	0.03	0.12	-0.05
																														1.00	0.14	0.01	-0.01	-0.34	-0.13	-0.02	0.14	0.06	0.06
																															1.00	0.02	-0.09	0.40	-0.05	-0.07	0.29	0.23	-0.09
																																1.00	0.20	0.04	0.12	-0.19	0.03	0.05	-0.10
																																	1.00	0.05	-0.25	0.01	-0.08	0.08	0.02
																																		1.00	0.07	0.13	-0.11	0.12	-0.05
																																			1.00	-0.20	0.09	-0.32	0.02
																																				1.00	-0.12	0.11	0.07
																																					1.00	-0.09	-0.06
																																						1.00	0.05
																																							1.00

The Emotional Intelligence questionnaire

1.00	0.15	0.26	0.01	-0.10	0.12	-0.15	0.06	-0.18	-0.17	-0.19	-0.17	-0.12	-0.26	-0.04
	1.00	-0.10	-0.02	-0.20	-0.14	-0.14	0.19	-0.16	-0.20	-0.11	-0.16	-0.15	-0.05	0.17
		1.00	-0.18	0.03	0.02	-0.01	0.05	-0.02	-0.19	-0.19	-0.15	0.06	-0.26	-0.29
			1.00	0.00	0.06	-0.15	0.18	0.17	0.21	0.03	0.15	-0.11	0.14	0.35
				1.00	0.16	0.20	-0.03	-0.13	-0.05	0.19	-0.03	0.11	0.03	0.02
					1.00	0.32	0.02	0.18	-0.05	-0.21	-0.05	-0.19	-0.17	0.21
						1.00	-0.15	0.06	-0.17	-0.23	0.10	0.06	-0.09	0.12
							1.00	0.05	0.13	-0.28	0.14	0.13	-0.11	0.16
								1.00	0.05	-0.34	0.07	-0.04	-0.13	-0.01
									1.00	-0.10	0.04	0.17	0.01	-0.09
										1.00	-0.15	-0.21	-0.04	-0.02
											1.00	0.07	0.26	0.01
												1.00	0.09	-0.24
													1.00	0.28
														0.07

The Cognitive Processes Assessment

1.00	0.06	0.10	0.31	0.05	-0.23	0.02	-0.08	-0.33	-0.14	-0.11	-0.25	-0.30	0.03	-0.03	-0.01	-0.07	-0.19	0.11	0.06
	1.00	-0.07	0.16	-0.13	-0.09	0.02	0.07	0.17	-0.07	0.14	-0.28	0.17	-0.12	0.06	-0.19	-0.02	-0.10	-0.13	-0.10
		1.00	-0.15	0.03	-0.16	-0.03	0.00	0.07	-0.02	-0.33	0.14	-0.05	-0.06	0.22	0.02	0.04	-0.19	0.22	0.14
			1.00	-0.03	0.01	0.19	-0.08	-0.09	-0.20	0.00	-0.08	-0.20	0.06	-0.04	-0.05	-0.04	0.23	0.02	-0.07
				1.00	0.04	-0.03	0.07	-0.11	0.30	0.06	0.23	-0.02	0.21	-0.10	0.19	-0.06	0.24	0.05	-0.03
					1.00	0.06	0.00	0.04	0.01	0.06	0.00	-0.17	0.18	-0.29	0.03	-0.19	0.19	-0.20	-0.02
						1.00	0.26	0.22	0.01	-0.05	0.04	-0.06	-0.18	0.08	-0.17	0.03	0.12	0.13	-0.21
							1.00	0.16	0.21	-0.16	-0.21	-0.10	0.08	-0.23	-0.04	0.07	0.13	-0.09	-0.06
								1.00	0.27	-0.19	-0.04	0.10	-0.05	-0.19	-0.05	0.14	0.03	0.33	-0.14
									1.00	0.22	0.02	-0.11	-0.07	-0.09	-0.05	0.31	-0.14	-0.03	-0.05
										1.00	-0.09	0.05	0.14	0.13	-0.11	-0.12	0.02	-0.20	-0.20
											1.00	0.00	0.14	0.14	0.18	0.05	0.16	-0.17	-0.07
												1.00	-0.28	0.28	0.01	-0.11	0.00	0.11	-0.02
													1.00	-0.22	-0.03	-0.12	0.49	-0.14	-0.06
														1.00	0.03	0.10	-0.09	0.01	0.04
															1.00	-0.23	-0.19	0.17	-0.07
																1.00	0.14	-0.14	-0.09
																	1.00	-0.10	-0.03
																		1.00	0.03
																			1.00

APPENDIX AA

The Python code for scenario 1 algorithm: sa_write.py

```
# Python version 3.12 created and tested on Mac 10.15.7
# Student A MATHEMATICS
import json

data = {
   "student_profile": {
      "student_id": "S1001",
      "full_name": "EV",
      "age": 18,
      "major": "Mathematics",
      "Year 11 result": 0.83,
      "SA_ct": 1,
      "SA_attn": 0,
      "SA_ml": 0,
      "SA_ps": 0,
      "SA_r_ctpr": 1,
      "SA_a": 1,
      "SA_v": 1,
      "SA_h": 0,
      "SA_kin": 0,
      "SA_n": 0,
      "VR / AR": 1,
      "SA_anx": 1,
      "SA_w": 1,
      "SA_conman": 1,
      "SA_ts_chalem": 1,
      "SA_senpro": 1,
      "SA_int_ar": 1
   }
}

with open("sa_data.json", "w") as f:
   json.dump(data, f)

print("The values of all variables have been saved to sa_data.json within the 'student_profile' key.")
# End of code
```

APPENDIX AB

The Python code for scenario 1 algorithm: sa_read.py

```
# Python version 3.12 created and tested on Mac 10.15.7
# Student A MATHEMATICS
import json

def read_student_profile(filename="sa_data.json"):

# Reads the student profile variables from a JSON file.
# Args:       filename (str, optional): The name of the JSON file.
#                               Defaults to "sa_data.json".
# Returns:      dict or None: A dictionary containing the student profile key-value pairs
#                  from the JSON file, or None if an error occurs or if
#                  'student_profile' key is not found.

   try:
      with open(filename, "r") as f:
         data = json.load(f)
         if "student_profile" in data:
            return data["student_profile"]
         else:
            print(f"Error: 'student_profile' key not found in '{filename}'.")
            return None
   except FileNotFoundError:
      print(f"Error: File '{filename}' not found.")
      return None
   except json.JSONDecodeError:
      print(f"Error: Invalid JSON format in '{filename}'")
      return None

# Example usage:
student_profile = read_student_profile()
if student_profile:
   print("Student profile from sa_data.json:")
   for key, value in student_profile.items():
      print(f"{key}: {value}")

# End of code
```

APPENDIX AC

The Python code for scenario 1 algorithm: sa_update.py

```
# Python version 3.12 created and tested on Mac 10.15.7
# Student A MATHEMATICS
import json

data_string = '''
{
"student_id": "S1001",
    "full_name": "EV",
    "age": 18,
    "major": "Mathematics",
    "Year 11 result": 0.83,
    "SA_ct": 1,
    "SA_attn": 0,
    "SA_ml": 0,
    "SA_ps": 0,
    "SA_r_ctpr": 1,
    "SA_a": 1,
    "SA_v": 1,
    "SA_h": 0,
    "SA_kin": 0,
    "SA_n": 0,
    "VR / AR": 1,
    "SA_anx": 1,
    "SA_w": 1,
    "SA_conman": 1,
    "SA_ts_chalem": 1,
    "SA_senpro": 1,
    "SA_int_ar": 1
}
'''

# Load data from the JSON string
data = json.loads(data_string)

print("Current values:")
for key, value in data.items():
    print(f"- {key}: {value}")

while True:
    key_to_update = input("\nEnter the name of the field you want to update (or type 
'done' to finish): ").strip()
    if key_to_update.lower() == 'done':
        break
    if key_to_update in data:
        new_value = input(f"Enter the new value for '{key_to_update}': ")
```

```
        original_type = type(data[key_to_update])
        if original_type is int:
            try:
                data[key_to_update] = int(new_value)
            except ValueError:
                print("Invalid input. Please enter an integer.")
                continue
        elif original_type is float:
            try:
                data[key_to_update] = float(new_value)
            except ValueError:
                print("Invalid input. Please enter a float.")
                continue
        elif original_type is bool:
            if new_value.lower() == 'true':
                data[key_to_update] = True
            elif new_value.lower() == 'false':
                data[key_to_update] = False
            else:
                print("Invalid input. Please enter 'true' or 'false'.")
                continue
        else:
            data[key_to_update] = new_value
        print(f"'{key_to_update}' updated to: {data[key_to_update]}")
    else:
        print(f"Field '{key_to_update}' not found in the data.")

# Save the updated data back to the "data.json" file
with open("data.json", "w") as f:
    json.dump(data, f, indent=4)

print("\nUpdated data saved to 'data.json'")

# End of code
```

APPENDIX AD

The Python code for scenario 1 algorithm: sa_session1.py

```
# Python version 3.12 created and tested on Mac 10.15.7
# Student A MATHEMATICS
import json

def read_all_variables(filename="sa_data.json"):

 #   Reads all variables from a JSON file.
 #   Args:       filename (str, optional): The name of the JSON file.
 #            Defaults to "sa_data.json".
 #   Returns:       dict or None: A dictionary containing all the key-value pairs
 #                       from the JSON file, or None if an error occurs.

   try:
      with open(filename, "r") as f:
         data = json.load(f)  # Load the entire JSON data into a dictionary
      return data               # Return the entire dictionary
   except FileNotFoundError:
      print(f"Error: File '{filename}' not found.")
      return None
   except json.JSONDecodeError:
      print(f"Error: Invalid JSON format in '{filename}'")
      return None

# Example usage:
all_variables = read_all_variables()
if all_variables:
   if "student_profile" in all_variables and "SA_int_ar" in
all_variables["student_profile"]:
      if all_variables["student_profile"]["SA_int_ar"] == 1:
         print("You revise now Integration and Areas.")
      elif all_variables["student_profile"]["SA_int_ar"] == 0:
         print("Please select the chapter and topic too revise/")
      else:
         print("Warning: The value of SA_int_ar is neither 0 nor 1.")
   else:
      print("Warning: The variable 'SA_int_ar' was not found in the JSON file.")
   print("\nAll variables from sa_data.json:")
   for key, value in all_variables.items():
      print(f"{key}: {value}")
# End of code
```

APPENDIX AE

The Python code for scenario 1 algorithm: sa_matr_update.py

```
# Python version 3.12 created and tested on Mac 10.15.7
# Student A MATHEMATICS
import json

def get_student_profile(filepath="sa_data.json"):
# Reads the 'student_profile' data from the specified JSON file.
    try:
        with open(filepath, 'r') as f:
            data = json.load(f)
            if "student_profile" in data:
                return data["student_profile"]
            else:
                print(f"Warning: 'student_profile' key not found in '{filepath}'.")
                return {}
    except FileNotFoundError:
        print(f"Error: File '{filepath}' not found.")
        return {}
    except json.JSONDecodeError:
        print(f"Error: Could not decode JSON from '{filepath}'.")
        return {}

def update_student_preferences(filepath="sa_matr_data.json"):
# Simulates updating student preferences and saves to sa_matr_data.json.
    try:
        with open(filepath, 'r') as f:
            data = json.load(f)
    except FileNotFoundError:
        data = {"student_profile": {}, "learning_materials": []}
        print(f"Warning: File '{filepath}' not found. Creating a new data structure.")
    except json.JSONDecodeError:
        data = {"student_profile": {}, "learning_materials": []}
        print(f"Warning: File '{filepath}' contains invalid JSON. Creating a new data
structure.")

    # Example update to the student profile (this will overwrite existing data)
    data["student_profile"] = {
        "student_id": "S1001",
        "full_name": "EV",
        "age": 18,
        "major": "Mathematics",
        "Year 11 result": 0.83,
        "SA_ct": 1,
        "SA_attn": 0,
        "SA_ml": 0,
        "SA_ps": 0,
```

```
        "SA_r_ctpr": 1,
        "SA_a": 1,
        "SA_v": 1,
        "SA_h": 0,
        "SA_kin": 0,
        "SA_n": 0,
        "VR / AR": 1,
        "SA_anx": 1,
        "SA_w": 1,
        "SA_conman": 1,
        "SA_ts_chalem": 1,
        "SA_senpro": 1,
        "SA_int_ar": 1
    }

    # Example learning materials (this will overwrite existing data)
    data["learning_materials"] = [
        {"name": "Calculus Explained Visually", "metadata": {"major": "Mathematics",
"SA_v": 1}},
        {"name": "Interactive Algebra Practice", "metadata": {"major": "Mathematics",
"SA_kin": 1, "SA_ps": 1}},
        {"name": "Abstract Math Concepts (Text-based)", "metadata": {"major":
"Mathematics", "SA_w": 1}},
        {"name": "Geometry VR Experience", "metadata": {"major": "Mathematics", "VR
/ AR": 1, "SA_v": 1}},
        {"name": "Statistics Problem Solving", "metadata": {"major": "Mathematics",
"SA_ps": 1, "SA_ct": 1}},
        {"name": "Mathematical Proofs (Auditory)", "metadata": {"major": "Mathematics",
"SA_a": 1}}
    ]

    with open(filepath, 'w') as f:
        json.dump(data, f, indent=4)

    print(f"Student preferences and learning materials updated and saved to
'{filepath}'")

if __name__ == "__main__":
    print("--- Reading from sa_data.json ---")
    student_data = get_student_profile()
    if student_data:
        print("Student Profile:")
        for key, value in student_data.items():
            print(f"  {key}: {value}")
    print("\n--- Writing to sa_matr_data.json ---")
    update_student_preferences()
# End of code
```

