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Systematic Review

Leveraging AI in E-Learning: Personalized Learning and Adaptive Assessment through Cognitive Neuropsychology—A Systematic Analysis

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Abstract: This paper reviews the literature on integrating AI in e-learning, from the viewpoint of cognitive neuropsychology, for Personalized Learning (PL) and Adaptive Assessment (AA). This review follows the PRISMA systematic review methodology and synthesizes the results of 85 studies that were selected from an initial pool of 818 records across several databases. The results indicate that AI can improve students' performance, engagement, and motivation; at the same time, some challenges like bias and discrimination should be noted. The review covers the historic development of AI in education, its theoretical grounding, and its practical applications within PL and AA with high promise and ethical issues of AI-powered educational systems. Future directions are empirical validation of effectiveness and equity, development of algorithms that reduce bias, and exploration of ethical implications regarding data privacy. The review identifies the transformative potential of AI in developing personalized and adaptive learning (AL) environments, thus, it advocates continued development and exploration as a means to improve educational outcomes.

Keywords: artificial intelligence (AI); e-learning; personalized learning (PL); adaptive assessment (AA); cognitive neuropsychology; intelligent tutoring systems (ITS); neuropsychological assessment; machine learning (ML); brain-based learning; student engagement

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1. Introduction

Artificial intelligence (AI) in e-learning has become an object of interest for scientists and practitioners, as it has emerged as a significant driver of innovation in education, focusing on the development of modern tools [1–3]. AI can estimate which learning activity will be best suited for each student in this case, based on his/her current needs and context. This helps with personalized recommendations. This has become quite critical now, when, due to the COVID-19 pandemic, courses are being taken online and assessments are being made digitally. By analyzing a student's current knowledge and the context in which they learn, AI can propose activities [4–6]. These recommendations come from a profile that has been developed based on all the gathered data regarding the student's learning up to this date. The approach develops learning through several means of offering support and additional learning opportunities [7–10].

Since the introduction of AI into e-learning tools in the late 1960s, machinery has undergone vast development, with AI technologies proving an integral part of the design and delivery of technology-enhanced learning. In recent years, with the increasing interest in adaptive learning (AL) technologies, the utilization of AI in e-learning platforms has received considerable attention [11,12]. The use of AI technologies for question-crafting, scoring, and feedback provision is enabled by cognitive discrepancy theory [13–16].

2. Literature Review

2.1. Definition and Scope of AI in E-Learning

The term AI was first referred to in 1956 by John McCarthy in the Dartmouth Conference, where he defined it as "the science and engineering of making intelligent machines" [17]. Since then, the definition and understanding of AI have extended significantly, with an influence on many sectors, one of them being education. When e-learning was at its beginning, some researchers believed that AI would play the most important role in this area because the conventional teaching methodology would be changed due to AI and computing technologies. It is also important to note that not all e-learning systems are inherently aware of AI. These are intelligent tutoring systems performing tasks like automated grading that must be consciously integrated by course authors within the framework of online learning platforms, and not all e-learning systems use AI equally. The most prominent influence that AI has had on e-learning is in developing PL and AA. PL is an education suited to the skills, knowledge, and preferences of individual students when learning.

This requires e-learning systems to adapt the contents and their delivery sequence to the ability of the learner, adding an extra layer for which AI is crucial. Traditional computational approaches, integrated with technologies related to psychology and cognitive neuropsychology, are no longer good enough for AI systems [18–20]. Evidence-based workflows may, therefore, be generated, optimizing underlying cognitive processes responsible for learning [21,22]. Whereas the contributions of AI to e-learning are promising, several gaps mark the current state of the literature. Most of the studies have emphasized the role of AI-driven systems for personalization in education. However, critical discussions regarding their long-term effectiveness and scalability are required. Most research is of a descriptive nature, and the more realistic challenges that are in such implementations on a larger scale have not been explored in single-case studies, pilot programs, or small batches of adopters. Moreover, the incorporation of cognitive neuropsychology into AI-driven learning systems is still in its infancy, and further empirical research is required to establish its efficacy [23–25]. Therefore, although the literature has identified the conceptual benefits accruable from AI in e-learning, it often stops short of critical considerations of its limitations, especially regarding the adaptability of AI systems across varied educational contexts [26,27].

2.2. Historical Development and Evolution

Understanding the historical development of AI and e-learning forms an important ingredient in showing how these two fields have gradually merged into the development of AI-powered learning environments. Both domains have undergone serious development over the years, resulting in intelligent systems designed to support PL and AA in educational contexts [28–32]. First, this section will provide a short overview of AI's role in education, showing how AI became a tool for personalizing and managing smart education. This is further discussed by considering the parallel evolution of e-learning, which has advanced with AI technologies [33–35]. Preliminary research in AI introduced several learning theories that became the foundation of teaching strategies in early, primitive e-learning systems. At the dawn of cybernetics, several new theories emerged, based on empirical and theoretical advancements. Bruner's (1960) theory of adaptation to learning, influenced by Piaget (1970), marked a shift from teacher-centered instruction to student-centered learning, emphasizing discovery as a key element of education [36]. The transition introduced the idea of programmed instruction, at which Papert 1981 and Bruner 1960 extended the concept for computer-based learning processes controlled by early teaching machines [37,38]. Adaptive computer training systems developed in the 1960s and 1970s, inspired by Piagetian constructs, varied their training according to the estimated ability of the individual learner. In the late 1970s, Alexander and Leason (1978) took a significant step forward by proposing an intelligent tutoring system for teaching basic algebra [39]. Another critical step in AI learning was that, in 1978, PLATO (Practical Learning Authoring

Tool) was born. The result of collaboration between Norman Crowder and a team of cognitive psychologists at the University of Illinois, PLATO was the first online system for learning that users could interact with through a simulator or virtual world filled with character animation (avatars) and animated objects for better learning [40].