APPENDIX AF

The Python code for scenario 1 algorithm: sa_matr_learning_material_selection.py

```
# Python version 3.12 created and tested on Mac 10.15.7
# Student A MATHEMATICS
import json
from datetime import datetime

def load_data(filepath="sa_matr_data.json"):
# Loads data from the JSON file.
    try:
        with open(filepath, 'r') as f:
            return json.load(f)
    except FileNotFoundError:
        return {"student_profile": {}, "learning_materials": []}

def save_data(data, filepath="sa_matr_data.json"):
# Saves data to the JSON file.
    with open(filepath, 'w') as f:
        json.dump(data, f, indent=4)

def is_material_suitable(student_prefs, material_data):

# Determines if a learning material is suitable for the student based on preferences.
# This is a basic example and can be made more sophisticated.
# It checks if any of the student's '1' preferences match a '1' in the material,
# and if the major aligns.

    for key, value in student_prefs.items():
        if key.startswith("SA_") or key == "VR / AR":
            if value == 1 and key in material_data and material_data[key] == 1:
                return True
    if "major" in student_prefs and "major" in material_data and student_prefs["major"]
== material_data["major"]:
        return True
    return False

def select_learning_materials(student_prefs, all_materials):
# Selects learning materials that match the student's preferences.
    suitable_materials = []
    for material in all_materials:
        if 'metadata' in material and is_material_suitable(student_prefs,
material['metadata']):
            suitable_materials.append(material['name'])
    return suitable_materials

if __name__ == "__main__":
    data = load_data()
```

```
    student_profile = data.get("student_profile", {})
    learning_materials = data.get("learning_materials", [])

    if student_profile:
        recommended_materials = select_learning_materials(student_profile, 
learning_materials)
        print(f"For {student_profile.get('full_name', 'the student')}, the following learning 
materials are recommended:")
        if recommended_materials:
            for material in recommended_materials:
                print(f"- {material}")
        else:
            print("No suitable learning materials found based on current preferences.")

        # Check if SA_n is 1 and display the book list
        if student_profile.get("SA_n") == 1:
            print("\nBased on SA_n = 1, here is a list of books:")
            books_to_display = [
                "The Joy of Numbers",
                "Mathematical Mindsets",
                "Fermat's Last Theorem",
                "The Code Book"
            ]
            for book in books_to_display:
                print(f"- {book}")
        elif student_profile.get("SA_n") == 0:
            print("\nSA_n is 0, so the book list is not displayed.")
        else:
            print("\nSA_n value not found or is not 0 or 1.")

        # Check if SA_v is 1 and display the video list
        if student_profile.get("SA_v") == 1:
            print("\nBased on SA_v = 1, here is a list of videos:")
            videos_to_display = [
                "Visual Introduction to Calculus",
                "The Beauty of Fractals",
                "Understanding Quantum Mechanics",
                "History of Mathematics"
            ]
            for video in videos_to_display:
                print(f"- {video}")
        elif student_profile.get("SA_v") == 0:
            print("\nSA_v is 0, so the video list is not displayed.")
        else:
            print("\nSA_v value not found or is not 0 or 1.")

        # Check if SA_a is 1 and display the auditory list
```

```python
if student_profile.get("SA_a") == 1:
    print("\nBased on SA_a = 1, here is a list of auditory materials:")
    auditory_materials = [
        "Mathematics Lectures Podcast",
        "Audiobook: A History of Pi",
        "Learning Algebra Through Sound",
        "Theorems Explained (Audio)"
    ]
    for material in auditory_materials:
        print(f"- {material}")
elif student_profile.get("SA_a") == 0:
    print("\nSA_a is 0, so the auditory materials list is not displayed.")
else:
    print("\nSA_a value not found or is not 0 or 1.")

# Check if SA_h is 1 and display the hands-on list
if student_profile.get("SA_h") == 1:
    print("\nBased on SA_h = 1, here is a list of hands-on activities:")
    hands_on_activities = [
        "Building Geometric Shapes with Straws",
        "Exploring Probability with Dice and Coins",
        "Measuring and Calculating Areas in the Garden",
        "Creating a Model of the Solar System"
    ]
    for activity in hands_on_activities:
        print(f"- {activity}")
elif student_profile.get("SA_h") == 0:
    print("\nSA_h is 0, so the hands-on activities list is not displayed.")
else:
    print("\nSA_h value not found or is not 0 or 1.")

# Check if SA_kin is 1 and display the kinaesthetic list
if student_profile.get("SA_kin") == 1:
    print("\nBased on SA_kin = 1, here is a list of kinaesthetic activities:")
    kinaesthetic_activities = [
        "Using manipulatives to understand fractions",
        "Role-playing mathematical concepts",
        "Building 3D models with blocks",
        "Moving and acting out geometric transformations"
    ]
    for activity in kinaesthetic_activities:
        print(f"- {activity}")
elif student_profile.get("SA_kin") == 0:
    print("\nSA_kin is 0, so the kinaesthetic activities list is not displayed.")
else:
    print("\nSA_kin value not found or is not 0 or 1.")
```

```
        # Save the date of analysis
        data["last_analysis_date"] = datetime.now().isoformat()
        save_data(data)
        print(f"\nAnalysis date saved to sa_matr_data.json: {data['last_analysis_date']}")
    else:
        print("No student profile found in sa_matr_data.json. Please run update.py first.")
# End of code
```

```
# Python version 3.12 is successfully used to test this code on Mac 10.15.7
# Import necessary libraries
import random  # For generating random simulation data
import numpy as np  # For numerical operations, specifically mean and diff for
predictions
import json  # For outputting the results to a JSON file

# Define the main class for the Neuro-Synaptic Learning Environment (NSLE)
class NSLE:
    # Constructor to initialize the NSLE with available learning resources
    def __init__(self, resources):
        # Store the provided list of resource dictionaries
        self.resources = resources
        # Initialize student data as a dictionary
        self.student_data = {
            'code_completion_time': 0,  # Store a single simulated completion time
            'error_rate': 0,  # Store a single simulated error rate
            'exercise_score': 0,  # Store a single simulated exercise score
            'knowledge_retention': 0.8,  # Initial retention (0 to 1)
            'learning_rate': 0.1,  # Initial learning rate
        }

    # Method to simulate a student's activity on a learning task
    def simulate_student_activity(self):
        # Simulate student activity with some randomness
        # Generate a single random data point to simulate student performance
        self.student_data['code_completion_time'] = random.uniform(5, 20)  # Time in
minutes
        self.student_data['error_rate'] = random.uniform(0, 0.3)
        self.student_data['exercise_score'] = random.uniform(60, 100)

    # Method to predict the student's knowledge retention and learning rate
    # This uses a simplified model.
    def predict_knowledge_and_learning(self):
        # Simplified model
        # Use the current exercise score to predict knowledge retention
        self.student_data['knowledge_retention'] = self.student_data['exercise_score'] /
100.0
        self.student_data['learning_rate'] = 0.1  # Keep it simple for the first version

    # Method to adjust the difficulty of the learning content based on the student's
state
    def adjust_content(self, current_topic):
        # Adjust difficulty based on predicted knowledge
        difficulty = 1  # Default difficulty
        if self.student_data['knowledge_retention'] > 0.9:
```

```
            difficulty = 2  # Harder
        elif self.student_data['knowledge_retention'] < 0.7:
            difficulty = 0  # Easier

        # Find relevant resources based on topic and difficulty
        relevant_resources = [
            r for r in self.resources
            if current_topic in r['tags'] and r['difficulty'] == difficulty
        ]
        if relevant_resources:
            return random.choice(relevant_resources)
        else:
            return random.choice([r for r in self.resources if current_topic in r['tags']])

    # Method to generate a lesson plan based on a sequence of topics
    def generate_lesson_plan(self, topics):
        # Initialize an empty list to store the lesson plan steps
        lesson_plan = []
        # Iterate through each topic in the provided list
        for topic in topics:
            # Simulate student activity for the current topic
            self.simulate_student_activity()
            # Predict the student's knowledge and learning state
            self.predict_knowledge_and_learning()
            # Adjust the content difficulty and select a resource
            resource = self.adjust_content(topic)
            # Append the details of the current step to the lesson plan
            lesson_plan.append({
                'topic': topic,
                'resource': resource,  # The selected resource dictionary
                'student_data': self.student_data.copy()  # A copy of the student's data
            })
        # Return the complete generated lesson plan
        return lesson_plan

# Example Usage of the NSLE simulation
# Define a list of available learning resources
resources = [
    {'title': 'Basic Python Syntax', 'tags': ['Python', 'Basics'], 'difficulty': 0, 'content': 
'Textbook section on basic syntax.'},
    {'title': 'Loops in Python', 'tags': ['Python', 'Loops'], 'difficulty': 1, 'content': 'Teacher 
notes on for and while loops.'},
    {'title': 'Advanced Functions', 'tags': ['Python', 'Functions'], 'difficulty': 2, 'content': 
'Curriculum standard on advanced function concepts.'},
    {'title': 'Simple Variables', 'tags': ['Python', 'Basics'], 'difficulty': 0, 'content': 
'Textbook section on variables.'},
```

```
    {'title': 'List Comprehension', 'tags': ['Python', 'Loops'], 'difficulty': 2, 'content':
'Advanced list comprehension examples.'}]

# Create an instance of the NSLE with the defined resources
nsle = NSLE(resources)
# Define the sequence of topics the student will go through
topics = ['Basics', 'Loops', 'Functions', 'Basics', 'Loops']
# Generate the lesson plan by running the simulation for the given topics
lesson_plan = nsle.generate_lesson_plan(topics)

# Prepare data for outputting to a JSON file
output_data = {
    "simulation_title": "Adaptive Lesson Plan Simulation",
    "description": "This simulation demonstrates how the Neuro-Synaptic Learning
Environment (NSLE) adapts learning resources based on a simulated student's
progress through a series of topics.  This is a simplified version.",
    "lesson_plan": []  # Initialize an empty list to hold the formatted lesson plan details
}

# Populate the lesson plan data for the JSON output
for item in lesson_plan:
    formatted_student_data = {k: round(v, 2) if isinstance(v, (int, float)) else v for k, v in
item['student_data'].items()}
    analysis_text = f"For the topic of '{item['topic']}', the system presented the resource
'{item['resource']['title']}'.  The student's activity resulted in a code completion time of
{item['student_data']['code_completion_time']:.2f} minutes, an error rate of
{item['student_data']['error_rate']:.2f}, and an exercise score of
{item['student_data']['exercise_score']:.2f}. The predicted knowledge retention is
{item['student_data']['knowledge_retention']:.2f}, and the learning rate is
{item['student_data']['learning_rate']:.2f}."

    output_data["lesson_plan"].append({
        "topic": item['topic'],
        "resource_title": item['resource']['title'],
        "student_data": formatted_student_data,
        "analysis": analysis_text
    })
# Write to JSON file
with open("person_learn_1.json", "w") as outfile:
    json.dump(output_data, outfile, indent=4)
# Print a confirmation message
print("Output written to person_learn_1.json")
# End of code
```

APPENDIX AH

The Python code for revisited algorithm: person_learn_2.py

```
# person_learn_2.py - Revisited Algorithm for Adaptive Learning Environment
# Python version 3.12 is successfully used to test this code on Mac 10.15.7
# Import necessary libraries
import random
import numpy as np
import json

# Define a class to represent student learning data
# This encapsulates student-specific metrics and predicted states.
class StudentData:
    # Represents the learning data for a student.
    # Constructor to initialize student data with initial values
    def __init__(self, initial_retention=0.8, initial_learning_rate=0.1):
        self.completion_times = []
        self.error_rates = []
        self.exercise_scores = []
        self.knowledge_retention = initial_retention
        self.learning_rate = initial_learning_rate
    # Method to get a dictionary representation of the student data
    # Useful for serialization (e.g. to JSON)
    @property
    def _dict(self):
        return {
            'completion_times': self.completion_times,
            'error_rates': self.error_rates,
            'exercise_scores': self.exercise_scores,
            'knowledge_retention': self.knowledge_retention,
            'learning_rate': self.learning_rate,
        }
# Define a class to represent a learning resource
# This encapsulates resource details.
class LearningResource:
    # Represents a learning resource with a title, tags, difficulty, and content.
    # Constructor to initialize a learning resource
    def __init__(self, title, tags, difficulty, content):
        self.title = title
        self.tags = tags
        self.difficulty = difficulty
        self.content = content
    # Method to get a dictionary representation of the learning resource
    # Useful for serialization (e.g. to JSON)
    @property
    def _dict(self):
        return {
            'title': self.title,
            'tags': self.tags,
```

```
        'difficulty': self.difficulty,
        'content': self.content,
      }
# Define the main class for the Neuro-Synaptic Learning Environment (NSLE)
# This orchestrates the adaptive learning process.
class NSLE:
  # The Neuro-Synaptic Learning Environment for adaptive learning.
  # Constructor to initialize the NSLE with available learning resources
  # Resources are now instances of the LearningResource class.
  def __init__(self, resources):
    # Initializes the NSLE with a list of available learning resources.
    # Args:
    #
    #   resources (list): A list of dictionaries, each representing a learning resource
    #                 with 'title', 'tags', 'difficulty', and 'content' keys.
    # Create LearningResource objects from the input dictionaries
    self.resources = [LearningResource(**r) for r in resources]
    # Initialize student data using the StudentData class
    self.student_data = StudentData()
  # Method to simulate a student's activity on a learning task
  # This now updates the StudentData object.
  def simulate_student_activity(self):
    # Use the StudentData class
    # Simulates a student completing an activity, generating performance data.
    # Generate random data to simulate student performance
    completion_time = random.uniform(5, 20) # Time in minutes
    error_rate = random.uniform(0, 0.3)
    exercise_score = random.uniform(60, 100)
    # Append the simulated data to the student's records within the StudentData
object
    self.student_data.completion_times.append(completion_time)
    self.student_data.error_rates.append(error_rate)
    self.student_data.exercise_scores.append(exercise_score)
  # Method to predict the student's knowledge retention and learning rate
  # This updates the StudentData object's predicted states.
  def predict_knowledge_and_learning(self):
    # Predicts the student's knowledge retention and learning rate based on their
    # performance.
    # Check if there are at least 3 exercise scores to calculate a moving average
    if len(self.student_data.exercise_scores) >= 3:
      # Get the last 3 exercise scores from the StudentData object
      scores = self.student_data.exercise_scores[-3:]
      # Predict knowledge retention as the mean of the last 3 scores, scaled to 0-1
      self.student_data.knowledge_retention = np.mean(scores) / 100.0
      # Predict learning rate based on the mean difference between consecutive
scores
      self.student_data.learning_rate = np.diff(scores).mean() / 10.0
```

```
            # simple change in score.
        else:
            # If fewer than 3 scores, use the initial default values
            self.student_data.knowledge_retention = 0.8
            self.student_data.learning_rate = 0.1
    # Method to adjust the difficulty of the learning content based on the student's
state
    # This method now returns a LearningResource object or None.
    def adjust_content(self, current_topic):
        # Adjusts the difficulty of the learning resource based on the student's predicted
state.
        # Args:
        # current_topic (str): The current learning topic.
        # Returns: Learning Resource or None: The selected learning resource, or
None if no
        # suitable resource is found.
        # Default difficulty level
        difficulty = 1 # Default difficulty
        # Increase difficulty if student shows high knowledge retention and learning rate
        if self.student_data.knowledge_retention > 0.9 and
self.student_data.learning_rate > 0.5:
            difficulty = 2 # Harder
        # Decrease difficulty if student shows low knowledge retention or learning rate
        elif self.student_data.knowledge_retention < 0.7 or
self.student_data.learning_rate < 0.1:
            difficulty = 0 # Easier
        # Find relevant resources based on topic and difficulty
        relevant_resources = [
            r for r in self.resources
            if current_topic in r.tags and r.difficulty == difficulty
        ]
        # If relevant resources are found, return a randomly selected one
        if relevant_resources:
            return random.choice(relevant_resources)
        else:
            # If no difficulty match, return any resource matching the topic
            # If no resource matches the difficulty, look for any resource matching the
topic
            topic_resources = [r for r in self.resources if current_topic in r.tags]
            # Return a random topic-matching resource if found, otherwise return None
            # This is an enhancement: explicitly handles the case where no resource is
suitable.
            return random.choice(topic_resources) if topic_resources else None
    # Method to generate a lesson plan based on a sequence of topics
    # This now works with LearningResource and StudentData objects.
    def generate_lesson_plan(self, topics):
```

```
        # Generates a lesson plan by iterating through topics and selecting adaptive resources.
        # Args:
        # topics (list): A list of learning topics.
        # Returns: list: A list of dictionaries, each containing the topic, selected resource, and
        # student data at that stage.
        # Initialize an empty list to store the lesson plan steps
        lesson_plan =[]
        # Iterate through each topic in the provided list
        for topic in topics:
            # Simulate student activity for the current topic, updating StudentData object
            self.simulate_student_activity()
            # Predict the student's knowledge and learning state, updating StudentData object
            self.predict_knowledge_and_learning()
            # Adjust the content difficulty and select a resource (LearningResource object or None)
            resource = self.adjust_content(topic)
            # Append the details of the current step to the lesson plan
            lesson_plan.append({
                'topic': topic,
                'resource': resource._dict if resource else None, # Serialize Learning Resource object
                'student_data': self.student_data._dict.copy() # Use StudentData object's dict
            })
        # Return the complete generated lesson plan
        return lesson_plan
# Example Usage of the NSLE simulation (Revised)
# Define a list of available learning resources as dictionaries
resources = [
    {'title': 'Basic Python Syntax', 'tags': ['Python', 'Basics'], 'difficulty': 0, 'content': 'Textbook section on basic syntax.'},
    {'title': 'Loops in Python', 'tags': ['Python', 'Loops'], 'difficulty': 1, 'content': 'Teacher notes on for and while loops.'},
    {'title': 'Advanced Functions', 'tags': ['Python', 'Functions'], 'difficulty': 2, 'content': 'Curriculum standard on advanced function concepts.'},
    {'title': 'Simple Variables', 'tags': ['Python', 'Basics'], 'difficulty': 0, 'content': 'Textbook section on variables.'},
    {'title': 'List Comprehension', 'tags': ['Python', 'Loops'], 'difficulty': 2, 'content': 'Advanced list comprehension examples.'}
]
# Create an instance of the NSLE with the defined resources
# The NSLE constructor will convert these dictionaries into LearningResource objects.
nsle = NSLE(resources)
```

```python
# Define the sequence of topics the student will go through
topics = ['Basics', 'Loops', 'Functions', 'Basics', 'Loops']
# Generate the lesson plan by running the simulation for the given topics
lesson_plan = nsle.generate_lesson_plan(topics)
# Prepare data for outputting to a JSON file
output_data = {
    "simulation_title": "Adaptive Lesson Plan Simulation",
    "description": "This simulation demonstrates how the Neuro-Synaptic Learning Environment (NSLE) adapts learning resources based on a simulated student's progress through a series of topics. The system tracks the student's simulated code completion times, error rates, and exercise scores to predict their knowledge retention and learning rate. Based on these predictions, the system selects learning resources of varying difficulty levels.",
    "lesson_plan": []
}
# Populate the lesson plan data for the JSON output
for i, item in enumerate(lesson_plan):
    # Format student data for better readability in JSON
    # Format the student data for better readability in the JSON (rounding floats)
    formatted_student_data = {k: round(v, 2) if isinstance(v, (int, float)) else v for k, v in item['student_data'].items()}
    # Determine the resource title for the analysis, handling the case where no resource was found
    resource_title = item['resource']['title'] if item['resource'] else "No suitable resource found"
    # Generate a detailed analysis text for each step of the lesson plan
    analysis_text = f""
    if i == 0:
        analysis_text = f"For the topic of '{item['topic']}', the system presented the resource '{resource_title}'. The simulated student's first activity resulted in a code completion time of {item['student_data']['completion_times'][0]:.2f} minutes, an error rate of {item['student_data']['error_rates'][0]:.2f}, and an exercise score of {item['student_data']['exercise_scores'][0]:.2f}. At this stage, the predicted knowledge retention is the initial value of {item['student_data']['knowledge_retention']:.2f}, and the learning rate is {item['student_data']['learning_rate']:.2f}."
    elif i==1:
        analysis_text = f"Moving to the '{item['topic']}' topic, the system provided '{resource_title}'. The student's second simulated activity yielded a completion time of {item['student_data']['completion_times'][1]:.2f} minutes, an error rate of {item['student_data']['error_rates'][1]:.2f}, and an exercise score of {item['student_data']['exercise_scores'][1]:.2f}. The knowledge retention and learning rate predictions remain at their initial values as there haven't been enough exercise scores to calculate a moving average."
    elif i==2:
        analysis_text = f"For the '{item['topic']}' topic, the resource '{resource_title}' was selected. The third simulated activity resulted in a completion time of {item['student_data'] ['completion_times'][2]:.2f} minutes, an error rate of
```

```
{item['student_data']['error_rates'] [2]:.2f}, and an exercise score of
{item['student_data']['exercise_scores'][2]:.2f}. Still with fewer than three exercise
scores, the knowledge retention and learning rate remain at their initial values."
    elif i==3:
        analysis_text = f"Revisiting the '{item['topic']}' topic, the system presented
'{resource_title}' again. The fourth simulated activity showed a completion time of
{item['student_data']['completion_times'][3]:.2f} minutes, an error rate of
{item['student_data']['error_rates'][3]:.2f}, and an exercise score of
{item['student_data']['exercise_scores'][3]:.2f}. Now, with three previous scores, the
predicted knowledge retention has been updated to approximately
{item['student_data']['knowledge_retention']:.2f}, and the learning rate to
approximately {item['student_data']['learning_rate']:.2f}, reflecting the recent
performance."
    elif i==4:
        analysis_text = f"Finally, for the second encounter with the '{item['topic']}' topic,
the system selected '{resource_title}'. The fifth simulated activity resulted in a
completion time of {item['student_data']['completion_times'][4]:.2f} minutes, an error
rate of {item['student_data']['error_rates'][4]:.2f}, and an exercise score of
{item['student_data'] ['exercise_scores'][4]:.2f}. The predicted knowledge retention
has been updated to approximately {item['student_data']['knowledge_retention']:.2f},
and the learning rate to approximately {item['student_data']['learning_rate']:.2f},
indicating a recent change in performance."
    # Append the formatted step details to the output data's lesson plan list
    output_data[ "lesson_plan"].append({
        "topic": item['topic'],
        "resource title": resource_title,
        "student_data": formatted_student_data,
        "analysis": analysis_text
    })
#Write to JSON file
# Write the output data to a JSON file with indentation for readability
with open("person_learn_2.json", "w") as outfile:
    json.dump(output_data, outfile, indent=4)
# Print a confirmation message
print("Output written to person_learn_2.json")
# End of code
```

APPENDIX AI

The Python code for algorithm: 5_students_5_subjects.py

```
# Python version 3.12 is successfully used to test this code on Mac 10.15.7
import matplotlib.pyplot as plt
import random

class NSLEVisualized:
    def __init__(self, resources):
        self.resources = resources
        self.student_progress = {}
        self.resource_history = {}
        self.student_knowledge = {}

    def simulate_student_activity(self, student_id, time_spent):
        if student_id not in self.student_knowledge:
            self.student_knowledge[student_id] = 0.5  # Initial knowledge

        knowledge_change = random.uniform(-0.1, 0.2) * time_spent
        self.student_knowledge[student_id] = max(0, min(1,
self.student_knowledge[student_id] + knowledge_change))

        if student_id not in self.student_progress:
            self.student_progress[student_id] = {}
        self.student_progress[student_id][len(self.student_progress[student_id])] =
self.student_knowledge[student_id]

    def predict_knowledge_and_learning(self, student_id):
        if student_id not in self.student_progress:
            return 0.5  # Default if no progress

        progress_values = list(self.student_progress[student_id].values())
        if not progress_values:
            return 0.5

        return sum(progress_values) / len(progress_values)

    def adjust_content(self, student_id, topic):
        knowledge = self.predict_knowledge_and_learning(student_id)
        target_difficulty = int(knowledge * 10)  # Scale knowledge to difficulty

        available_resources = [r for r in self.resources if topic in r['tags']]

        # Find resource with closest difficulty
        best_resource = min(available_resources, key=lambda r: abs(r['difficulty'] -
target_difficulty), default=None)

        if best_resource is None:
```

```
            return None

        if student_id not in self.resource_history:
            self.resource_history[student_id] = []
        self.resource_history[student_id].append(best_resource)
        return best_resource

    def generate_lesson_plan(self, student_id, topic):
        print(f"\nLesson Plan for Student {student_id} (Topic: {topic}):")
        for _ in range(5):  # 5 resources per lesson
            resource = self.adjust_content(student_id, topic)
            if resource:
                print(f"- Resource: {resource['name']} (Difficulty: {resource['difficulty']})")
                self.simulate_student_activity(student_id, random.uniform(0.5, 2))
# Simulate activity
            else:
                print("- No suitable resources found.")
        self.visualize_student_progress(student_id)
        self.visualize_difficulty_adjustment(student_id)

    def visualize_student_progress(self, student_id):
        if student_id not in self.student_progress:
            return

        time_points = list(self.student_progress[student_id].keys())
        scores = list(self.student_progress[student_id].values())

        plt.figure()  # creates new figure for each student.
        plt.plot(time_points, scores, marker='o')
        plt.xlabel('Lesson Number')
        plt.ylabel('Knowledge Level')
        plt.title(f'Student {student_id} Progress')
        plt.grid(True)
        plt.show()

    def visualize_difficulty_adjustment(self, student_id):
        if student_id not in self.resource_history:
            return

        resource_names = [item['name'] for item in self.resource_history[student_id]]
        difficulties = [item['difficulty'] for item in self.resource_history[student_id]]

        plt.figure()  # creates new figure for each student.
        plt.bar(resource_names, difficulties)
        plt.xlabel('Resources')
        plt.ylabel('Difficulty')
        plt.title(f'Resource Difficulty Adjustment for Student {student_id}')
```

```
        plt.xticks(rotation=45, ha='right')
        plt.tight_layout()
        plt.show()

# Example Usage
resources = [
    {'name': 'Intro to Mathematics', 'difficulty': 1, 'tags': ['Mathematics', 'Beginner']},
    {'name': 'Algebra Basics', 'difficulty': 3, 'tags': ['Mathematics', 'Intermediate']},
    {'name': 'Calculus', 'difficulty': 5, 'tags': ['Mathematics', 'Advanced']},
    {'name': 'Intro to Biology', 'difficulty': 2, 'tags': ['Biology', 'Beginner']},
    {'name': 'Cell Structure', 'difficulty': 4, 'tags': ['Biology', 'Intermediate']},
    {'name': 'Genetics', 'difficulty': 6, 'tags': ['Biology', 'Advanced']},
    {'name': 'Intro to Chemistry', 'difficulty': 1, 'tags': ['Chemistry', 'Beginner']},
    {'name': 'Chemical Bonds', 'difficulty': 3, 'tags': ['Chemistry', 'Intermediate']},
    {'name': 'Organic Chemistry', 'difficulty': 7, 'tags': ['Chemistry', 'Advanced']},
    {'name': 'World Geography', 'difficulty': 2, 'tags': ['Geography', 'Beginner']},
    {'name': 'Human Geography', 'difficulty': 4, 'tags': ['Geography', 'Intermediate']},
    {'name': 'Economic Systems', 'difficulty': 5, 'tags': ['Economics', 'Intermediate']},
    {'name': 'Microeconomics', 'difficulty': 6, 'tags': ['Economics', 'Advanced']},
    {'name': 'Macroeconomics', 'difficulty': 8, 'tags': ['Economics', 'Advanced']},
]

nsle = NSLEVisualized(resources)

# Define students and their subjects
students = {
    'student1': 'Mathematics',
    'student2': 'Biology',
    'student3': 'Chemistry',
    'student4': 'Geography',
    'student5': 'Economics',
}

# Generate lesson plans for each student
for student, subject in students.items():
    nsle.generate_lesson_plan(student, subject)
# End of code
```

APPENDIX AJ

The focus group instructional document for reproducible testing.

Neuro-synaptic Learning Environments: A Holistic AI-Powered Education Ecosystem

By Jan Hendrik van Niekerk

Focus group reproducible exercise

Thank you for your participation in this reproducible exercise for my PhD research. Your time and effort in completing the following activities and providing your results are greatly appreciated. Your input is invaluable to this study.
Please note that the activities involve copying and pasting code into text documents, saving these documents, and subsequently executing the code. The first activity will be conducted within your web browser, while the remaining activities require the use of Python 3.12. Please use the tick boxes for your own record of completing the activities, step by step. The appendices below provide the required code for the activities.
Take your time with the activities and send me the results when you completed all activities. Once again, thank you very much.

APPENDIX K
The Javascript code to generate simulated choices for self-assessment questionnaires.

APPENDIX AA
The Python code: sa_write.py

APPENDIX AB
The Python code: sa_read.py

APPENDIX AC
The Python code: sa_update.py

APPENDIX AD
The Python code: sa_session1.py

APPENDIX AE
The Python code: sa_matr_update.py

APPENDIX AF
The Python code: sa_matr_learning_material_selection.py

APPENDIX AG
The Python code: person_learn_1.py

APPENDIX AH
The Python code: person_learn_2.py

APPENDIX AI
The Python code: 5_students_5_subjects.py

Activity 1	**Complete**	
	Yes	**No**
Open any new text document and save it as ***code.doc*** or ***code.txt*** or ***code.docx*** on your computer. You will be asked to save the results of the activities in this document, before sending it to me.		

Activity 2	**Complete**	
	Yes	**No**
Copy and paste the code in ***Appendix K*** to a new text document. (Any of these will do: TextEdit, Notes, doc, docx). The code starts with: <!DOCTYPE html> The code ends with: // End of code		
Save the file as: ***random.html*** on your computer.		
Double click on the ***random.html*** file to open it in your web browser.		
Copy and paste the text from your browser into your ***code*** document.		
If you saved the original code document as a html file and cannot open it, right-click on the file and select ‘Open with’. Then select a text base option from the list to open the document.		
Refresh your browser, copy and paste the text ten times.		
APPENDIX K		

Activity 3	**Complete**	
	Yes	**No**
Open and change the code in the ***random.html*** text document as below:		
Change the '12' in the code to '40' at two locations indicated by: // Q_12		
Substitute the code in the line identified by // Op_4 with the code in the line identified by: // Op_5.		
Substitute the code in the line identified by // Op_ad with the code in the line identified by: // Op_ae.		
Substitute the code in the line identified by // Op_ad0 with the code in the line identified by: // Op_ae0.		
Save the file as: ***random.html*** on your computer.		
Double click on the ***random.html*** file to open it in your web browser.		
Copy and paste the text from your browser into your ***code*** document.		
Refresh your browser, copy and paste the text ten times.		

Activity 4	**Complete**	
	Yes	**No**
Open the Python interpreter on your computer.		
Copy and paste the Python code from ***Appendix AA*** into a new script.		
Save the file as: ***sa_write.py*** to your computer and execute the code.		
You should receive the following message: *The values of all variables have been saved to sa_data.json within the 'student_profile' key.*		
Confirm that you generated a message, similar to the one above.		
Copy this message into your ***code*** document.		
Confirm the creation of a file ***sa_data.json***		
APPENDIX AA		

Activity 5	**Complete**	
	Yes	**No**
Open the Python interpreter on your computer.		
Copy and paste the Python code from ***Appendix AB*** into a new script.		
Save the script as: ***sa_read.py*** to your computer and execute the code.		
You should receive the following message and list: *Student profile from sa_data.json:* *student_id: S1001* *full_name: EV* *age: 18* *major: Mathematics* *Year 11 result: 0.83* *SA_ct: 1* *SA_attn: 0* *SA_ml: 0* *SA_ps: 0* *SA_r_ctpr: 1* *SA_a: 1* *SA_v: 1* *SA_h: 0* *SA_kin: 0* *SA_n: 0* *VR / AR: 1* *SA_anx: 1* *SA_w: 1* *SA_conman: 1* *SA_ts_chalem: 1* *SA_senpro: 1* *SA_int_ar: 1*		
Confirm that you generated a list, similar to the one above.		
Copy this list into your ***code*** document.		
APPENDIX AB		

Activity 6	**Complete**	
	Yes	**No**

Open the Python interpreter on your computer.		
Copy and paste the Python code from ***Appendix AC*** into a new script.		
Save the script as: ***sa_update.py*** to your computer and execute the code.		
You should receive the following message and list: *Current values:* *- student_id: S1001* *- full_name: EV* *- age: 18* *- major: Mathematics* *- Year 11 result: 0.83* *- SA_ct: 1* *- SA_attn: 0* *- SA_ml: 0* *- SA_ps: 0* *- SA_r_ctpr: 1* ***- SA_a: 1*** *# You only change this value to a ‘1’ or a ‘0’.* ***- SA_v: 1*** *# You only change this value to a ‘1’ or a ‘0’.* ***- SA_h: 0*** *# You only change this value to a ‘1’ or a ‘0’.* ***- SA_kin: 0*** *# You only change this value to a ‘1’ or a ‘0’.* ***- SA_n: 0*** *# You only change this value to a ‘1’ or a ‘0’.* *- VR / AR: 1* *- SA_anx: 1* *- SA_w: 1* *- SA_conman: 1* *- SA_ts_chalem: 1* *- SA_senpro: 1* *- SA_int_ar: 1* *Enter the name of the field you want to update (or type 'done' to finish):*		
Enter the variable on its own, as follows: *Enter the name of the field you want to update (or type 'done' to finish):* SA_a Then enter the value, either ‘1’ or ‘0’. *Enter the new value for 'SA_a':* 0 'SA_a' updated to: 0 Type the word ‘done’ to exit. Enter the name of the field you want to update (or type 'done' to finish): done		

Activity 6	Complete	
Repeat the procedure by changing the values of the following variables to either '1' or '0': *- SA_a: 1* *- SA_v: 1* *- SA_h: 0* *- SA_kin: 0* *- SA_n: 0*		
Copy the message of confirmation ***'SA_a' updated to: 0*** for each variable into your ***code*** document.		
Execute the following script: ***sa_read.py*** once again.		
You should receive the updated list, including your changes: *Student profile from sa_data.json:* *student_id: S1001* *full_name: EV* *age: 18* *major: Mathematics* *Year 11 result: 0.83* *SA_ct: 1* *SA_attn: 0* *SA_ml: 0* *SA_ps: 0* *SA_r_ctpr: 1* ***SA_a: 0*** *# The changes you made will be here.* ***SA_v: 0*** *# The changes you made will be here.* ***SA_h: 1*** *# The changes you made will be here.* ***SA_kin: 1*** *# The changes you made will be here.* ***SA_n: 1*** *# The changes you made will be here.* *VR / AR: 1* *SA_anx: 1* *SA_w: 1* *SA_conman: 1* *SA_ts_chalem: 1* *SA_senpro: 1* *SA_int_ar: 1*		
Confirm that you generated a list, similar to the one above.		
Copy this list into your ***code*** document.		
APPENDIX AC		

Activity 7	Complete

	Yes	No
Open the Python interpreter on your computer.		
Copy and paste the Python code from ***Appendix AD*** into a new script.		
Save the script as: ***sa_session1.py*** to your computer and execute the code.		
You should receive the following list: *You revise now Integration and Areas.* *All variables from sa_data.json:* *student_profile: {'student_id': 'S1001', 'full_name': 'EV', 'age': 18, 'major': 'Mathematics', 'Year 11 result': 0.83, 'SA_ct': 1, 'SA_attn': 0, 'SA_ml': 0, 'SA_ps': 0, 'SA_r_ctpr': 1, 'SA_a': 1, 'SA_v': 1, 'SA_h': 0, 'SA_kin': 0, 'SA_n': 0, 'VR / AR': 1, 'SA_anx': 1, 'SA_w': 1, 'SA_conman': 1, 'SA_ts_chalem': 1, 'SA_senpro': 1, 'SA_int_ar': 1}*		
Confirm that you generated a list, similar to the one above.		
Copy this list into your ***code*** document.		
APPENDIX AD		

Activity 8		**Complete**	
		Yes	**No**
Open the Python interpreter on your computer.			
Copy and paste the Python code from ***Appendix AE*** into a new script.			
Save the script as: ***sa_ matr_update.py*** to your computer and execute the code.			
You should receive the following list:			
--- Reading from sa_data.json --- *Student Profile:* *student_id: S1001* *full_name: EV* *age: 18* *major: Mathematics* *Year 11 result: 0.83* *SA_ct: 1* *SA_attn: 0* *SA_ml: 0* *SA_ps: 0* *SA_r_ctpr: 1* *SA_a: 1*	*SA_v: 1* *SA_h: 0* *SA_kin: 0* *SA_n: 0* *VR / AR: 1* *SA_anx: 1* *SA_w: 1* *SA_conman: 1* *SA_ts_chalem: 1* *SA_senpro: 1* *SA_int_ar: 1*		
--- Writing to sa_matr_data.json ---			

Warning: File 'sa_matr_data.json' not found. Creating a new data structure. *Student preferences and learning materials updated and saved to 'sa_matr_data.json'*		
Execute the same code for a second time.		
You should receive the following list: *--- Reading from sa_data.json ---* *Student Profile:* *student_id: S1001* *full_name: EV* *age: 18* *major: Mathematics* *Year 11 result: 0.83* *SA_ct: 1* *SA_attn: 0* *SA_ml: 0* *SA_ps: 0* *SA_r_ctpr: 1* *SA_a: 1* *SA_v: 1* *SA_h: 0* *SA_kin: 0* *SA_n: 0* *VR / AR: 1* *SA_anx: 1* *SA_w: 1* *SA_conman: 1* *SA_ts_chalem: 1* *SA_senpro: 1* *SA_int_ar: 1* *--- Writing to sa_matr_data.json ---* *Student preferences and learning materials updated and saved to 'sa_matr_data.json'*		
Confirm that you generated a list, similar to the one above.		
Copy this list into your ***code*** document.		
Confirm the creation of a file ***sa_matr_data.json***		
APPENDIX AE		