While the historical progress in AI in education is impressive, the literature has largely remained descriptive, listing technological advances without deep critical analysis. Many such studies focus on the potential of the AI systems to transform learning, and not many addresses practical challenges associated with large-scale implementation. In addition, most of the early learning theories have yet to be integrated with state-of-the-art AI technologies. Thus, how these theories can inform contemporary AI-driven systems remains a wide-open research area. The field would further benefit from a more critical assessment of how these early innovations have, indeed, translated into effective tools in today's e-learning environments and rigorous studies that assess the real-world impact of AI technologies on improving education outcomes.

2.3. Personalized Learning (PL) in E-Learning

A huge quantity of research has targeted PL, most of which has theoretically validated the approach. PL represents a significant part of modern education and training. It does, indeed, open new perspectives on the stimulation of learners and on enhancing their motivation to learn, hence optimizing learning [41–43]. PL is, therefore, an instructional method in education, which is aimed at adapting learning to match unique needs and preferences of individual learners. Through PLSs, learners are able to choose resources and activities related to their learning style and preference [44]. There are several definitions and dimensions of PLSs [45–48] that are based on three main educational theories.

First, cognitive psychology focuses on the way learners process, store, and retrieve information. Knowledge is fundamental in developing tools that will match learning experiences to individuals' cognitive abilities and learning speeds. Furthermore, constructivism is informed by the view that learners build their own knowledge from experience. Hence, interaction activities, problem-solving, and authenticity are important for individualized learning [49,50]. Connectivism, a digital-age-appropriate theory, states that learning is not limited to the brain of an individual but distributed within networks, and that the very ability of one to learn depends on their capacity to construct and surf networks [51–57]. That is particularly relevant today in the information-rich environment in which students are constantly dealing with new information and adapting to it through PL systems. These combined theories put forward a robust framework for creating AL environments that take into consideration the students' diverse needs and learning styles [58–60].

PL in e-learning, in its turn, will try to take advantage of the individual student profile by analyzing his or her long-term retention patterns and learning curves. This could have far-reaching consequences. For instance, the system might recommend that learners only focus their attention on the content that is relevant to their goals, and disregard all other content, such as the assignment and examination methods [61,62]. It may recommend that a student studies for examinations by repeating exercises that they already know they will later forget because it may be useful for delivering an optimal personal learning route. Doing so will promote inclusion and, more importantly, avoid discrimination against learners with special needs. This is done by accounting for individual differences in preferences and cognitive profiles [63–65]. Nevertheless, these ideas remain highly speculative, as current systems have not acquired such capabilities yet [66–68].

While PL offers substantial benefits, it is also fraught with challenges. Personalization in learning could help enhance motivation by fostering autonomy, an important drive in the engagement of learners. On the other hand, too much individualization may create a situation in which those learners who benefit from shared learning would be alienated. Over-individualization is likely to get in the way when students might otherwise benefit from the communal aspects of learning. Therefore, adaptive e-learning systems must be critically analyzed, especially those that integrate cognitive neuropsychology, to weigh the benefits of personalization against the drawbacks, particularly in modern-day complex cultural and social contexts [69–75].

2.4. Adaptive Assessment (AA) in E-Learning

Assessment is a crucial component of e-learning, directly influenced by the learner's abilities. Traditional "one-size-fits-all" assessment models are often unsuitable for diverse learners, as individual abilities vary widely. In large classrooms with high student-to-teacher ratios, it becomes challenging to implement personalized, one-on-one assessments. This has led to growing interest in AA techniques, with substantial ongoing research exploring their application in e-learning environments [76–81].

An adaptive system of AA continuously readjusts its assessment process with respect to difficulty level, and according to the performance, preferences, motivations, knowledge, and educational objectives expressed by the learner. The flexibility of AA is able not only to address individual characteristics but also differentiates itself from traditional assessments or even personalized assessments that fail to consider dynamic learning profiles [82–85]. While conventional assessments rely on matching responses to predefined answers, AA systems interpret student responses to understand their knowledge level and track progress. By leveraging learner models, AA can select appropriate test questions from a large pool based on the student's abilities and learning style [86–89].

AA uses AL principles while testing, and uses real-time data to keep analyzing and refining assessments. Just as AL modifies learning pathways based on individual needs, AA tailors the content and administration of test items according to a student's previous performance and need for learning. This technique thus involves more accurate estimates of student skills and increased efficiency in test development, as fewer questions are placed well beyond a student's skill level. AA also dynamically adjusts test length, question difficulty, and other parameters, as informed by real-time analytics [90–95]. While research has demonstrated the potential of AA, the effectiveness and fairness of this system are still in its early stages of exploration, and the full impact of such systems has yet to be realized [96–99].

One promising development in AA is the use of Bayesian mastery models. These models predict the student's mastery by analyzing the expected number of correct responses, thereby enabling the system to make some inferences about the ability of a student in general. The statistical approach helps determine the probability of the student passing a terminal test based on their performance against various items [100–103]. However, all continuous items recycled within AA systems carry several possible security risks, such as the issue of students sharing information about particular questions. The systems must develop an approach to this problem, which is both practically and theoretically daunting [104,105].

Overall, AA has great potential to transform assessment in e-learning by offering more personalized and effective testing experiences. Yet, while the promise of AA is clear, the current literature remains for the most part descriptive. Although there is an entrenched need for more empirical research in the field to critically investigate the real-world implementation of AA systems in terms of effectiveness and fairness, the challenges associated with security, item recycling, and adapting to diverse learning environments should be addressed carefully to fully exploit the benefits of AA technologies [106].

2.5. Cognitive Neuropsychology in E-Learning

Recent developments in cognitive neuroscience and neuropsychology have opened new perspectives on how human learning and cognition work at the level of the human brain. In particular, cognitive neuropsychology has striven to disclose the processes hidden from view when learning occurs through the operation of the brain. With the rise of e-learning, huge opportunities appeared for cognitive neuropsychology applications in such areas as PL, image processing, and assessment. E-learning has several advantages, such as real-time feedback and standardization, with the ability for extensive data collection, thereby making it a very promising platform to integrate cognitive neuropsychology. However, despite the potential, various studies on AI-based e-learning still lack solid theoretical or empirical evidence to prove such cognitive neuropsychological effects on learning outcomes [107–113].