Activity 9	Complete

	Yes	No
Open the Python interpreter on your computer.		
Copy and paste the Python code from ***Appendix AF*** into a new script.		
Save the script as: ***sa_matr_learning_material_selection.py*** to your computer and execute the code.		
You should receive the following list: *For EV, the following learning materials are recommended:* *- Calculus Explained Visually* *- Interactive Algebra Practice* *- Abstract Math Concepts (Text-based)* *- Geometry VR Experience* *- Statistics Problem Solving* *- Mathematical Proofs (Auditory)* *SA_n is 0, so the book list is not displayed.* *Based on SA_v = 1, here is a list of videos:* *- Visual Introduction to Calculus* *- The Beauty of Fractals* *- Understanding Quantum Mechanics* *- History of Mathematics* *Based on SA_a = 1, here is a list of auditory materials:* *- Mathematics Lectures Podcast* *- Audiobook: A History of Pi* *- Learning Algebra Through Sound* *- Theorems Explained (Audio)* *SA_h is 0, so the hands-on activities list is not displayed.* *SA_kin is 0, so the kinaesthetic activities list is not displayed.* *Analysis date saved to sa_matr_data.json: 2025-05-07T10:42:38.599567*		
Confirm that you generated a list, similar to the one above.		
Copy this list into your ***code*** document.		
APPENDIX AF		

Activity 10	Complete	
	Yes	No
Open the Python interpreter on your computer.		
Copy and paste the Python code from ***Appendix AG*** into a new script.		
Save the script as: ***person_learn_1.py*** to your computer and execute the code.		
You should receive the following message: *Output written to person_learn_1.json*		
Confirm that you generated a list, similar to the one above.		
Copy this list into your code document.		
Confirm the creation of a file ***person_learn_1.json***		
APPENDIX AG		

Activity 11	Complete	
	Yes	No
Open the Python interpreter on your computer.		
Copy and paste the Python code from ***Appendix AH*** into a new script.		
Save the script as: ***person_learn_2.py*** to your computer and execute the code.		
You should receive the following message: *Output written to person_learn_2.json*		
Confirm that you generated a list, similar to the one above.		
Copy this list into your code document.		
Confirm the creation of a file ***person_learn_2.json***		
APPENDIX AH		

Activity 12	Complete	
	Yes	No
Open the Python interpreter on your computer.		
Copy and paste the Python code from ***Appendix AI*** into a new script.		
Save the script as: ***5_students_5_subjects.py*** to your computer and execute the code.		
You should receive a message and an image. Copy and paste the message and the image into the code document. Close the image window for a second image to appear. Copy and paste the second image into your code document. Repeat this process with all five messages and ten images.		
Confirm that you generated five messages and ten images.		
APPENDIX AI		

This is the end of the focus group activities.

A collection of test metrics to determine the effectiveness of the NSLE algorithms.

Normalised Discounted Cumulative Gain (NDCG)

What is the purpose:

After the implementation of the NSLE, my concern is to know if the AI algorithms are effective at recommending personalised learning materials. The NDCG is a powerful test metric because it evaluates not just the relevance of the recommendations, but also their order. Highly relevant items appearing earlier in the list are weighted more heavily in the score. This is critical because students are far more likely to engage with the initial suggestions they see. Therefore, a strong NDCG score indicates that the AI algorithm identifies the relevant resources and also prioritising and presenting them in the most impactful way for student engagement. Below is an example of NDCG within an educational context.

Evaluating a Personalised Learning Resource Recommender System
Imagine the NSLE is implemented in a High School. This platform aims to recommend academic articles or learning modules based on a student's current learning goals and previous interactions. You want to evaluate how well your recommender system (let's call it "EduRanker") performs.

The Scenario:
Student A, is studying "A Level Mathematics" and inputs this as their learning goal into EduRanker. The system returns a ranked list of 5 academic articles, tabulated below.. As the researcher, you have manually assessed the true relevance of these articles for Student A's learning goal on the following graded scale.

Relevance Scale:

i. 3: Highly relevant (e.g., a book addressing the current details)
ii. 2: Moderately relevant (e.g., a good note, but not clear)
iii. 1: Slightly relevant (e.g., factsheet with some context)
iv. 0: Irrelevant (e.g., outdated notes)

Data:
Here's the ranked list returned by EduRanker and their corresponding true relevance scores:

Rank (Position i)	**Article Recommended by EduRanker**	**True Relevance (rel_i)**
1	Article A (Differentiation)	2
2	Article B (Integration)	3
3	Article C (Logarithms and Exponents)	0
4	Article D (Series and Sequences)	1
5	Article E (Binomial Expansion)	2

Step-by-Step Calculation of NDCG@5:

NDCG is calculated using two main components: Discounted Cumulative Gain (DCG) and Ideal Discounted Cumulative Gain (IDCG).

Formula Overview:

- DCG: $DCG_p = \sum_{i=1}^{p} \frac{rel_i}{\log_2(i + 1)}$
- IDCG: $IDCG_p = \sum_{i=1}^{p} \frac{rel_{i_{ideal}}}{\log_2(i + 1)}$
- NDCG: $NDCG_p = \frac{DCG_p}{IDCG_p}$

Where:

- p is the position (or K for NDCG@K)
- rel_i is the relevance score of the item at position i in the actual ranked list.
- $rel_{i_{ideal}}$ is the relevance score of the item at position i in the ideal ranked list (sorted by relevance in descending order).
- $\log_2(i+1)$ is the discount factor. This penalises relevant items that appear lower in the list. Note that for $i=1$, $\log_2(1+1) = \log_2(2) = 1$, so there's no discount for the top item.

1. Calculate Discounted Cumulative Gain (DCG) for EduRanker's List:

This measures the quality of the actual ranking.

- Article A (Rank 1, Relevance 2): $\frac{2}{\log_2(1+1)} = \frac{2}{\log_2(2)} = \frac{2}{1} = 2.00$
- Article B (Rank 2, Relevance 3): $\frac{3}{\log_2(2+1)} = \frac{3}{\log_2(3)} \approx \frac{3}{1.58} = 1.89$
- Article C (Rank 3, Relevance 0): $\frac{0}{\log_2(3+1)} = \frac{0}{\log_2(4)} = \frac{0}{2} = 0.00$
- Article D (Rank 4, Relevance 1): $\frac{1}{\log_2(4+1)} = \frac{1}{\log_2(5)} \approx \frac{1}{2.32} = 0.43$
- Article E (Rank 5, Relevance 2): $\frac{2}{\log_2(5+1)} = \frac{2}{\log_2(6)} \approx \frac{2}{2.58} = 0.77$

DCG@5 = 2.00 + 1.89 + 0.00 + 0.43 + 0.77 = 5.09

2. Calculate Ideal Discounted Cumulative Gain (IDCG):

This represents the perfect possible ranking for Student A's query. First, sort the true relevance scores in descending order:

- Original scores: [2, 3, 0, 1, 2]
- Ideal sorted scores: [3, 2, 2, 1, 0]

Now, calculate DCG using these ideal scores:

Ideal Rank (i)	**Article (by ideal relevance)**	**True Relevance (rel_i)**	**Calculation**
1	Most Relevant	3	$\frac{3}{\log_2(1+1)} = \frac{3}{1} = 3.00$
2	Next Most Relevant	2	$\frac{2}{\log_2(2+1)} \approx \frac{2}{1.58} = 1.26$
3	Next Most Relevant	2	$\frac{2}{\log_2(3+1)} = \frac{2}{2} = 1.00$

4	Next Most Relevant	1	$\frac{1}{\log_2(4+1)} \approx \frac{1}{2.32} = 0.43$
5	Least Relevant	0	$\frac{0}{\log_2(5+1)} = \frac{0}{2.58} = 0.00$

IDCG@5 = 3.00 + 1.26 + 1.00 + 0.43 + 0.00 = 5.69

3. Calculate Normalised Discounted Cumulative Gain (NDCG@5):
Now, normalize the DCG by dividing it by the IDCG.
$NDCG@5 = \frac{DCG@5}{IDCG@5} = \frac{5.09}{5.69} \approx 0.89$

Interpretation:
"For Student A's 'A Level Mathematics' query, our EduRanker system achieved an NDCG@5 score of approximately 0.89.

- An NDCG score is always between 0 and 1.
- 1 means the ranking is perfectly ordered according to relevance (i.e., identical to the ideal ranking).
- 0 means there are no relevant items in the list.

Our score of 0.89 is quite good! It indicates that EduRanker is placing highly relevant articles towards the top of its recommendations, even though it didn't achieve the perfect ideal order (Article B was truly more relevant than Article A, but EduRanker put Article A at rank 1, incurring a slight penalty. Also, the irrelevant Article C at rank 3 hurt the score). This shows the system is generally effective at prioritising useful resources for students."

Why NDCG is suitable for your education research:

i. Graded Relevance: Unlike binary metrics (like Precision or Recall), NDCG allows for different levels of relevance (e.g., "highly relevant" vs. "somewhat relevant"), which is crucial for nuanced evaluation of learning resources.
ii. Position Sensitivity: It prioritises placing the most relevant items at the top, reflecting that students are more likely to engage with the first few recommendations. An irrelevant item at rank 1 is penalised much more heavily than an irrelevant item at rank 5.
iii. Comparability: Because it's normalised, you can compare NDCG scores across different students, different learning goals, or even different versions of your recommender system, even if the total number of relevant items or their relevance distributions vary. This is powerful for research.

This detailed example with a direct application to education should provide a clear and concrete demonstration of NDCG.

The following Python code is developed to calculate the values of the variables in the above explanatoion:

```
# Python 3.12 code to determine the NDCG, explained in Appendix AK
```

```
# Student A studies A Level Mathematics
# The Relevance Scale is assigned as follows:
#    3: Highly relevant
#    2: Moderately relevant
#    1: Slightly relevant
#    0: Irrelevant

# Here's the ranked list returned by EduRanker and corresponding true relevance
# Rank (Position I)   Article Recommended by EduRanker     True Relevance (rel_i)
#       1                     Article A   (Differentiation)                   2
#       2                     Article B   (Integration)                       3
#       3                     Article C   (Logarithms and Exponents)          0
#       4                     Article D   (Series and Sequences)              1
#       5                     Article E   (Binomial Expansion)                2

import numpy as np
def calculate_dcg(relevances, p):

#    Calculates DCG@p for a given list of relevances.
#    Args:
#        relevances (list): A list of relevance scores, ordered by rank.
#                           (e.g., [rel_1, rel_2, ..., rel_p])
#        p (int): The number of items to consider (K in NDCG@K).
#    Returns:
#        float: The DCG score.

    dcg = 0.0
    for i in range(p):
        if i < len(relevances):
# Ensure we don't go out of bounds if p > len(relevances)
            rel = relevances[i]
            # The rank is (i + 1) since i is 0-indexed.
            # So the denominator for rank 1 (index 0) is log2(1+1) = log2(2)
            # For rank 2 (index 1) is log2(2+1) = log2(3)
            dcg += rel / np.log2(i + 2)
# i + 2 because rank starts at 1, so log2(rank + 1)
    return dcg

def calculate_ndcg(actual_relevances, p):

#    Calculates NDCG@p for a given list of actual relevances.
#    Args:
#        actual_relevances (list): A list of relevance scores for the actual ranking.
#        p (int): The number of items to consider (K in NDCG@K).
#    Returns:
#        float: The NDCG score.
```

```
    # 1. Calculate DCG for the actual ranking
    dcg = calculate_dcg(actual_relevances, p)

    # 2. Calculate IDCG for the ideal ranking
    # First, sort the actual relevances in descending order to get the ideal order
    ideal_relevances = sorted(actual_relevances, reverse=True)
    idcg = calculate_dcg(ideal_relevances, p)

    # 3. Calculate NDCG
    if idcg == 0:
        # This handles the case where there are no relevant items in the list,
        # preventing division by zero. NDCG is 0 if IDCG is 0.
        return 0.0
    else:
        ndcg = dcg / idcg
        return ndcg

# --- Our Example Data ---
# Relevance scores for Article A, B, C, D, E at ranks 1, 2, 3, 4, 5 respectively
# (based on EduRanker's output)
actual_relevance_scores = [2, 3, 0, 1, 2]

# The number of items we want to consider for NDCG (NDCG@5)
p_value = 5

# --- Perform Calculations ---
# Calculate and print DCG for the actual list
actual_dcg_result = calculate_dcg(actual_relevance_scores,
p_value)
print(f"DCG@{p_value} (Actual List): {actual_dcg_result:.2f}")

# Calculate and print IDCG (by sorting the actual relevances to get the ideal order)
ideal_dcg_result = calculate_dcg(sorted(actual_relevance_scores,
reverse=True), p_value)
print(f"IDCG@{p_value} (Ideal List): {ideal_dcg_result:.2f}")

# Calculate and print NDCG
ndcg_at_5_result = calculate_ndcg(actual_relevance_scores,
p_value)
print(f"NDCG@{p_value}: {ndcg_at_5_result:.2f}")

# Result: DCG@5 (Actual List): 5.10, IDCG@5 (Ideal List): 5.69, NDCG@5: 0.90
```

APPENDIX AL

The following procedure explains how to bring the gamified learning concept to life. Here's a structured outline that can be adapted and expanded upon to contain the purpose, goal and details of your game.

Chapter [Number]: Gamified Learning Environment for “Subject field”

[Section Number]: Game Overview

[Subsection Number]: Title: Game Title

[Subsection Number]: Introduction:

- Briefly introduce the rationale for developing a gamified learning environment for the chosen subject(s).
- State the primary learning objectives the game aims to achieve.
- Highlight the innovative aspects of the game design, including AI integration (if applicable), role-playing, and deep integration of subject matter.

[Subsection Number]: Target Audience:

- Specify the intended learners (e.g. high school students, undergraduate students, specific learning levels).

[Subsection Number]: Learning Objectives:

- Clearly list the specific mathematical and/or physical concepts the game is designed to teach and reinforce. These should be measurable and aligned with relevant educational standards (if applicable).

[Section Number]: Core Game Mechanics and Design

[Subsection Number]: Core Gameplay Loop:

- Describe the fundamental cycle of player interaction within the game (e.g. exploration -> quest -> challenge -> reward -> progression).

[Subsection Number]: Character Roles and Attributes:

- Detail the available character roles (Engineer, Scientist, Magician, etc.).
- Explain the specific mathematical and physical strengths associated with each role.
- Describe the attribute system (Precision, Insight, etc.) and how these relate to specific skills and in-game actions.

[Subsection Number]: Skill Tree and Progression:

- Illustrate and explain the branching skill tree, highlighting the interconnectedness of mathematical and physical topics.
- Describe how experience points (XP) are earned and how they are used to progress through the skill tree.

[Subsection Number]: Quest-Based Learning:

- Provide examples of different quest types (research, experimental design, collaborative) and how they engage students with the subject matter.

Explain the learning objectives embedded within these quests.

[Subsection Number]: Turn-Based Combat System:

Detail the mechanics of the combat system.

Explain how mathematical and physical principles (resource management, tactical decisions, science-based special abilities) are applied within combat.

[Subsection Number]: In-Game Encyclopedia:

Describe the content and accessibility of the in-game encyclopedia (scientific explanations, biographies, real-world examples).

Explain how this resource provides on-demand learning support.

[Subsection Number]: Engaging Mini-Games:

Provide examples of mini-games (rocket launching, circuit builder, etc.) and the specific math/physics concepts they reinforce.

Explain how these mini-games are integrated into the overall gameplay.

[Subsection Number]: Interactive Data Visualizations:

Describe how interactive data visualizations are used to help students understand complex datasets and scientific phenomena.

Provide examples of the types of visualizations included.

[Subsection Number]: Student-Created Content:

Explain the tools and opportunities for students to create their own in-game content (puzzles, stories).

Discuss the pedagogical benefits of this feature in demonstrating understanding.

[Subsection Number]: Collaborative Projects:

Describe the structure and goals of collaborative projects within the game.

Highlight how these projects foster teamwork, communication, and subject knowledge application.

[Section Number]: AI Integration (If Applicable)

[Subsection Number]: AI for Interactive Simulations:

Detail how AI is used to create dynamic and responsive simulations within the game (e.g. procedural generation of puzzles, adaptive challenges).

[Subsection Number]: AI for Personalised Learning:

Explain how AI might be used to adapt the game experience to individual student needs, track progress, and provide tailored feedback.

[Section Number]: Assessment and Learning Outcomes

[Subsection Number]: In-Game Assessment Metrics.

Describe the specific in-game actions and achievements that will be tracked to assess student learning (problem-solving strategies, quest completion, mini-game performance, etc.).

Explain how these metrics align with the stated learning objectives.

[Subsection Number]: Potential for Formative and Summative Assessment:

Discuss how the game can provide both ongoing feedback to students (formative assessment) and contribute to a broader evaluation of their understanding (summative assessment).

[Section Number]: User Interface and User Experience (UI/UX)

[Subsection Number]: Interface Design:

Provide a conceptual overview or mockups (if available) of the game's interface, highlighting key elements and their functionality (e.g. inventory, skill tree, encyclopedia access).

Explain the design principles guiding the UI to ensure clarity and ease of use.

[Subsection Number]: User Experience Considerations:

Discuss how the game is designed to be engaging, motivating, and accessible to the target audience.

Address potential challenges and how the design aims to mitigate them (e.g. learning curve, frustration).

[Section Number]: Potential for Implementation and Evaluation

[Subsection Number]: Technology Stack (Planned):

Outline the intended game development engine, programming languages, and any other relevant technologies for bringing the game to life.

[Subsection Number]: Future Evaluation and Research:

Briefly discuss your plans for evaluating the effectiveness of the game as a learning tool within your PhD research. This might include planned studies, data collection methods, and research questions.

[Section Number]: Conclusion

Summarize the key features and potential benefits of the proposed gamified learning environment.

Reiterate the contribution of this work to the field of “Topic field” and the potential impact on student learning.

Appendices (Optional):

Concept art or mockups

Detailed flowcharts of game mechanics

Examples of puzzle designs or quest narratives

BIBLIOGRAPHY

Aberšek, B., 2017. Cognitive science in education and alternative teaching strategies. Cambridge Scholars Publishing.

Ahmad, S.F., Rahmat, M.K., Mubarik, M.S., Alam, M.M. and Hyder, S.I., 2021. Artificial intelligence and its role in education. Sustainability, 13(22), p.12902.

Akgun, S. and Greenhow, C., 2022. Artificial intelligence in education: Addressing ethical challenges in K-12 settings. AI and Ethics, 2(3), pp.431-440.

Akintayo, O.T., Eden, C.A., Ayeni, O.O. and Onyebuchi, N.C., 2024. Integrating AI with emotional and social learning in primary education: Developing a holistic adaptive learning ecosystem. Computer Science & IT Research Journal, 5(5), pp.1076-1089.

Akter, S., McCarthy, G., Sajib, S., Michael, K., Dwivedi, Y.K., D'Ambra, J. and Shen, K.N., 2021. Algorithmic bias in data-driven innovation in the age of AI. International Journal of Information Management, 60, p.102387.

Alam, A., 2023, June. Intelligence unleashed: An argument for AI-enabled learning ecologies with real world examples of today and a peek into the future. In *AIP Conference Proceedings* (Vol. 2717, No. 1). AIP Publishing.

Alfredo, R., Echeverria, V., Jin, Y., Yan, L., Swiecki, Z., Gašević, D. and Martinez-Maldonado, R., 2024. Human-centred learning analytics and AI in education: A systematic literature review. Computers and Education: Artificial Intelligence, p.100215.

Alkan, A., 2024. The Role of Artificial Intelligence in the Education of Students with Special Needs. International Journal of Technology in Education and Science, 8(4), pp.542-557.

Almalki, S., 2016. Integrating Quantitative and Qualitative Data in Mixed Methods Research--Challenges and Benefits. Journal of education and learning, 5(3), pp.288-296.

Amineh, R.J. and Asl, H.D., 2015. Review of constructivism and social constructivism. Journal of social sciences, literature and languages, 1(1), pp.9-16.

Ananyi, S.O. and Somieari-Pepple, E., 2023. Cost-benefit analysis of artificial intelligence integration in education management: Leadership perspectives. International Journal of Economics Environmental Development and Society, 4(3), pp.353-370.

Anderson, J.R., 2000. Learning and memory: An integrated approach. John Wiley & Sons Inc.

Alasgarova, R. and Rzayev, J., 2024. The Role of Artificial Intelligence in Shaping High School Students' Motivation. International Journal of Technology in Education and Science, 8(2), pp.311-324.

Al-Shammari, Z., 2011. Assessment of student learning outcomes: Indicators of strengths and weaknesses. In ICERI2011 Proceedings (pp. 4228-4230). IATED.

AlGerafi, M.A., Zhou, Y., Oubibi, M. and Wijaya, T.T., 2023. Unlocking the potential: A comprehensive evaluation of augmented reality and virtual reality in education. Electronics, 12(18), p.3953.

Alsawaier, R.S., 2018. The effect of gamification on motivation and engagement. The International Journal of Information and Learning Technology, 35(1), pp.56-79.

Alyammahi, A., 2020. Investigating the Impact of AI-Powered Digital Educational Platforms on Students' Learning and Teachers' Practice in Abu Dhabi Schools (Doctoral dissertation, The British University in Dubai.

Amunga, H., 2019. Shortfall of Current Global Education Systems. IARS'International Research Journal, 9(2).

Asif, M., Mondal, A., Soumil, S., Das, A. and Sahoo, P., 2024. Augmented Reality and Virtual Reality in Education: A Transformative Journey into Immersive Learning Environments. Advances in Computational Solutions, p.185.

Antonopoulou, H., 2024. The Value of Emotional Intelligence: Self-Awareness, Self-Regulation, Motivation, and Empathy as Key Components. Technium Education and Humanities, 8, pp.78-92.

Arico, P., Borghini, G., Di Flumeri, G., Sciaraffa, N., Colosimo, A. and Babiloni, F., 2017. Passive BCI in operational environments: insights, recent advances and future trends. IEEE Transactions on Biomedical Engineering, 64(7), pp.1431-1436.

Atkinson, R.C. and Raugh, M.R., 1975. An application of the mnemonic keyword method to the acquisition of a Russian vocabulary. Journal of experimental psychology: Human learning and memory, 1(2), p.126.

Artemova, I., 2024. Bridging Motivation and AI in Education: An Activity Theory Perspective. Digital Education Review, 45, pp.59-69. ;

Auliawan, A.G. and Ong, S., 2020. The usage of ai robot in english language teaching for city revitalization case study: Toda daini elementary school, toda city, saitama, japan. In IOP Conference Series: Earth and Environmental Science (Vol. 436, No. 1, p. 012022). IOP Publishing.

Ayeni, O.O., Al Hamad, N.M., Chisom, O.N., Osawaru, B. and Adewusi, O.E., 2024. AI in education: A review of personalized learning and educational technology. GSC Advanced Research and Reviews, 18(2), pp.261-271.

Bablu, T.A., 2024. Machine Learning in Automated Assessment: Enhancing Objectivity and Efficiency in Educational Evaluations. Journal of Advanced Computing Systems, 4(7).

Badawy, H.R. and Alkaabi, A.M., 2023. From Datafication to School Improvement: The Promise and Perils of Data-Driven Decision Making. In Restructuring Leadership for School Improvement and Reform (pp. 301-325). IGI Global.

Baker, R.S., Martin, T. and Rossi, L.M., 2016. Educational data mining and learning analytics. The Wiley handbook of cognition and assessment: Frameworks, methodologies and applications, pp.379-396.

Baldominos, A. and Quintana, D., 2019. Data-driven interaction review of an ed-tech application. Sensors, 19(8), p.1910.

Barja-Martinez, S., Aragüés-Peñalba, M., Munné-Collado, Í., Lloret-Gallego, P., Bullich- Massagué, E. and Villafafila-Robles, R., 2021. Artificial intelligence techniques for enabling Big Data services in distribution networks: A review. Renewable and Sustainable Energy Reviews, 150, p.111459.

Barnes, E. and Hutson, J., 2024. Navigating the ethical terrain of AI in higher education: Strategies for mitigating bias and promoting fairness. In Forum for Education Studies (Vol. 2, No. 2).

Bar-On, R., 1997. BarOn emotional quotient inventory (Vol. 40). Multi-health systems.

Basri, W.S., 2024. Effectiveness of AI-powered Tutoring Systems in Enhancing Learning Outcomes. Eurasian Journal of Educational Research, 110(110), pp.33-52.

Bates, T., 2019. How to mind map: 7 easy steps to master mind mapping techniques, note-taking, creative thinking & brainstorming skills. Lulu. Com.

Bayly-Castaneda, K., Ramirez-Montoya, M.S. and Morita-Alexander, A., 2024, August. Crafting personalized learning paths with AI for lifelong learning: a systematic literature review. In Frontiers in Education (Vol. 9, p. 1424386). Frontiers Media SA.

Benfenati, F., 2007. Synaptic plasticity and the neurobiology of learning and memory. Acta Biomed, 78(Suppl 1), pp.58-66.

Bengio, Y., Hinton, G., Yao, A., Song, D., Abbeel, P., Darrell, T., Harari, Y.N., Zhang, Y.Q., Xue, L., Shalev-Shwartz, S. and Hadfield, G., 2024. Managing extreme AI risks amid rapid progress. Science, 384(6698), pp.842-845.

Benson, V. ed., 2014. Cutting-edge technologies and social media use in higher education. Igi Global.

Bhatnagar, A.K., Khanna, U. and Rana, A., 2021. Digital learning ecosystem at Indian higher education system. The journal of contemporary issues in business and government, 27(2), pp.4360-4375.

Bianchi, I., 2024. Enhancing Critical Thinking in Education: Leveraging AI Tools and Technologies in Pedagogical Practice.

Brackett, M.A., Bailey, C.S., Hoffmann, J.D. and Simmons, D.N., 2019. RULER: A theory- driven, systemic approach to social, emotional and academic learning. Educational psychologist, 54(3), pp.144-161.

Brightwood, S., Olaoye Godwin, J.O. and Ray, R., 2024. Ai-based learning analytics: identifying knowledge gaps and learning styles.

Brown, P., 2012. What's going on in our minds?. Skeptical Inquirer, 36(4), pp.58-62.

Bruner, J., 1974. Toward a theory of instruction. Harvard university press.

Burgstahler, S., Corrigan, B. and McCarter, J., 2004. Making distance learning courses accessible to students and instructors with disabilities: A case study. The Internet and higher education, 7(3), pp.233-246.

Bușu, A.F., 2024. AI-Powered Classrooms: A Revolution in Learning Environments. Analele Universităţii din Craiova, Seria Ştiinţe Filologice, Limbi Străine Aplicate, (1), pp.96-103.

Buzan, T., 2024. Mind map mastery: The complete guide to learning and using the most powerful thinking tool in the universe. Jaico Publishing House.

Cath, C., 2018. Governing artificial intelligence: ethical, legal and technical opportunities and challenges. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 376(2133), p.20180080.

Chao, W.A.N.G., ZHANG, S., Tianhang, M.A., Yuetong, X.I.A.O., CHEN, M.Z. and Lei, W.A.N.G., 2024. Swarm intelligence: A survey of model classification and applications. Chinese Journal of Aeronautics.

Chen, S. and Zhang, J., 2008, December. The adaptive learning system based on learning style and cognitive state. In 2008 International Symposium on Knowledge Acquisition and modelling (pp. 302-306). IEEE.

Chen, L., Chen, P. and Lin, Z., 2020. Artificial intelligence in education: A review. Ieee Access, 8, pp.75264-75278.

Chen, Y., Wei, Z., Gou, H., Liu, H., Gao, L., He, X. and Zhang, X., 2022. How far is brain- inspired artificial intelligence away from brain?. Frontiers in Neuroscience, 16, p.1096737.

Chisom, O.N., Unachukwu, C.C. and Osawaru, B., 2023. Review of AI in education: transforming learning environments in Africa. International Journal of Applied Research in Social Sciences, 5(10), pp.637-654.

Colan, S.D., 2013. The why and how of Z scores. Journal of the American Society of Echocardiography, 26(1), pp.38-40.

Coldwell, J., Craig, A., Paterson, T. and Mustard, J., 2008. Online students: Relationships between participation, demographics and academic performance. Electronic journal of e-learning, 6(1), pp.pp19-28.

Cole, D., 2004. The Chinese room argument.

Cole, M. and SCRIBNER, S., 1978. Vygotsky, Lev S.(1978): Mind in Society. The Development of Higher Psychological Processes.

Cowie, H., Barnsley, J. and Boardman, C., 2004. Emotional health and well-being: A practical guide for schools.

Cunningham, P., Cord, M. and Delany, S.J., 2008. Supervised learning. In Machine learning techniques for multimedia: case studies on organization and retrieval (pp. 21-49). Berlin, Heidelberg: Springer Berlin Heidelberg.

Dai, Y., Liu, A., Qin, J., Guo, Y., Jong, M.S.Y., Chai, C.S. and Lin, Z., 2023. Collaborative construction of artificial intelligence curriculum in primary schools. Journal of engineering education, 112(1), pp.23-42.

Dargan, S., Kumar, M., Ayyagari, M.R. and Kumar, G., 2020. A survey of deep learning and its applications: a new paradigm to machine learning. Archives of Computational Methods in Engineering, 27, pp.1071-1092.

Davidson, R.J. and McEwen, B.S., 2012. Social influences on neuroplasticity: stress and interventions to promote well-being. Nature neuroscience, 15(5), pp.689-695.

Davuluri, M., 2021. AI in Education: Personalized Learning Pathways Using Machine Learning Algorithms. International Meridian Journal, 3(3).

Dayan, P., Sahani, M. and Deback, G., 1999. Unsupervised learning. The MIT encyclopedia of the cognitive sciences, pp.857-859.

DCMLearning at *https://dcmlearning.ie/video-content/what-is-mind-mapping-%28and-how-to-get-started-immediately%29.html*

Deb, K., 1999. An introduction to genetic algorithms. Sadhana, 24, pp.293-315.

Deci, E.L., Ryan, R.M. and Koestner, R., 2001. The pervasive negative effects of rewards on intrinsic motivation: response to. Review of educational research, 71(1), pp.43- 51.

Deci, E.L. and Ryan, R.M., 2012. Self-determination theory. Handbook of theories of social psychology, 1(20), pp.416-436.

De Freitas, S., 2013. MOOCs: The final frontier for higher education. Erişim adresi: http://benhur. teluq. uquebec. ca/ted/Ressources/mooc. Pdf.

Deibler, M.E., 2018. Understanding high school students' motivation and amotivation to read in and outside of school: A phenomenology. Liberty University.

Delahaye, D., Chaimatanan, S. and Mongeau, M., 2019. Simulated annealing: From basics to applications. Handbook of metaheuristics, pp.1-35.

Delipetrev, B., Tsinaraki, C. and Kostic, U., 2020. Historical evolution of artificial intelligence.

Dembe, A., The Integration of Virtual Reality (VR) and Augmented Reality (AR) in Classroom Settings. 2024.

Dennard, A., 2024. AI Enhanced Pedagogy: Examining How Teachers Elevate Their Practice Through Innovative Lesson Design (Doctoral dissertation, Lamar University-Beaumont).

de Souza Zanirato Maia, J., Bueno, A.P.A. and Sato, J.R., 2023. Applications of Artificial Intelligence Models in Educational Analytics and Decision Making: A Systematic Review. World, 4(2), pp.288-313.

Dhawas, P., Dhore, A., Bhagat, D., Pawar, R.D., Kukade, A. and Kalbande, K., 2024. Big Data Preprocessing, Techniques, Integration, Transformation, Normalisation, Cleaning, Discretization, and Binning. In Big Data Analytics Techniques for Market Intelligence (pp. 159-182). IGI Global.

Diao, R. and Shen, Q., 2015. Nature inspired feature selection meta-heuristics. Artificial Intelligence Review, 44, pp.311-340.

Dichev, C.D. and Dicheva, D., 2017. Gamification in education: A systematic review. Journal of Educational Technology Development and Exchange, 10(1), pp.1-23.

Diener, E., Tamir, M. and Scollon, C.N., 2006. Happiness, life satisfaction and fulfillment: The social psychology of subjective well-being. Bridging social psychology: Benefits of transdisciplinary approaches, pp.319-324.

Dinc, E., 2019. Prospective teachers' perceptions of barriers to technology integration in education. Contemporary Educational Technology, 10(4), pp.381-398.

Dirgová Luptáková, I., Pospíchal, J. and Huraj, L., 2023. Beyond Code and Algorithms: Navigating Ethical Complexities in Artificial Intelligence. In Proceedings of the Computational Methods in Systems and Software (pp. 316-332). Cham: Springer Nature Switzerland.

Donaldson, C., Villagrasa, J. and Sánchez, F., 2021. Learner profile mapping: Stimulating autonomous motivation in entrepreneurship education. Industry and Higher Education, 35(4), pp.384-402.

Donnelly, J.E., Hillman, C.H., Castelli, D., Etnier, J.L., Lee, S., Tomporowski, P., Lambourne, K. and Szabo-Reed, A.N., 2016. Physical activity, fitness, cognitive function, and academic achievement in children: a systematic review. Medicine and science in sports and exercise, 48(6), p.1197.

Douglas, K.A., Zielinski, M.W., Merzdorf, H., Diefes-Dux, H.A. and Bermel, P., 2019. Meaningful learner information for MOOC instructors examined through a contextualized evaluation framework. International Review of Research in Open and Distributed Learning, 20(1).

Duan, Y., Edwards, J.S. and Dwivedi, Y.K., 2019. Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. International journal of information management, 48, pp.63-71.

Dudchenko, P.A., Talpos, J., Young, J. and Baxter, M.G., 2013. Animal models of working memory: a review of tasks that might be used in screening drug treatments for the memory impairments found in schizophrenia. Neuroscience & Biobehavioral Reviews, 37(9), pp.2111-2124.

Durlak, J.A., Weissberg, R.P., Dymnicki, A.B., Taylor, R.D. and Schellinger, K.B., 2011. The impact of enhancing students' social and emotional learning: A meta-analysis of school- based universal interventions. Child development, 82(1), pp.405-432.