E-learning platforms employ Internet and multimedia technologies in the delivery of diverse instructional media, including text, audio, and video. These technologies enable learners to gain knowledge, skills, and huge amounts of information. The development of intelligent e-learning systems, including learning management systems, assignment checkers, and generators of learning resources, is based on several sub-areas that include cognitive psychology, neuropsychology, and linguistics. Cognitive neuropsychology, in its study of the natural processes of the development of the brain and learning, helps to work out and improve the methodology of teaching for better processes of learning. It applies plausible procedures in the study of animals for understanding mental processes, translating brain functions into strategies for improved teaching. These have, in addition, been highly useful in medical education and optimization of e-learning to adapt to learning styles for efficiency [114–118].

Cognitive neuropsychology makes its contribution to understanding how the brain handles information and diagnosing dysfunctions of the brain. Linking cognitive deficits to performance problems enables researchers to comprehend how certain aspects of brain functioning impact learning. Neuroimaging technologies and cognitive approaches have made it possible to conduct research on the functioning of the brain through non-invasive means, thus providing valuable insights into how e-learning systems can mirror brain processes. For example, representations and algorithms in digital technologies can model how brain systems are organized and work, suggesting sound theoretical connections between neuroscience and digital technologies used in e-learning [119–122].

The literature reviews different studies related to the use of cognitive and psychological theories in e-learning. Among these, cognitive neuropsychology develops models that explain how a learner interacts with educational programs, defining the most effective methods to engage them. AI optimizes teaching strategies and informs them in e-learning systems. Individualized instruction has emerged, and there is a great desire to implement this in each e-learning system where adaptation to specific cognitive needs of every single learner will be pursued. Such systems respond actively to user data and improve the whole learning process by giving focused content and personalized instruction. In the next ten years, research into intelligent systems known as “Intelligent Strains” will further develop these capabilities to even more efficient and effective e-learning environments [123–126].

The scope of this study, therefore, underlines a many-faceted impact of AI in e-learning with reference to the integration of cognitive neuropsychological principles. This integration of AI and cognitive science thus offers immense promise for the furtherance of educational technology and the addition of depth to the existing discourse in this arena.

2.6. Research Questions

Some of the key gaps and grey areas of literature were identified with respect to applying AI in e-learning, particularly integrating cognitive neuropsychology for the advancement of PL and AA. Although the existing literature has demonstrated various possibilities using AI, they are mostly theoretical and not deep, especially where they concern how to apply cognitive neuropsychology to inform AI-driven systems. Moreover, there is a need to develop more empirical evidence and critical analysis about how AI can really fit the bill regarding optimization for the learner’s profile, cognitive processes, and psychological factors.

In view of these observations, criticisms, and gaps identified in the above sections, this research develops five RQs, each targeting how cognitive neuropsychological principles might guide AI to develop more effective PL environments. These RQs will go on to directly address the deficiencies identified in the literature:

- **RQ1: How to leverage the principles of attention and perception to create an AI system that can better personalize learning?**
  This question responds to the gap in current AI systems' ability to account for attention and perception, two critical cognitive processes that influence learning efficiency. The literature review noted that many AI systems fail to incorporate real-time, cognitive-based adaptations. By addressing how AI can tailor learning experiences based on a learner's attentional focus and perceptual capabilities, this research aims to fill that gap.
- **RQ2: How to leverage the principles of language systems in the brain to create an AI system that can better personalize learning?**
  Current AI-driven PL systems hardly ever consider the level of complexity in how the brain processes and comprehends language. The question now aims to understand how AI can apply neuropsychological insights to adapt learning materials to match a range of language processing abilities, thereby helping to fill an important gap in the current ways AI supports diverse linguistic skills.
- **RQ3: How can the principles of reasoning and problem-solving processes in the brain be leveraged to create an AI system that can better personalize learning?**
  Reasoning and problem-solving are the very core of learning that most AI systems poorly address. The focus on these cognitive processes in this research would help better critique and improve the way AI adapts to individual learners' problem-solving approaches, ensuring more effective support for higher-order thinking skills, which have been under-explored in the existing literature.
- **RQ4: How can the principles of memory storage and retrieval, along with numeric cognition in the brain, be leveraged to create an AI system that can better personalize learning?**
  This question concerns the problem of how individual patterns of memory and numeric cognition could be considered in AI. It is common in literature not to address how AI systems could be optimized to support long-term retention and recall, key aspects of effective learning. By drawing on an in-depth analysis of how AI can leverage memory processes as a source of personalization, this study investigates methods for improving the precision and depth of PL systems.
- **RQ5: How to leverage the principles of affective, motivational, and meta-cognitive processes in the brain to create an AI system that can better personalize learning?**
  The role of emotions, motivation, and meta-cognition in learning has sometimes been ignored by AI systems. This question aspires to bridge that gap by asking how AI may use neuropsychological insights in the service of creating more emotionally aware and motivationally adaptive systems, leading, in turn, to more engaged and self-regulated learners.

This research explicitly seeks to answer the following research questions, thereby addressing the following identified gaps in the literature: Each RQ is specifically designed to target an area of failure in current AI systems, with a way forward in creating more cognitively informed, adaptive, and PL environments. These RQs are collectively used here to promote both theoretical and practical integration of cognitive neuropsychology in AI-driven e-learning systems for an increased overall effectiveness and accessibility.