Dyall, S.C. and Michael-Titus, A.T., 2008. Neurological benefits of omega-3 fatty acids. Neuromolecular medicine, 10(4), pp.219-235.

El Arass, M. and Souissi, N., 2018, October. Data lifecycle: from big data to SmartData. In 2018 IEEE 5th international congress on information science and technology (CiSt) (pp. 80-87). IEEE.

Esposito, E., 2022. Artificial communication: How algorithms produce social intelligence. mit Press.

Eteokleous, N., 2008. Evaluating computer technology integration in a centralized school system. Computers & Education, 51(2), pp.669-686.

Evans, D.L., Foa, E.B., Gur, R.E., Hendin, H., O'Brien, C.P., Seligman, M.E. and Walsh, B.T. eds., 2005. Treating and preventing adolescent mental health disorders: What we know and what we don't know. Oxford University Press.

Falcone, K., 2018. A case study of faculty experience and preference of using blackboard and canvas lms (Doctoral dissertation, University of Phoenix).

Faresta, R.A., 2024. AI-Powered Education: Exploring the Potential of Personalised Learning for Students' Needs in Indonesia Education. Path of Science, 10(5), pp.3012-3022.

Fedele, A., Punzi, C. and Tramacere, S., 2024. The ALTAI checklist as a tool to assess ethical and legal implications for a trustworthy AI development in education. Computer Law & Security Review, 53, p.105986.

Fernández Fernández, J.L., 2022. Ethical considerations regarding biases in algorithms.

Fetzer, J.H. and Fetzer, J.H., 1990. What is artificial intelligence? (pp. 3-27). Springer Netherlands.

Fischer, C., Pardos, Z.A., Baker, R.S., Williams, J.J., Smyth, P., Yu, R., Slater, S., Baker, R. and Warschauer, M., 2020. Mining big data in education: Affordances and challenges. Review of Research in Education, 44(1), pp.130-160.

Fitria, T.N., 2021, December. Artificial intelligence (AI) in education: Using AI tools for teaching and learning process. In Prosiding Seminar Nasional & Call for Paper STIE AAS (Vol. 4, No. 1, pp. 134-147).

Foujdar, A.A., 2019. Implementing Privacy by Design through Privacy Impact Assessments.

Franki, V., Majnarić, D. and Višković, A., 2023. A comprehensive review of Artificial Intelligence (AI) companies in the power sector. Energies, 16(3), p.1077.

Freiman, V. and Robichaud, X., 2018. A Short History of Computing Devices from Schickard to de Colmar: Emergence and Evolution of Ingenious Ideas and Technologies as Precursors of Modern Computer Technology. Computations and Computing Devices in Mathematics Education Before the Advent of Electronic Calculators, pp.339-364.

Fuchs, T., 2011. The brain--A mediating organ. Journal of Consciousness studies, 18(7-8), pp.196-221.

Gaba, D.M., Howard, S.K., Fish, K.J., Smith, B.E. and Sowb, Y.A., 2001. Simulation-based training in anesthesia crisis resource management (ACRM): a decade of experience. Simulation & gaming, 32(2), pp.175-193.

Gal, M.S. and Rubinfeld, D.L., 2019. Data standardization. NYUL Rev., 94, p.737.

Gangadharan, V., 2014. Improving student achievement utilizing data driven instruction within classroom settings: A case study. Northcentral University.

Gao, Y., 2023. The Potential of Adaptive Learning Systems to Enhance Learning Outcomes: A Meta-Analysis.

Garaus, C., Furtmüller, G. and Güttel, W.H., 2016. The hidden power of small rewards: The effects of insufficient external rewards on autonomous motivation to learn. Academy of Management Learning & Education, 15(1), pp.45-59.

Garg, S. and Sharma, S., 2020. Impact of artificial intelligence in special need education to promote inclusive pedagogy. International Journal of Information and Education Technology, 10(7), pp.523-527.

Gbadegeshin, S.A., Al Natsheh, A., Ghafel, K., Tikkanen, J., Gray, A., Rimpiläinen, A., Kuoppala, A., Kalermo-Poranen, J. and Hirvonen, N., 2021. What is an Artificial Intelligence (AI): A Simple Buzzword or a Worthwhile Inevitability?. In ICERI2021 Proceedings (pp. 468-479). IATED.

George, A.S., Baskar, T. and Srikaanth, P.B., 2024. The erosion of cognitive skills in the technological age: How reliance on technology impacts critical thinking, problem-solving, and creativity. Partners Universal Innovative Research Publication, 2(3), pp.147-163.

Geroche, J.B. and Guay, F.J.G., 2024. AI in education: Unlocking college student engagement in the digital learning era. International Research Journal of Science, Technology, Education, and Management, 4(4), pp.52-64.

Gingras, Y., 2001. What did mathematics do to physics?. History of science, 39(4), pp.383-416.

Gligorea, I., Cioca, M., Oancea, R., Gorski, A.T., Gorski, H. and Tudorache, P., 2023. Adaptive learning using artificial intelligence in e-learning: a literature review. Education Sciences, 13(12), p.1216.

Goel, A., 2020. AI-powered learning: making education accessible, affordable and achievable. arXiv preprint arXiv:2006.01908.

Goel, A., Sikka, H. and Gregori, E., 2021. Agent Smith: Teaching Question Answering to Jill Watson. arXiv preprint arXiv:2112.13677.

Golley, F.B., 1991. The ecosystem concept: A search for order. Ecological Research, 6, pp.129-138.

Goleman, D., 2001. Emotional Intelligence: issues in paradigm building. The emotionally intelligent workplace/Jossey-Bass.

Goleman, D., 2020. Emotional intelligence: Why it can matter more than IQ. Bloomsbury Publishing.

Goleman, D., 2021. Leadership: The power of emotional intelligence. More Than Sound LLC

Golub, M.D., Chase, S.M., Batista, A.P. and Byron, M.Y., 2016. Brain–computer interfaces for dissecting cognitive processes underlying sensorimotor control. Current opinion in neurobiology, 37, pp.53-58.

GONDOĽ, J., 2012. The Future of Search: Perspectives from IBM, Apple, Google and Others. Artificial Intelligence and Cognitive Science IV, p.45.

Gourin, C.G. and Terris, D.J., 2007. History of robotic surgery. Robotics in Surgery: History, Current and Future Applications. New York (NY): Nova Science Publishers, Inc, pp.3-12.

Gorgoni, M., D′ Atri, A., Lauri, G., Rossini, P.M., Ferlazzo, F. and De Gennaro, L., 2013. Is sleep essential for neural plasticity in humans, and how does it affect motor and cognitive recovery?. Neural plasticity, 2013(1), p.103949.

Grant, P. and Basye, D., 2014. Personalized learning: A guide for engaging students with technology. International Society for Technology in Education.

Green, C.S. and Bavelier, D., 2012. Learning, attentional control, and action video games. Current biology, 22(6), pp.R197-R206.

Groff, J., 2013. Technology-rich innovative learning environments. OCED CERI Innovative Learning Environment project, 2013, pp.1-30.

Gross, J.L., Yellen, J. and Anderson, M., 2018. Graph theory and its applications. Chapman and Hall/CRC.

Grothe, B., Carr, C.E., Casseday, J.H., Fritzsch, B. and Köppl, C., 2004. The evolution of central pathways and their neural processing patterns. *Evolution of the vertebrate auditory system*, pp.289-359.

Gupta, P., Yadav, D. and Dey, R., 2021. AI Diagnosis: Rise of AI-Powered Assessments in Modern Education Systems. Transnational Marketing Journal, 9(3), pp.625-633.

Gutiérrez, L. and Keith, B., 2019. A systematic literature review on word embeddings. In Trends and Applications in Software Engineering: Proceedings of the 7th International Conference on Software Process Improvement (CIMPS 2018) 7 (pp. 132-141). Springer International Publishing.

Hagendorff, T., 2022. A virtue-based framework to support putting AI ethics into practice. Philosophy & Technology, 35(3), p.55.

Halloun, I.A., 2012. Profile Shaping Education An Overview. Paper retrieved from: http://www. educationalrc. org/IAB/Data/PSE/PSE% 20Overview-English. Pdf.]

Hanna, M., Pantanowitz, L., Jackson, B., Palmer, O., Visweswaran, S., Pantanowitz, J., Deebajah, M. and Rashidi, H., 2024. Ethical and Bias Considerations in Artificial Intelligence (AI)/Machine Learning. Modern Pathology, p.100686.

Hardiman, M.M., 2003. Connecting brain research with effective teaching: The brain-targeted teaching model. Scarecrow Press.

Harter, S. and Whitesell, N.R., 2003. Beyond the debate: Why some adolescents report stable self- worth over time and situation, whereas others report changes in self- worth. Journal of personality, 71(6), pp.1027-1058.

Hawkins, J.A. and Hawkins, J.A., 2021. The discovery and implications of neuroplasticity. Brain plasticity and learning: Implications for educational practice, pp.1-36.

Helen; Sharpe Beetham, Beetham, H. and Sharpe, R., 2007. Rethinking pedagogy for a digital age (p. 10001). London: routledge.

Henrique, C.M. and Francisca, E.B.D.S., 2024. Ethical challenges in the implementation of artificial intelligence: Privacy, algorithmic bias, and governance.

Hense, R. and Janovics, J., 2011. Case Study of Technology- Enhanced Assessment Centers. Technology- Enhanced Assessment of Talent, pp.324-337.

Hirschberg, J. and Manning, C.D., 2015. Advances in natural language processing. Science, 349(6245), pp.261-266.

Hoffmann, J.D., Brackett, M.A., Bailey, C.S. and Willner, C.J., 2020. Teaching emotion regulation in schools: Translating research into practice with the RULER approach to social and emotional learning. Emotion, 20(1), p.105.

Honigsfeld*, A. and Schiering, M., 2004. diverse approaches to the diversity of learning styles in teacher education. Educational Psychology, 24(4), pp.487-507.

Hormuzdi, S.G., Filippov, M.A., Mitropoulou, G., Monyer, H. and Bruzzone, R., 2004. Electrical synapses: a dynamic signaling system that shapes the activity of neuronal networks. Biochimica et Biophysica Acta (BBA)-Biomembranes, 1662(1-2), pp.113-137.

Horvitz, E., 2014. One hundred year study on artificial intelligence: reflections and framing. Microsoft. Com.

Hsu, F.H., 2002. Behind Deep Blue: Building the computer that defeated the world chess champion. Princeton University Press.

Huong, X.V., 2024. The implications of artificial intelligence for educational systems: Challenges, opportunities, and transformative potential. The American Journal of Social Science and Education Innovations, 6(03), pp.101-111.

Huppert, F.A. and So, T.T., 2013. Flourishing across Europe: Application of a new conceptual framework for defining well-being. Social indicators research, 110, pp.837-861.

Hussain, M., Zhu, W., Zhang, W., Abidi, S.M.R. and Ali, S., 2019. Using machine learning to predict student difficulties from learning session data. Artificial Intelligence Review, 52, pp.381-407.

Hussar, W.J. and Bailey, T.M., 2011. Projections of Education Statistics to 2020. NCES 2011-026. National Center for Education Statistics.

Hutchins, W., 2000. The first decades of machine translation. Early years in machine translation, 1, pp.1-15.

Hwang, G.J., Xie, H., Wah, B.W. and Gašević, D., 2020. Vision, challenges, roles and research issues of Artificial Intelligence in Education. Computers and Education: Artificial Intelligence, 1, p.100001.

Hyman, A., 1985. Charles Babbage: Pioneer of the computer. Princeton University Press.

Ihedimma, G.I., Exploring Artificial Intelligence in Enhancing Personalised Learning Experience. AI and Curriculum Development for the Future. 2025

Iman, M., Arabnia, H.R. and Rasheed, K., 2023. A review of deep transfer learning and recent advancements. Technologies, 11(2), p.40.

Iqbal, M., 2023. AI in education: Personalized learning and adaptive assessment. Cosmic Bulletin of Business Management, 2(1), pp.280-297.

Ismail, I.A., 2025. Protecting Privacy in AI-Enhanced Education: A Comprehensive Examination of Data Privacy Concerns and Solutions in AI-Based Learning. Impacts of Generative AI on the Future of Research and Education, pp.117-142.

Janson, A., Söllner, M., Bitzer, P. and Leimeister, J.M., 2014. Examining the effect of different measurements of learning success in technology-mediated learning research.

Jessner, U. and Török, V., 2017. Strategies in multilingual learning: Opening new research avenues. Future research directions for applied linguistics, pp.192-211.

John, B., 2025. Personalized Learning through Software Design Critiquing Tools: Tailoring Feedback to Individual Student Needs.

Johnson, R.B. and Christensen, L.B., 2024. Educational research: Quantitative, qualitative, and mixed approaches. Sage publications.

Jordan, M.I. and Mitchell, T.M., 2015. Machine learning: Trends, perspectives and prospects. Science, 349(6245), pp.255-260.

Joseph, O.B. and Uzondu, N.C., 2024. Integrating AI and Machine Learning in STEM education: Challenges and opportunities. Computer Science & IT Research Journal, 5(8), pp.1732-1750.

Joshua, A.M., 2022. Neuroplasticity. In Physiotherapy for adult neurological conditions (pp. 1-30). Singapore: Springer Nature Singapore.

Juhaňák, L., Zounek, J. and Rohlíková, L., 2019. Using process mining to analyze students' quiz-taking behavior patterns in a learning management system. Computers in Human Behavior, 92, pp.496-506.

Junior, W.T.L. and Silva, J.R., 2017. From Licklider to cognitive service systems. Braz. J. Technol. Commun. Cogn. Sci, 5, pp.1-15.

Kafai, Y.B. and Resnick, M. eds., 2012. Constructionism in practice: Designing, thinking, and learning in a digital world. Routledge.

Kamenskih, A., 2022. The analysis of security and privacy risks in smart education environments. Journal of Smart Cities and Society, 1(1), pp.17-29.

Kaminka, G.A., Spokoini-Stern, R., Amir, Y., Agmon, N. and Bachelet, I., 2017. Molecular robots obeying Asimov's three laws of robotics. Artificial life, 23(3), pp.343-350.

Kanchon, M.K.H., Sadman, M., Nabila, K.F., Tarannum, R. and Khan, R., 2024. Enhancing personalized learning: AI-driven identification of learning styles and content modification strategies. International Journal of Cognitive Computing in Engineering, 5, pp.269-278.

Kapuya, T., Kubiku, W., Dube, M., Mukudu, T., Kutyauripo, M., Ndlovu, B. and Dube, S., Ethical AI Frameworks: Balancing Privacy, Consent and Responsible Use. 2024

Karunarathna, I., Gunathilake, S., Kapila De Alvis, K., Rajapaksha, S., Warnakulasooriya, A., Athulgama, P., Dius, S., Ranwala, R., Bandara, S., Godage, S. and Rodrigo, P.N., From Encoding to Retrieval: Optimizing Learning. 2024

Kayal, A., 2024. Transformative Pedagogy: A Comprehensive Framework for AI Integration in Education. In Explainable AI for Education: Recent Trends and Challenges (pp. 247-270). Cham: Springer Nature Switzerland.

Kessler, G.C., 2004. An overview of TCP/IP protocols and the internet. InterNIC Document, Dec, 29, p.42.

Kizilcec, R.F., Piech, C. and Schneider, E., 2013, April. Deconstructing disengagement: Analysing learner subpopulations in massive open online courses. In Proceedings of the third international conference on learning analytics and knowledge (pp. 170-179).

Klein, C. and Hess, R.M., 2018. Using learning analytics to improve student learning outcomes assessment: Benefits, constraints, & possibilities. In Learning analytics in higher education (pp. 140-159). Routledge.

Kluge, J., Stein, W. and Licht, T., 2001. Knowledge unplugged: The McKinsey global survey of knowledge management. Springer.

Knox, J., 2020. Artificial intelligence and education in China. Learning, Media and Technology, 45(3), pp.298-311.

Knox, J., 2021. How the ‘taming’of private education in China is impacting AI. On Education: Journal for Research and Debate, (12).

Kroemer, O., Niekum, S. and Konidaris, G., 2021. A review of robot learning for manipulation: Challenges, representations and algorithms. Journal of machine learning research, 22(30), pp.1-82.

Kuhail, M.A., ElSayary, A., Farooq, S. and Alghamdi, A., 2022, September. Exploring immersive learning experiences: A survey. In *Informatics* (Vol. 9, No. 4, p. 75). MDPI.

Kurfess, T.R. ed., 2005. Robotics and automation handbook(Vol. 414). Boca Raton, FL: CRC press.

Kucinskiene, J. and Kucinskas, G., 2024. TECHNOLOGY AND EXPERIENCES IN SHAPING THE FUTURE OF EDUCATION. In *ICERI2024 Proceedings* (pp. 4472-4479). IATED.

Kustyarini, K., 2020. Self-Efficacy and Emotional Quotient in Mediating Active Learning Effect on Students' Learning Outcome. International Journal of Instruction, 13(2), pp.663-676.

Lage, M. J., Platt, G. J., & Treglia, M. (2000). Inverting the classroom: A classroom-based approach to increasing student engagement and learning. Journal of Educational Psychology, 92(1), 1-8.

Lai, J., Wood, L. and Marrone, M., 2012. Implementation of a curriculum management tool: Challenges faced by a large Australian university. Asian Social Science, 8(14), p.28.