3. Materials and Methods

3.1. Data Collection and Analysis

The methodology employed in this systematic review adhered to the guidelines outlined in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses by the PRISMA Statement [127]. The Data Extraction and Synthesis process (Figure 1) involves several meticulous steps designed to ensure a comprehensive and rigorous review. Initially, relevant records were identified from multiple databases such as MEDLINE, Web of Science, PsycINFO, and Scopus, resulting in a total of 818 records. After removing duplicates and applying language restrictions, 552 records were screened for eligibility. This screening process involved filtering out non-relevant records based on titles and further refining the pool by examining abstracts, which reduced the number to 357. Subsequently, 257 full-text papers were assessed for eligibility to ensure relevance and quality. Following this, 172 papers were excluded based on specific criteria, leaving 85 studies included in the final review. Each step was crucial in systematically filtering out irrelevant studies, thereby ensuring that the synthesis was based on the most pertinent and high-quality research available. The synthesis process included analyzing and summarizing the findings of these studies to draw comprehensive conclusions about the topic under review (Table 1).

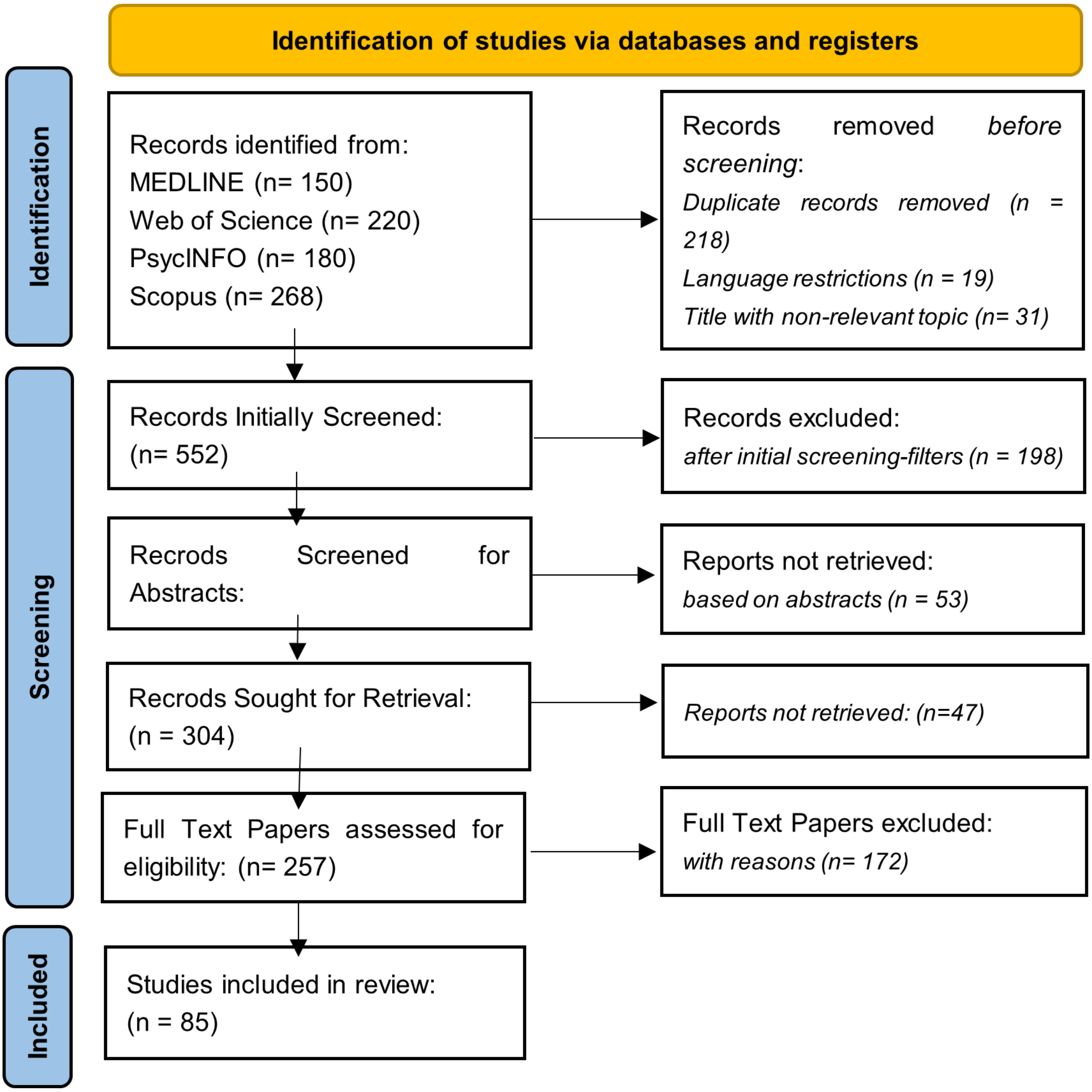

Figure 1. Flowchart of PRISMA methodology.

Table 1. Main results of systematic analysis (N = 85).

Authors	Study Objective	Main Findings	Outcome
Abdurrahman et al. (2021) [128]	- To determine the effects of neuro-cognitive load on learning transfer using a novel VR-based driving system. - To apply multimodal data fusion, ML, and analytics to measure neuro-cognitive load.	A VR-based driving system used multimodal data fusion and ML to measure neurocognitive load during learning transfer.	Positive
Alam et al. (2021) [129]	- Investigating the influence of e-learning and emotional intelligence on study stress, burnout, and performance of Pakistani students. - Applying emotion regulation theory to understand these relationships. - Expanding on previous research in this area.	E-learning and emotional intelligence influence study stress, burnout, and performance.	Mixed
Al-aqbi et al. (2019) [130]	- To assess the effectiveness of ITS through a systematic review of the latest literature. - To determine if ITS enhances student education more than traditional teaching methods.	ITS enhance student learning more than traditional teaching methods.	Positive
Almulla and Al-rahmi (2023) [131]	- Examine the relationships between social cognitive theory and learning input factors. - Examine the relationships between social cognitive theory/learning input factors and reflective thinking and inquiry learning style. - Examine the indirect effects of student problem-solving and critical thinking skills.	How social cognitive theory, learning input factors, problem-solving skills, and critical thinking skills impact learning performance.	Positive
Alwadei et al. (2020) [132]	- To explore the impact of an Adaptive Learning Platform (ALP) on student learning. - To compare learning effectiveness between students who used the ALP and those who did not use the ALP (face-to-face). - To measure learning effectiveness on students' performance on the final exam in a single review preparatory course over multiple academic years.	ALP can significantly improve student learning performance compared to traditional instruction.	Positive
Ayala et al. (2014) [133]	- Apply activity theory (AT) to design adaptive e-learning systems (AeLS). - Demonstrate that AT is a useful framework to design AeLS and provide student-centered education.	Activity theory provides a useful framework for designing adaptive e-learning systems that personalize teaching–learning experiences.	Positive

Table 1. *Cont.*

Authors	Study Objective	Main Findings	Outcome
Balconi et al. (2023) [134]	- To investigate the effects of remote training on distance learning using neurometrics. - To investigate the features of remote training that promote better synchronization between trainers and trainees in terms of cognitive and emotional processes favorable to learning.	Use of neurophysiological measures to assess remote online training and identify features that promote synchronization between trainers and trainees.	Positive
Belfer et al. (2022) [135]	- Develop an AL ITS that uses contextual bandits to personalize the assignment of learning activities to students. - Train the model on student data to maximize exercise completion rates and have it continuously adapted to new activities. - Evaluate the effectiveness of the ALS through a randomized controlled trial, measuring student completion rates and engagement compared to other approaches.	An ALS using contextual bandits can improve student exercise completion rates and engagement.	Positive
Benchoff et al. (2018) [136]	- Design and apply personalized formative self-assessment tests in virtual learning environments. - Customize the tests based on the learning styles of the students and their knowledge level. - Compare the results between two groups of students in different semesters of the same course, as part of a continuous improvement process.	Personalized formative self-assessment tests can improve learning outcomes in virtual learning environments.	Positive
Benz (2010) [137]	- Improve the quality of e-learning by enhancing individuals' deployment of self-regulated learning (SRL) processes. - Conduct a meta-analysis to evaluate the relevance of SRL for learning quality and the impact of SRL interventions on academic achievement. - Provide guidance for future SRL research by identifying effective and ineffective features of SRL interventions. - Develop a concept for providing SRL support in e-learning. - Evaluate whether the SRL support concept (ELWMS) enhances the quality of the learning process and outcome. - Further investigate the effectiveness of the SRL scaffolding concept with an elaborated study design.	Enhancing SRL can improve the quality of e-learning by providing scaffolding and prompting.	Positive

Table 1. *Cont.*

Authors	Study Objective	Main Findings	Outcome
Bobrytska et al. (2020) [138]	- To determine if automated vocational e-courses can lead to the same academic achievements as tutor-moderated courses. - To understand how education stakeholders perceive the automation of e-learning and what factors influence their perceptions.	Automated e-course delivery can lead to similar improvements in student outcomes as tutor-moderated courses in vocational education.	Positive
Dabingaya (2022) [139]	- To experimentally examine the effectiveness of AI-powered ALP in improving mathematics instruction. - To provide an in-depth examination of how AI-powered ALP impacts student learning results, engagement levels, and overall educational experiences	AI-powered ALP improve student engagement and learning outcomes in mathematics education.	Positive
Darejeh et al. (2024) [140]	- Propose and implement an AI-based decision framework for e-learning systems to assess learners' emotions and adjust learning activities to improve performance. - Test the proposed framework through a case study with English as a second language learners over one semester. - Evaluate whether the system with micro-break activities can improve learning performance compared to a control group.	An AI-based framework that assesses learners' emotions and adjusts learning activities to improve performance in e-learning systems.	Positive
Dingli and Montaldo (2020) [141]	- Develop a PLS for students in mathematics, using a browser-based application that can be used by both teachers and students. - Provide immediate feedback to students and allow teachers to create their own exercises or use pre-loaded curricula within the application. - Test the FAIE app with 280 students, divided into a control group and three test groups that use the app at school and/or at home.	The FAIE AI-powered system provides PL and AA for primary school students, with promising initial results.	Mixed
Escalante et al. (2023) [142]	- Examine the learning outcomes of ENL learners receiving AI-generated vs. human-generated writing feedback. - Analyze the perceptions of ENL learners receiving both AI-generated and human-generated writing feedback.	AI-generated writing feedback can be incorporated into English, though a blended approach with human feedback is recommended.	Neutral
Fazlollahi et al. (2022a) [143]	- To compare the effectiveness of an AI tutoring system (VOA) versus remote expert instruction in teaching medical students a simulated surgical procedure. - To evaluate the impact on surgical performance improvement over time. - To evaluate the impact on learning and skill retention.	Learning surgical skills in simulation was more effective with metric-based assessment and formative feedback from an AI tutor than remote expert instruction.	Positive