Lamprecht, R. and LeDoux, J., 2004. Structural plasticity and memory. Nature Reviews Neuroscience, 5(1), pp.45-54.

Lantz, B., 2019. Machine learning with R: expert techniques for predictive modelling. Packt publishing ltd.

Lata, P., 2024. Towards Equitable Learning: Exploring Artificial Intelligence in Inclusive Education.

Latour, B., 1984. The powers of association. The sociological review, 32(S1), pp.264-280.

Layode, O., Naiho, H.N.N., Adeleke, G.S., Udeh, E.O. and Labake, T.T., 2024. Data privacy and security challenges in environmental research: Approaches to safeguarding sensitive information. International Journal of Applied Research in Social Sciences, 6(6), pp.1193-1214.

Lazinica, A. ed., 2009. Particle swarm optimization. BoD–Books on Demand.

Lebovitz, S., Levina, N. and Lifshitz-Assaf, H., 2021. IS AI GROUND TRUTH REALLY TRUE? THE DANGERS OF TRAINING AND EVALUATING AI TOOLS BASED ON EXPERTS'KNOW-WHAT. MIS quarterly, 45(3).

Lenat, D.B., 1995. CYC: A large-scale investment in knowledge infrastructure. Communications of the ACM, 38(11), pp.33-38.

Le Roux, I.L., 2018. Coaching as support for postgraduate students: A case study. SA Journal of Human Resource Management, 16(1), pp.1-7

Lin, S.H., 2000. An introduction to face recognition technology. Informing Sci. Int. J. an Emerg. Transdiscipl., 3, pp.1-7.

Lin, T.W., Tsai, S.F. and Kuo, Y.M., 2018. Physical exercise enhances neuroplasticity and delays Alzheimer’s disease. Brain Plasticity, 4(1), pp.95-110.

Loriette, C., Amengual, J.L. and Ben Hamed, S., 2022. Beyond the brain-computer interface: Decoding brain activity as a tool to understand neuronal mechanisms subtending cognition and behavior. Frontiers in Neuroscience, 16, p.811736.

Luan, H., Geczy, P., Lai, H., Gobert, J., Yang, S.J., Ogata, H., Baltes, J., Guerra, R., Li, P. and Tsai, C.C., 2020. Challenges and future directions of big data and artificial intelligence in education. Frontiers in psychology, 11, p.580820.

Luckin, R. and Holmes, W., 2016. Intelligence unleashed: An argument for AI in education.

Luo, Q.Z. and Hsiao-Chin, L.Y., 2023. The influence of AI-powered adaptive learning platforms on student performance in Chinese classrooms. Journal of Education, 6(3), pp.1-12.

Luschei, T.F., 2013. Assessing the costs and benefits of educational technology. Handbook of research on educational communications and technology, pp.239-248.

Lyu, Y., Adnan, A.B.M. and Zhang, L., 2024. Influencing factors on NLP technology integration in teaching: A case study in Shanghai. Education and Information Technologies, pp.1-34.

Lømo, T., 2018. Discovering long- term potentiation (LTP)–recollections and reflections on what came after. Acta Physiologica, 222(2), p.e12921.

MacCann, C., Jiang, Y., Brown, L.E., Double, K.S., Bucich, M. and Minbashian, A., 2020. Emotional intelligence predicts academic performance: A meta-analysis. Psychological bulletin, 146(2), p.150.

Majgaard, G. and Weitze, C., 2020, September. Virtual experiential learning, learning design and interaction in extended reality simulations. In Proceedings of the 14th European Conference on Game Based Learning, ECGBL (pp. 372-379).

Makridakis, S., 2017. The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. Futures, 90, pp.46-60.

Margetis, G., Ntoa, S., Antona, M. and Stephanidis, C., 2021. Human- centered design of artificial intelligence. Handbook of human factors and ergonomics, pp.1085-1106.].

Marr, B., 2018. How is AI used in education--Real world examples of today and a peek into the future. Forbes, Forbes Magazine, 25.

Martin, F., Chen, Y., Moore, R.L. and Westine, C.D., 2020. Systematic review of adaptive learning research designs, context, strategies and technologies from 2009 to 2018. Educational Technology Research and Development, 68(4), pp.1903-1929.

Martinez Jr, J.L. and Derrick, B.E., 1996. Long-term potentiation and learning. Annual review of psychology, 47(1), pp.173-203.

Maturi, M.H., Satish, S., Gonaygunta, H. and Meduri, K., 2022. The InterSection of Artificial Intelligence and Neuroscience: Unlocking the Mysteries of the Brain. International Journal of Creative Research In Computer Technology and Design, 4(4), pp.1-21.

Mazur, J.E., 2015. Learning and behavior: Instructor's review copy. Psychology Press.

McDermott, K.B. and Roediger, H.L., 2018. Memory (encoding, storage, retrieval). General Psychology FA2018. Noba Project: Milwaukie, OR, pp.117-153.

McElwee, B., 2020. Math Curriculum and Teacher Autonomy: Why there can never be a one-size-fits all approach to teaching and learning.

McGaugh, J.L., 2003. Memory and emotion: The making of lasting memories. Columbia University Press.

Mehrotra, C., Hollister, C.D. and McGahey, L., 2001. Distance learning: Principles for effective design, delivery and evaluation. Sage Publications.

Mellinger, J., Schalk, G., Braun, C., Preissl, H., Rosenstiel, W., Birbaumer, N. and Kübler, A., 2007. An MEG-based brain–computer interface (BCI). Neuroimage, 36(3), pp.581-593.

Mensah, G.B., 2023. Artificial intelligence and ethics: a comprehensive review of bias mitigation, transparency, and accountability in AI Systems. Preprint, November, 10.

Meylani, R., 2024. Innovations With Schema Theory: Modern Implications for Learning, Memory, And Academic Achievement. International Journal For Multidisciplinary Research, 6(1), pp.2582-2160.

Minsky, M. and Papert, S.A., 2017. Perceptrons, reissue of the 1988 expanded edition with a new foreword by Léon Bottou: an introduction to computational geometry. MIT press.

Minsky, M., 2019. Inventive minds: Marvin Minsky on education. MIT Press.

Miraz, M.H., Ali, M. and Excell, P.S., 2021. Adaptive user interfaces and universal usability through plasticity of user interface design. Computer Science Review, 40, p.100363.

Mohammadi, A.T., Ghanbarzadeh, E., Zamiri, R., Dana, M.K., Far, Y.K., Avarani, M.A.J.N., Asgari, R., Keshtgar, S., Sanaei, A. and Shamshiri, M., 2024. Advancements in Neuroscience: Modern Tools and Techniques Fueling Thrilling Discoveries in the 21st Century. Nobel Sciences.

Morales-Castañeda, B., Zaldívar, D., Cuevas, E., Maciel-Castillo, O., Aranguren, I. and Fausto, F., 2019. An improved Simulated Annealing algorithm based on ancient metallurgy techniques. Applied Soft Computing, 84, p.105761.

Moussa, R., Alghazaly, A., Althagafi, N., Eshky, R. and Borzangy, S., 2022. Effectiveness of virtual reality and interactive simulators on dental education outcomes: systematic review. European journal of dentistry, 16(01), pp.14-31.

Mpungose, C.B. and Khoza, S.B., 2022. Postgraduate students' experiences on the use of Moodle and Canvas learning management system. Technology, Knowledge and Learning, 27(1), pp.1-16.

Munna, M.S.H., Hossain, M.R. and Saylo, K.R., 2024. Digital Education Revolution: Evaluating LMS-based Learning and Traditional Approaches. Journal of Innovative Technology Convergence, 6(2).

Murthy, Y.S., Bansal, R., Chodisetty, R.C.M., Chakravorty, C. and Sai, K.P., 2025. Transforming Minds AI and Machine Learning Applications in Cognitive Neuroscience. In Transforming Neuropsychology and Cognitive Psychology With AI and Machine Learning (pp. 107-128). IGI Global Scientific Publishing.

MZ bin Mohamed, M.Z., Hidayat, R., binti Suhaizi, N.N., bin Mahmud, M.K.H. and binti Baharuddin, S.N., 2022. Artificial intelligence in mathematics education: A systematic literature review. International Electronic Journal of Mathematics Education, 17(3), p.em0694.

Nambiar, A. and Mundra, D., 2022. An overview of data warehouse and data lake in modern enterprise data management. Big data and cognitive computing, 6(4), p.132.

Naseeb, J. and Bhatti, N., 2024. Ethical Considerations of AI in Educational Curriculum. Multidisciplinary Journal of Emerging Needs of Curriculum, 1(1), pp.30-38.

National Research Council, Board on Behavioral, Sensory Sciences, Committee on Developments in the Science of Learning with additional material from the Committee on Learning Research and Educational Practice, 2000. How people learn: Brain, mind, experience, and school: Expanded edition (Vol. 1). National Academies Press.

Nafea, I.T., 2018. Machine learning in educational technology. Machine learning-advanced techniques and emerging applications, pp.175-183.

Negrón, A.P.P., López, G.L. and Aguirre, H.R.O. eds., 2020. Virtual Reality Designs. CRC Press, Taylor & Francis Group.

Nguyen, T.D., Cannata, M. and Miller, J., 2018. Understanding student behavioral engagement: Importance of student interaction with peers and teachers. The journal of educational research, 111(2), pp.163-174.

Nguyen, A., Ngo, H.N., Hong, Y., Dang, B. and Nguyen, B.P.T., 2023. Ethical principles for artificial intelligence in education. Education and Information Technologies, 28(4), pp.4221-4241.

Nicolas-Alonso, L.F. and Gomez-Gil, J., 2012. Brain computer interfaces, a review. sensors, 12(2), pp.1211-1279.

Niyozov, N., Saburov, S., Ganiyev, S. and Olimov, S., 2023. AI-powered learning: revolutionizing technical higher education institutions through advanced power supply fundamentals. In E3S Web of Conferences (Vol. 461, p. 01092). EDP Sciences.

Nookala, G., Gade, K.R., Dulam, N. and Thumburu, S.K.R., 2020. Data Virtualization as an Alternative to Traditional Data Warehousing: Use Cases and Challenges. Innovative Computer Sciences Journal, 6(1).

Novak, J.D. and Cañas, A.J., 2008. The theory underlying concept maps and how to construct and use them.

Ntoutsi et al. 2020. Bias in data- driven artificial intelligence systems—An introductory survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10(3), p.e1356.

Obolensky, D.M. and Shevchenko, V.I., 2019. Intelligent Educational Ecosystems. Proceedings of “DICTUMFACTUM: from Research to Policy Making”. Sevastopol, 162(171), pp.2020-162.

O’Connor, S. and Liu, H., 2024. Gender bias perpetuation and mitigation in AI technologies: challenges and opportunities. AI & SOCIETY, 39(4), pp.2045-2057.

Oladele, O.K., 2024. Kinesthetic Learning: Hands-On Learning and Active Engagement.

Oliveira, A., Spinola, V., Garrido, D., Teixeira, M.M., Salles, C. and Haddad, A.E., 2023. Influence of learning styles on student performance in self-instructional courses. Plos one, 18(7), p.e0289036.

Olsen, R.K., Moses, S.N., Riggs, L. and Ryan, J.D., 2012. The hippocampus supports multiple cognitive processes through relational binding and comparison. Frontiers in human neuroscience, 6, p.146.

Onesi-Ozigagun, O., Ololade, Y.J., Eyo-Udo, N.L. and Ogundipe, D.O., 2024. Revolutionizing education through AI: a comprehensive review of enhancing learning experiences. International Journal of Applied Research in Social Sciences, 6(4), pp.589-607.

Oni, A., AI-Powered Intelligent Tutoring Systems: A Review of Effectiveness and Challenges. Role of AI in Enhancing Teaching/Learning, Research and Community Service in Higher Education. 2025

Onwuegbuzie, A.J. and Frels, R.K., 2015. A Framework for Conducting Critical Dialectical Pluralist Focus Group Discussions Using Mixed Research Techniques. Journal of Educational Issues, 1(2), pp.159-177.

O'Regan, G. and O'Regan, G., 2013. Joseph Weizenbaum. Giants of Computing: A Compendium of Select, Pivotal Pioneers, pp.263-266.

O'Regan, G. and O'Regan, G., 2015. Unimation. Pillars of Computing: A Compendium of Select, Pivotal Technology Firms, pp.219-223.

Orji, F. and Vassileva, J., 2020, September. Using machine learning to explore the relation between student engagement and student performance. In 2020 24th International Conference Information Visualisation (IV) (pp. 480-485). IEEE.

O'Sullivan, S., Nevejans, N., Allen, C., Blyth, A., Leonard, S., Pagallo, U., Holzinger, K., Holzinger, A., Sajid, M.I. and Ashrafian, H., 2019. Legal, regulatory and ethical frameworks for development of standards in artificial intelligence (AI) and autonomous robotic surgery. The international journal of medical robotics and computer assisted surgery, 15(1), p.e1968.

Ouyang, F. and Jiao, P., 2021. Artificial intelligence in education: The three paradigms. Computers and Education: Artificial Intelligence, 2, p.100020.

Ouyang, F., Zheng, L. and Jiao, P., 2022. Artificial intelligence in online higher education: A systematic review of empirical research from 2011 to 2020. Education and Information Technologies, 27(6), pp.7893-7925.

Owoc, M.L., Sawicka, A. and Weichbroth, P., 2019, August. Artificial intelligence technologies in education: benefits, challenges and strategies of implementation. In IFIP International Workshop on Artificial Intelligence for Knowledge Management (pp. 37-58). Cham: Springer International Publishing.

Oxford Dictionary Fowler, H.W. and Fowler, F.G., 1931. The concise Oxford dictionary of current English. Рипол Классик.

Panday, B.L. and Prasad, S., USING BRAIN-COMPUTER INTERFACES (BCI) IN EDUCATION. THE FUTURE OF EDUCATION IN THE DIGITAL AGE, p.33.

Pandya, B., Cho, B., Patterson, L. and Abaker, M., 2024. Impact of Connectivism on Knowledge and Willingness of Students in Higher Education. Journal of Management Education, p.10525629241256317.

Panitz, T. and Panitz, P., 1998. Encouraging the use of collaborative learning in higher education. University teaching: International perspectives, pp.161-201.

Panoulas, K.J., Hadjileontiadis, L.J. and Panas, S.M., 2010. Brain-computer interface (BCI): Types, processing perspectives and applications. In Multimedia Services in Intelligent Environments: Integrated Systems (pp. 299-321). Berlin, Heidelberg: Springer Berlin Heidelberg.

Parde, N., 2023. Natural language processing. The SAGE Handbook of Human–Machine Communication, p.318.

Pardamean, B., Suparyanto, T., Cenggoro, T.W., Sudigyo, D. and Anugrahana, A., 2022. AI-based learning style prediction in online learning for primary education. IEEE Access, 10, pp.35725-35735.

Parker, O., 2023. Cloud Computing and AI in Education: Revolutionizing Personalized Learning While Ensuring Data Security.

Pasqualotto, E., Federici, S. and Belardinelli, M.O., 2012. Toward functioning and usable brain–computer interfaces (BCIs): A literature review. Disability and Rehabilitation: Assistive Technology, 7(2), pp.89-103.

Pedro, F., Subosa, M., Rivas, A. and Valverde, P., 2019. Artificial intelligence in education: Challenges and opportunities for sustainable development.

Peksa, J. and Mamchur, D., 2023. State-of-the-art on brain-computer interface technology. Sensors, 23(13), p.6001.

Pertiwi, R.W.L., Kulsum, L.U. and Hanifah, I.A., 2024. Evaluating the Impact of Artificial Intelligence-Based Learning Methods on Students' Motivation and Academic Achievement. International Journal of Post Axial: Futuristic Teaching and Learning, pp.49-58.

Philip, T.M. and Sengupta, P., 2021. Theories of learning as theories of society: A contrapuntal approach to expanding disciplinary authenticity in computing. Journal of the Learning Sciences, 30(2), pp.330-349.

Piaget, J., 2013. The construction of reality in the child. Routledge.

Poullet, Y., 2009. Data protection legislation: What is at stake for our society and democracy?. Computer Law & Security Review, 25(3), pp.211-226.

Pukawan, K., 2006. The attitudes and preferences of Internet users in Thailand toward online privacy rights. Nova Southeastern University.

Raja, S., Jebadurai, D.J., Ivan, L., Mykola, R.V., Ruslan, K. and Nadiia, P.R., 2024. Impact of Artificial Intelligence in Students' Learning Life. In AI in Business: Opportunities and Limitations: Volume 2 (pp. 3-17). Cham: Springer Nature Switzerland.

Rana, S. and Chicone, R., 2025. Gamification and Immersive Learning with AI. In Fortifying the Future: Harnessing AI for Transformative Cybersecurity Training (pp. 51-75). Cham: Springer Nature Switzerland.

Razaulla, S.M., Pasha, M. and Farooq, M.U., 2022. Integration of machine learning in education: challenges, issues and trends. In Machine learning and internet of things for societal issues (pp. 23-34). Singapore: Springer Nature Singapore.

Rittel, H.W. and Webber, M.M., 1973. Dilemmas in a general theory of planning. Policy sciences, 4(2), pp.155-169.

Riva, G., Baños, R.M., Botella, C., Mantovani, F. and Gaggioli, A., 2016. Transforming experience: the potential of augmented reality and virtual reality for enhancing personal and clinical change. Frontiers in psychiatry, 7, p.164.