Table 1. *Cont.*

Authors	Study Objective	Main Findings	Outcome
Fazlollahi et al. (2022b) [144]	- To develop an AI-powered tutor called the Virtual Operative Assistant (VOA) for neurosurgical simulation training. - To evaluate the effectiveness of the VOA in improving technical skills acquisition compared to expert instruction and no-feedback controls.	Leveraging AI in e-learning for PL and AA.	Positive
Flores et al. (2019) [145]	- To use AI algorithms (K-Nearest Neighbor and Random Forest) to train a model that can predict the academic success of college-level engineering students. - To compare the performance of control and experimental groups to see if adaptive measures had an impact on student success.	AI algorithms can be used to predict academic success of engineering students.	Positive
Grawemeyer et al. (2017) [146]	- To adapt formative feedback based on students' affective states (what type of feedback and how it is presented). - To evaluate the impact of this affect-aware feedback compared to feedback based only on student performance.	Affect-aware feedback in an intelligent learning environment can reduce boredom and off-task behavior, and may improve learning.	Negative
Gutiérrez-Maldonado et al. (2010) [147]	- Develop a training program for improving differential diagnosis skills using VR and AI. - Evaluate the effectiveness of the VR-/AI-based training program compared to traditional training methods.	A training program using VR and AI improved psychology students' differential diagnosis skills compared to traditional methods.	Positive
Hammerschmidt-Snidarich et al. (2019) [148]	- To evaluate the effectiveness of a personalized system of instruction (PSI) that incorporates AA, incremental rehearsal, and peer-assisted learning to teach sight words to students in grades 1–3. - To evaluate the efficiency of the PSI for teaching sight words to students in grades 1–3.	A personalized system of instruction incorporating AA, incremental rehearsal, and peer-assisted learning can effectively teach sight words.	Positive
Hampton et al. (2018) [149]	- To analyze the differences in knowledge decay between learners randomly assigned to use an ALS (the intervention group) during a long gap between courses, compared to a control group that did not use the adaptive system.	Voluntary use of an ALS can mitigate knowledge decay during breaks in instruction	Neutral
Harvey (2022) [150]	- To examine the efficacy of a digital therapeutic intervention (AKL-T03) in improving cognitive function in individuals with major depressive disorder. - To understand how cognitive gains from the digital therapeutic can translate into functional improvements.	Using digital therapeutics, leveraging AI in e-learning or PL to enhance cognition in major depression.	Neutral

Table 1. *Cont.*

Authors	Study Objective	Main Findings	Outcome
Hickmann et al. (2022) [151]	- To develop a two-step blended learning course for neurosurgery resident training, consisting of an adaptive e-learning module followed by simulator training. - To evaluate the developed blended learning course by the first participants.	Development and evaluation of a blended neurosurgery training course using adaptive AI e-learning and simulator training.	Neutral
Hinkle et al. (2020) [152]	- To compare a course developed in an ALP with one in a traditional learning management system (LMS). - To evaluate student perceptions and experiences with the AL platform, including whether they felt they learned better, were more engaged, and would want to use the platform again.	ALPs can support student learning and engagement in graduate nursing education.	Positive
Huang et al. (2017) [153]	- Design a digital pen and paper interaction platform (DPPIP) with an attention recognition and review mechanism (ARRM) based on brainwave detection to assist English language learning. - Examine the effects of different cognitive styles, learning abilities, and attention levels on learning performance and reviewed attention when using the DPPIP with ARRM compared to a control group using a DPPIP without ARRM. - Compare the learning performance between the experimental group using the DPPIP with ARRM and the control group using the DPPIP without ARRM.	A digital pen and paper interaction platform with attention recognition and review mechanism based on brainwave detection can improve English learning performance, especially for field-dependent, low-ability, and high-attention learners.	Positive
Huang et al. (2023) [154]	- To examine the effects of AI-enabled personalized video recommendations on learners' learning engagement, motivation, and outcomes in a flipped classroom setting	AI-enabled personalized video recommendations can improve learning performance and engagement of moderately motivated students in a flipped classroom.	Positive
Hur et al. (2022) [155]	- Exploring a method for personalizing learning using ML explainability techniques (specifically SHAP). - Testing this approach in an online learning system for introductory statistics that provides personalized interventions to encourage SRL. - Comparing the effectiveness of the XAI-informed interventions to an "expert system" comparison condition.	ML explainability methods can be used to personalize interventions for students in online learning systems.	Neutral
Kanokngamwitroj and Srisa-An (2022) [156]	- Classify a "risk group" of students who are likely to fail. - Offer a personalized, self-tutoring program to the risk group. - Improve student learning outcomes, as measured by final exam performance.	A PL management system using ML can improve student performance by identifying and providing self-tutoring for at-risk students.	Positive

Table 1. *Cont.*

Authors	Study Objective	Main Findings	Outcome
Kaur et al. (2021) [157]	- To identify the effect of mood on student performance in an online assessment. - To identify the effect of sleep hours on student performance in an online assessment. - To identify the effect of time of day on student performance in an online assessment. - To identify the effect of energy level on student performance in an online assessment.	Mood and time of day affect student performance in online assessments, suggesting potential for adaptive tutoring systems based on cognitive skills.	Mixed
Kerfoot, B. (2010) [158]	- To compare the learning efficiency of an adaptive spaced education system vs. a non-adaptive spaced education system. - To perform this comparison among surgery students at two medical schools.	Adaptive spaced education improves learning efficiency compared to non-adaptive spaced education.	Positive
Khalil et al. (2022) [159]	- Develop a series of ADDIE (analysis, design, development, implementation, and evaluation) framework-based and quiz-based interactive videos on E-Portfolio instructional content. - Examine the impact of these interactive videos on students' e-portfolio design skills and learning engagement. - Contribute to the knowledge of how interactive quiz-based videos can provide self-feedback for students' attention, performance, and comprehension.	Quiz-based interactive videos in personal learning environments can improve e-portfolio design skills and learning engagement	Positive
Kim et al. (2023) [160]	- To implement an online learning system based on EEG-based passive brain–computer interface technology, referred to as the "adaptive neuro-learning system (ANLS)". - To evaluate the educational effects of the proposed ANLS system compared to conventional online lectures without feedback or online lectures with randomized video feedback.	An ANLS that uses EEG-based passive brain–computer interface technology to monitor learners' mental states and provide interactive video feedback can improve learning performance compared to conventional online lectures.	Positive
Kokoç and Altun (2019) [161]	- To investigate learners' interaction with learning dashboards as a predictor of online learning performance. - To determine the extent to which dashboard interaction data can be used to predict and guide learners' academic performance. - To develop a prescriptive learning dashboard as a learning analytics tool.	Learner interaction with prescriptive learning dashboards in e-learning environments can predict and improve academic performance.	Positive