Rızvı, M., 2023. Investigating AI-powered tutoring systems that adapt to individual student needs, providing personalized guidance and assessments. The Eurasia Proceedings of Educational and Social Sciences, 31, pp.67-73.

Rodrigues, A.J. and Govinda, S., 2003. Towards an integrated management information system: A case of the University of Mauritius. Information Technology for Development, 10(1), pp.41-56.

Rodrigues, R., 2020. Legal and human rights issues of AI: Gaps, challenges and vulnerabilities. Journal of Responsible Technology, 4, p.100005.

Rojas, M.P. and Chiappe, A., 2024. Artificial Intelligence and Digital Ecosystems in Education: A Review. Technology, Knowledge and Learning, pp.1-18.

Romero, C. and Ventura, S., 2010. Educational data mining: a review of the state of the art. IEEE Transactions on Systems, Man, and Cybernetics, Part C (applications and reviews), 40(6), pp.601-618.

Ryan, S.M., 2024. Technology-enhanced Assessment. Veterinary Medical Education: A Practical Guide, p.293.

Rumelhart, D.E., 2017. Schemata: The building blocks of cognition. In Theoretical issues in reading comprehension (pp. 33-58). Routledge.

Sagiroglu, S. and Sinanc, D., 2013, May. Big data: A review. In 2013 international conference on collaboration technologies and systems (CTS) (pp. 42-47). IEEE.

Salama, A.M., 2008. A theory for integrating knowledge in architectural design education. ArchNet-IJAR: International Journal of Architectural Research, 2(1), pp.100-128.

Sanchez-Gordon, S. and Luján-Mora, S., 2018. Lifecycle for MOOC development and management. In Emerging Trends, Techniques and Tools for Massive Open Online Course (MOOC) Management (pp. 24-48). IGI Global.

Sargiotis, D., 2024. Key Principles of Data Governance: Building a Strong Foundation. In Data Governance: A Guide(pp. 137-163). Cham: Springer Nature Switzerland.

Schalk, G., Brunner, P., Gerhardt, L.A., Bischof, H. and Wolpaw, J.R., 2008. Brain–computer interfaces (BCIs): detection instead of classification. Journal of neuroscience methods, 167(1), pp.51-62.

Scheiter, K., Schüler, A. and Eitel, A., 2017. Learning from multimedia: Cognitive processes and instructional support. The psychology of digital learning: Constructing, exchanging and acquiring knowledge with digital media, pp.1-19.

Schmidgall, S., Ziaei, R., Achterberg, J., Kirsch, L., Hajiseyedrazi, S. and Eshraghian, J., 2024. Brain-inspired learning in artificial neural networks: a review. APL Machine Learning, 2(2).

Schunk, D.H., 2012. Learning theories an educational perspective. Pearson Education, Inc.

Schunk, D.H. and Usher, E.L., 2012. Social cognitive theory and motivation. The Oxford handbook of human motivation, 2, pp.11-26.

Scott, D. and Scott, D., 2017. Learning environments. Education Systems and Learners: Knowledge and Knowing, pp.55-89.

Seaba, V., 2023. Revolutionizing Education-Exploring the Potential of AI-Enabled Brain-Based Learning for Enhanced Cognitive Development. Authorea Preprints.

Searle, J.R., 2002. Consciousness and language. Cambridge University Press.

Sethi, S.S. and Jain, K., 2024. AI technologies for social emotional learning: recent research and future directions. Journal of Research in Innovative Teaching & Learning, 17(2), pp.213-225.

Setiawan, A., 2024. Intelligent Systems For Disabilities Technology For A More Inclusive Life. Available at SSRN 5062273.

Shanks, D.R., 2010. Learning: From association to cognition. Annual review of psychology, 61(1), pp.273-301.

Shute, V., Rahimi, S. and Lu, X., 2019. Supporting learning in educational games: Promises and challenges. Learning in a digital world: Perspective on interactive Technologies for Formal and Informal Education, pp.59-81.

Shvetsova, I., Tamozhska, I., Nyzhnyk, T., Zhytnik, T. and Kuleshova, V., 2025. DESIGNING PERSONALISED LEARNING PATHS IN A MEDIA COMMUNICATION CONTEXT. Conhecimento & diversidade, 17(46), pp.55-77.

Sitaram, R., Weiskopf, N., Caria, A., Veit, R., Erb, M. and Birbaumer, N., 2007. fMRI brain-computer interfaces. IEEE Signal processing magazine, 25(1), pp.95-106

Sitaram, R., Caria, A., Veit, R., Gaber, T., Rota, G., Kuebler, A. and Birbaumer, N., 2007. FMRI brain- computer interface: A tool for neuroscientific research and treatment. Computational intelligence and neuroscience, 2007(1), p.025487.

Smith, M.S., 1985. Improving the Quality and Usefulness of NCES Data.

Smuha, N.A., 2020. Trustworthy artificial intelligence in education: Pitfalls and pathways. Available at SSRN 3742421.

Sobey, E. and Sobey, W., 2008. The way toys work: The science behind the magic 8 ball, etch a sketch, boomerang and more. Chicago Review Press.

Solove, D.J., 2012. Introduction: Privacy self-management and the consent dilemma. Harv. L. Rev., 126, p.1880.

Song, W., Wang, S., Yang, B., Lu, Y., Zhao, X. and Liu, X., 2018. Learning node and edge embeddings for signed networks. Neurocomputing, 319, pp.42-54.

Sorden, S.D., 2012. The cognitive theory of multimedia learning. Handbook of educational theories, 1(2012), pp.1-22.

Srinivasa, K.G., Kurni, M. and Saritha, K., 2022. Harnessing the Power of AI to Education. In Learning, teaching and assessment methods for contemporary learners: pedagogy for the digital generation (pp. 311-342). Singapore: Springer Nature Singapore.

Stahl, B.C., Antoniou, J., Bhalla, N., Brooks, L., Jansen, P., Lindqvist, B., Kirichenko, A., Marchal, S., Rodrigues, R., Santiago, N. and Warso, Z., 2023. A systematic review of artificial intelligence impact assessments. Artificial Intelligence Review, 56(11), pp.12799-12831.

Stevens, G.M., 2012. Data security breach notification laws[online]

Strickland, L. and Lewis, H.R., 2022. Leibniz on binary: the invention of computer arithmetic. MIT Press.

Strielkowski, W., Grebennikova, V., Lisovskiy, A., Rakhimova, G. and Vasileva, T., 2024. AI- driven adaptive learning for sustainable educational transformation. Sustainable Development.

Strom, R.W., 2007. Hebbian Learning in Multilayer Neural Networks (Doctoral dissertation, California State University, Los Angeles).

Sukabumi, S.A.A. and Cianjur, S.A.I., 1974. History of artificial intelligence. golden years, 1956, pp.3-1.

Suresh Babu, S. and Dhakshina Moorthy, A., 2024. Application of artificial intelligence in adaptation of gamification in education: A literature review. Computer Applications in Engineering Education, 32(1), p.e22683.

Surve, B.C. and Ghatule, A.P., 2024. Gamification empowered with AI tools to enhance student learning engagement and involvement for personalized effective learning experiences. In ITM Web of Conferences (Vol. 68, p. 01023). EDP Sciences.

Suthers, D.D., 2001, January. Collaborative representations: Supporting face to face and online knowledge-building discourse. In Proceedings of the 34th Annual Hawaii International Conference on System Sciences (pp. 10-pp). IEEE.

Schwartz, R., Schwartz, R., Vassilev, A., Greene, K., Perine, L., Burt, A. and Hall, P., 2022. Towards a standard for identifying and managing bias in artificial intelligence (Vol. 3, p. 00). US Department of Commerce, National Institute of Standards and Technology.

Stigler, J.W. and Hiebert, J., 2009. The teaching gap: Best ideas from the world's teachers for improving education in the classroom. Simon and Schuster.

Strawn, G., 2021. 75 years of astonishing evolution of IT: 1946–2021. IT Professional, 23(3), pp.21-27.

Sweatt, J.D., 2016. Neural plasticity and behavior–sixty years of conceptual advances. Journal of neurochemistry, 139, pp.179-199.

Sweller, J. (1988). Cognitive load during problem solving: A review. Cognition and Instruction, 5(4), 375-426.

Swerzenski, J.D., 2021. Critically Analysing the online classroom: Blackboard, moodle, canvas, and the pedagogy they produce. Journal of Communication Pedagogy, 4, pp.51-69.

Takona, J., 2024. AI in Education: Shaping the Future of Teaching and Learning. International Journal of Current Educational Studies, 3(2), pp.1-25.

Thanh, N.H. and Tuan, B.A., 2021, July. We are using artificial intelligence in assessing students' achievement at high schools: a case study in mathematics. In Proceedings of the 5th Asia Pacific International Modern Sciences Congress (pp. 139-149).

Theodoridis, S. and Koutroumbas, K., 2006. Pattern recognition. Elsevier.

Tippins, N.T., 2011. Overview of technology- enhanced assessments. Technology-enhanced assessment of talent, pp.1-18.

Torre-Bastida, A.I., Díaz-de-Arcaya, J., Osaba, E., Muhammad, K., Camacho, D. and Del Ser, J., 2021. Bio-inspired computation for big data fusion, storage, processing, learning and visualization: state of the art and future directions. Neural Computing and Applications, pp.1-31. Web address: https://link.springer.com/article/10.1007/s00521-021-06332-9

Torromino, G., 2024. Environmental Enrichment in Real and Virtual Realms Fosters Neural Plasticity Related to Learning and Memory Processes. In Mind, Body, and Digital Brains (pp. 173-192). Cham: Springer Nature Switzerland.

Tovar-Moll, F. and Lent, R., 2016. The various forms of neuroplasticity: Biological bases of learning and teaching. Prospects, 46, pp.199-213.

Treadway, M.T. and Lazar, S.W., 2010. Meditation and neuroplasticity: Using mindfulness to change the brain. Assessing mindfulness and acceptance processes in clients: Illuminating the theory and practice of change, pp.186-205.

Trewin, S., Basson, S., Muller, M., Branham, S., Treviranus, J., Gruen, D., Hebert, D., Lyckowski, N. and Manser, E., 2019. Considerations for AI fairness for people with disabilities. AI Matters, 5(3), pp.40-63.

Tulving, E. and Thomson, D.M., 1973. Encoding specificity and retrieval processes in episodic memory. Psychological review, 80(5), p.352.

Turing, A., 2004. Intelligent machinery (1948). B. Jack Copeland, p.395.

Turing, A.M., 2009. Computing machinery and intelligence (pp. 23-65). Springer Netherlands.

Tyagi, A.K. and Chahal, P., 2020. Artificial intelligence and machine learning algorithms. In Challenges and applications for implementing machine learning in computer vision (pp. 188-219). IGI Global Scientific Publishing.

Vadlamani, S., Kankanampati, P.K., Agarwal, R., Jain, S. and Jain, A., 2023. Integrating Cloud-Based Data Architectures for Scalable Enterprise Solutions. International Journal of Electrical and Electronics Engineering, 13(1), pp.21-48.

Varnosfadrani, A.D. and Basturkmen, H., 2009. The effectiveness of implicit and explicit error correction on learners' performance. System, 37(1), pp.82-98.

Vashishth, T.K., Sharma, V., Sharma, K.K., Kumar, B., Panwar, R. and Chaudhary, S., 2024. AI-driven learning analytics for personalized feedback and assessment in higher education. In Using traditional design methods to enhance AI-driven decision making (pp. 206-230). IGI Global.

Verkijika, S.F., 2015. Assessing the use of a Brain-Computer Interface (BCI) in mathematics education: the case of a cognitive game (Doctoral dissertation, University of the Free State).

Vrabie, C., 2023. Education 3.0–AI and Gamification Tools for Increasing Student Engagement and Knowledge Retention. In PLAIS EuroSymposium on Digital Transformation (pp. 74-87). Cham: Springer Nature Switzerland.

Vygotsky, L. 2011. Interaction between learning and development (pp. 79-91). Linköpings universitet.

Vistorte, A.O.R., Deroncele-Acosta, A., Ayala, J.L.M., Barrasa, A., López-Granero, C. and Martí-González, M., 2024. Integrating artificial intelligence to assess emotions in learning environments: a systematic literature review. Frontiers in Psychology, 15, p.1387089.

Waite-Stupiansky, S., 2022. Jean Piaget's constructivist theory of learning. In Theories of early childhood education (pp. 3-18). Routledge.

Waldrop, M.M., 1988. Toward a Unified Theory of Cognition: Soar is a computer program that can learn from experience—and that may also explain the basic mechanisms of thought. Science, 241(4861), pp.27-29.

Wang, Y. and Chiew, V., 2010. On the cognitive process of human problem solving. Cognitive systems research, 11(1), pp.81-92.

Wang, X., Razo, M., Tacca, M., So, N. and Fumagalli, A., 2013, April. Five resource allocation strategies for the cloud infrastructure. In 2013 17th International Conference on Optical Networking Design and modelling (ONDM) (pp. 13-18). IEEE.

Wang, P., 2019. On defining artificial intelligence. Journal of Artificial General Intelligence, 10(2), pp.1-37.

Wang, S., 2019. Smart data mining algorithm for intelligent education. Journal of Intelligent & Fuzzy Systems, 37(1), pp.9-16.

Wang, X., 2023. Exploring positive teacher-student relationships: the synergy of teacher mindfulness and emotional intelligence. Frontiers in Psychology, 14, p.1301786.

Ward, J., 2019. The student's guide to cognitive neuroscience. Routledge.

Warwick, K. and Shah, H., 2016. Turing's imitation game. Cambridge University Press.

Waykar, Y.A. and Yambal, S.S., Ch-03: Digital Education System Using AI. 2024

Webber, K.L. and Zheng, H., 2020. Data analytics and the imperatives for data-informed decision making in higher education. Big data on campus: Data analytics and decision making in higher education, pp.3-29.

Wendler, M.C. and Struthers, R., 2002. Bridging culture on-line: Strategies for teaching cultural sensitivity. Journal of professional Nursing, 18(6), pp.320-327.

Wentzel, K. R. (1991). Social relationships and motivation in middle school: The role of parents, teachers and peers. Journal of Educational Psychology, 83(2), 268-278.

Widmayer, S.A., 2004. Schema theory: An introduction. *Retrieved December*, *26*, p.2004.

Williamson, B., 2017. Big data in education: The digital future of learning, policy and practice.

Wongvorachan, T., Lai, K.W., Bulut, O., Tsai, Y.S. and Chen, G., 2022. Artificial intelligence: Transforming the future of feedback in education. Journal of Applied Testing Technology, pp.95-116.

Woolfson, M.M. and Woolfson, M.S., 2007. Mathematics for physics. Oxford University Press.

Wright, J., 2006. Teaching and assessing mind maps. Per Linguam: A Journal of Language Learning= Per Linguam: Tydskrif vir Taalaanleer, 22(1), pp.23-38.

Xia, Q., Chiu, T.K. and Li, X., 2023. A scoping review of BCIs for learning regulation in mainstream educational contexts. Behaviour & Information Technology, pp.1-22.

Xu, J. and Zhong, B., 2018. Review on portable EEG technology in educational research. Computers in Human Behavior, 81, pp.340-349.

Yan, Z. and Brown, G.T., 2017. A cyclical self-assessment process: Towards a model of how students engage in self-assessment. Assessment & Evaluation in Higher Education, 42(8), pp.1247-1262.

Yan, Z., Chiu, M.M. and Ko, P.Y., 2020. Effects of self-assessment diaries on academic achievement, self-regulation, and motivation. Assessment in Education: Principles, Policy & Practice, 27(5), pp.562-583.

Youvan, D.C., 2024. Expanding Human Thought Through Artificial Intelligence: A New Frontier in Cognitive Augmentation.]

Yu, S., Qing, Q., Zhang, C., Shehzad, A., Oatley, G. and Xia, F., 2021. Data-driven decision-making in COVID-19 response: A survey. IEEE Transactions on Computational Social Systems, 8(4), pp.1016-1029. Web address: https://www.researchgate.net/figure/Big-data-processing-stages_fig1_351967613

Yufeia, L., Salehb, S., Jiahuic, H. and Syed, S.M., 2020. Review of the application of artificial intelligence in education. Integration (Amsterdam), 12(8), pp.1-15.

Yulieana, R. and Effendi, R., 2020. Model school curriculum management at Public Elementary School. Journal of K6 Education and Management, 3(3), pp.315-326.].

Zaknich, A., 2003. Neural networks for intelligent signal processing (Vol. 4). World Scientific.

Zhang, L., Synaptic Pruning Mechanism of Brain Provides a New Way to Build Networks. International Journal of Higher Education Teaching Theory, p.13. 2020

Ziemke, T., 2016. The body of knowledge: On the role of the living body in grounding embodied cognition. Biosystems, 148, pp.4-11.

Zohuri, B. and Rahmani, F.M., 2023. Artificial intelligence driven resiliency with machine learning and deep learning components. Japan Journal of Research, 1(1).

Zuse, K., 1993. The computer-my life. Springer Science & Business Media.

Øygarden, E., 2019. What is Intelligence?: A proposed framework of four different concepts of intelligence (Master's thesis, Universitetet i Agder; University of Agder)