Table 1. *Cont.*

Authors	Study Objective	Main Findings	Outcome
Kosch et al. (2022) [162]	- To investigate whether user expectations can be manipulated by descriptions of an adaptive AI system (H1). - To investigate whether user performance and performance ratings can be manipulated by descriptions of an adaptive system (H2). - To investigate whether workload decreases when participants believe they are being supported by an adaptive AI system (H3).	The belief of receiving adaptive AI support can increase user expectations and performance, even without actual AI support.	Positive
Kozierkiewicz-Hetmanska (2012) [163]	- Develop an e-learning system that incorporates learning styles. - Evaluate the effectiveness of PL scenarios compared to a universal learning scenario. - Measure the learning results of students in the personalized and universal groups.	PL scenarios in an e-learning system lead to significantly higher learning results compared to a universal learning scenario.	Positive
Kretzschmar et al. (2024) [164]	- Learners can complete more tasks at the same time with the help of the AI learning assistant or when they have learned with the AI tool, than learners who do not have the AI assistant available, or who have learned without it. - Learners who used the AI learning assistant can build deeper knowledge and apply it more effectively to transfer tasks than learners who did not use the AI learning assistant. - Learners who learned with the AI learning assistant can recall the acquired knowledge for longer time periods than those who learned without AI assistance.	An AI-based learning assistant can enhance students' understanding of mathematics through personalized video-based learning.	Positive
Lamia and Laskri (2012) [165]	- Propose an AEHS model based on thinking styles and domain ontology. - Support learning styles as a source for adaptation in AEHS. - Address the problems of lack of maintenance adaptation to learning style, less attention paid to thinking styles, and the insertion of specific teaching strategies into learning content.	The paper proposes an adaptive e-learning hypermedia system model based on thinking styles and domain ontology.	Neutral
Leyzberg et al. (2018) [166]	- To evaluate the benefits of personalized social robots in real-world educational contexts over longer periods of time. - To investigate the effectiveness of a personalization system that orders curriculum based on an adaptive Hidden Markov Model (HMM) that evaluates students' skill proficiencies.	Personalized lessons from a robot tutor using an adaptive Hidden Markov Model led to significantly greater learning gains compared to non-personalized lessons.	Neutral

Table 1. *Cont.*

Authors	Study Objective	Main Findings	Outcome
Lim et al. (2022) [167]	- To investigate the effects of analytics-based personalized scaffolds on students' learning process and outcomes. - To use a rule-based AI system to provide real-time measurement and support of SRL using trace data.	Analytics-based personalized scaffolds facilitated by AI can induce more SRL activities, but do not necessarily improve learning outcomes.	Positive
Lin and Chen (2018) [168]	- To develop an attention-based video lecture review mechanism (AVLRM) that can identify video segments for students to review based on their sustained attention levels, as measured by brainwave signals. - To evaluate the effectiveness of the AVLRM system by comparing the review effectiveness of students in the experimental group (using AVLRM) to the control group (using autonomous review).	An attention-based video lecture review mechanism using brainwave signals can improve the effectiveness of learners' review of video lectures.	Positive
Looi et al. (2016) [169]	- Investigate if combining tDCS with cognitive training can enhance cognitive performance compared to training alone. - Examine if combining tDCS with training can promote transfer of learning to other cognitive domains within a short time period. - Investigate the role of training by including an active control group that received tDCS during a non-mathematical task.	Combining brain stimulation and video game training can promote long-term transfer of learning and cognitive enhancement.	Positive
Mark et al. (2022) [170]	- Develop and assess a novel neuroadaptive training approach using a flight simulator and fNIRS neuroimaging. - Compare a neuroadaptive group (progressing based on performance and workload) to a control group (progressing based on performance only). - Analyze the effects of the neuroadaptive training on speed of progression, skill retention/transfer, and overall workload levels.	Neuroadaptive training using fNIRS in flight simulators can enhance learning speed and efficiency compared to performance-based training alone.	Positive
McCarthy et al. (2020) [171]	- To describe how efforts to increase PL have improved the iSTART system. - To provide results of an implementation of an adaptive logic that adjusts text difficulty based on student performance. - To evaluate the effects of the adaptive text selection on student learning outcomes, including sense of learning and comprehension test gains, especially for less-skilled readers.	Adaptive text selection in the iSTART computer-based learning environment improves PL and reading comprehension, especially for less-skilled readers.	Positive
Mishan-Shamay et al. (2013) [172]	- Identify an ML algorithm that can optimally integrate computerized cognitive testing scores to improve neuropsychological assessment of older adults. - Evaluate the potential of ML algorithms to incorporate other clinical data and predict conversion to mild cognitive impairment (MCI) or dementia.	ML algorithms can improve the accuracy and efficiency of integrating computerized cognitive testing scores to assess older adults for neurological conditions.	Neutral

Table 1. *Cont.*

Authors	Study Objective	Main Findings	Outcome
Mitsea et al. (2022) [173]	- To examine the relationship between breathing and learning disabilities. - To investigate the efficacy of breathwork as an intervention strategy. - To identify the role of assistive technologies in breathing training interventions.	Leveraging AI in e-learning on the use of breathwork and assistive technologies for learning disabilities in special education.	Neutral
Mohamad et al. (2019) [174]	- Enhance learning engagement and collaboration among TVET students. - Promote critical thinking and communication skills. - Develop an ALS based on student intelligence. - Implement gamification in an educational website to improve student engagement and motivation.	AL strategies using gamification can enhance learning engagement for TVET students.	Positive
Morales-Martinez et al. (2024) [175]	- To determine the pattern of cognitive knowledge structure changes that students experience after learning a specific topic (computational cognition). - To discriminate the pattern of cognitive changes among students enrolled and not enrolled in the computational cognition course.	Cognitive assessment tools can be used to evaluate academic learning of psychology students, particularly for a course on computational cognition.	Positive
Mu and Yuan (2023) [176]	- Addressing the issue of ignoring students' cognitive structure and knowledge mastery in building student models in ALS. - Addressing the issue of knowledge forgetting and its impact on students' abilities to progress to the next learning stage. - Improving the semantic information in the system by incorporating multimodal data and knowledge graphs. - Developing a cognitive graph-based learning path recommendation system.	A PL path recommendation system based on cognitive graph can improve students' knowledge mastery and learning satisfaction.	Positive
Nalli et al. (2022) [177]	- Develop successful collaborative activities for undergraduate students to improve their knowledge and soft skills. - Create effective heterogeneous groups for a collaborative writing activity (Wiki) to benefit students in terms of learning and soft skills. - Use clustering techniques to group students into heterogeneous groups for the collaborative activity.	An AI-based software can assist teachers in forming heterogeneous student groups for effective online collaborative learning activities.	Positive
Nazari et al. (2022) [178]	- The study objective is to examine the efficacy of an AI-powered writing tool for English second language postgraduate students in the context of English academic writing.	AI-powered writing tools can promote learning behavior and attitudinal technology acceptance for non-native postgraduate students in English academic writing.	Mixed

Table 1. *Cont.*

Authors	Study Objective	Main Findings	Outcome
Neri et al. (2021) [179]	- To compare the impact of a personalized/adaptive version of the first-person shooter game Counter-Strike: Global Offensive (A-CS:GO) versus the standard version (D-CS:GO) on in-game performance. - To compare the impact of the A-CS:GO versus D-CS:GO on cognitive abilities in the short-term (immediately after training) and long-term (three months after training).	Personalized, adaptive training in a first-person shooter game improves in-game performance and leads to improved cognitive abilities.	Positive
Ostrow and Heffernan (2014) [180]	- To assess the effects of feedback medium (video vs. text) on learning outcomes within an adaptive math tutoring system. - To assess the effects of feedback medium (video vs. text) on student perceptions within an adaptive math tutoring system. - To optimize e-learning design based on the findings.	Video feedback enhances learning outcomes compared to text feedback in an adaptive math tutor.	Positive
Palo et al. (2012) [181]	- To assess the relationship between cognitive styles and the learning process in a SCORM setting. - To compare the learning outcomes of e-learners who received teaching materials adapted to their preferred cognitive style, versus traditional learners who received non-adapted materials.	Adapting e-learning content to students' cognitive styles can improve the learning process, despite low intrinsic motivation.	Neutral
Park et al. (2019) [182]	- To evaluate the effectiveness of a personalized social robot learning companion system that utilizes children's affective cues to modulate their engagement and maximize their long-term learning gains. - To compare the engagement and learning outcomes of children in the personalized robot group, non-personalized robot group, and a baseline group with no robot intervention.	An affective reinforcement learning approach to train a personalized policy for each student during an educational activity with a social robot improves engagement and learning outcomes.	Positive
Parkinson and Redmond (2002) [183]	- To investigate the impact of different computer media (text, CD-ROM, Internet site) on learning performance. - To investigate the impact of student cognitive styles on learning performance. - To discuss the results in terms of individual differences (cognitive styles) and implications for website design.	Cognitive styles affect learning performance in different computer media like text, CD-ROM, and Internet.	Positive

Table 1. *Cont.*

Authors	Study Objective	Main Findings	Outcome
Pei et al. (2018) [184]	- Develop an integrated neurofeedback system with dry electrode EEG acquisition, neurofeedback training, and cognitive function assessment. - Explore the effects of regulating alpha power through short-term neurofeedback training on memory and attention performance. - Evaluate the ability of the integrated neurofeedback system to improve cognitive function for clinical research and personal training.	Leveraging AI in e-learning on an integrated neurofeedback system and its effects on cognitive function.	Positive
Piette et al. (2022) [185]	- To examine whether an AI-driven cognitive behavioral therapy for chronic pain (AI-CBT-CP) program can increase its effectiveness through patient interactions. - To optimize a "reward function" reflecting changes in patient-reported pedometer step counts and pain-related interference. - To predict increases in program effectiveness if AI-CBT-CP experienced more patient interactions than occurred during the trial.	Leveraging AI in e-learning, and in how AI-driven cognitive behavioral therapy for chronic pain can learn and improve through patient interactions.	Positive
Renn et al. (2021) [186]	- Assess the feasibility of using an intelligent tutoring system (ITS) as a classroom adjunct. - Assess the acceptability of the ITS to students. - Assess the effectiveness of the ITS in improving student competencies in client engagement strategies.	An intelligent tutoring system can improve training in psychotherapy competencies in Bachelor of Social Work students.	Positive
Ristić et al. (2023) [187]	- Determine if the adaptive e-learning model provides higher knowledge and more positive knowledge duration compared to a standard non-adaptive e-learning system. - Determine if the adaptive e-learning model increases student learning motivation compared to a standard non-adaptive e-learning system. - Determine if there is a relationship between learning styles and achievement scores. - Determine if there are differences between gender, learning motivation, achievement scores, and satisfaction with the adaptive e-learning system.	Adaptive e-learning systems can increase student learning effectiveness, satisfaction, and motivation compared to standard e-learning.	Positive
Rosalin and Tjong (2022) [188]	- The main study objective is to develop an AI system that can serve as a learning partner for students in a practice-based learning system, with the results yielding 98% accuracy.	Deep learning methods in education can support PL and AA.	Neutral

Table 1. *Cont.*

Authors	Study Objective	Main Findings	Outcome
Rosen et al. (2018) [189]	- To explore the effects of two different AL strategies: remediation and continuity. - To compare the outcomes of these two adaptive groups to a control group with no adaptive algorithms.	AL strategies in MOOCs, such as prioritizing remediation, can increase learning gains compared to non-adaptive courses.	Positive
Sancenon et al. (2022) [190]	- Implement and evaluate the effectiveness of an adaptive recommendation system for Singapore primary and secondary education. - Use the system to generate customized assessment worksheets based on individual learner's proficiency. - Measure students' skill levels and monitor their progress using online data analysis. - Evaluate the impact of the personalized content on academic performance through a randomized controlled trial.	An adaptive recommendation system that personalizes learning content based on student data can improve academic performance.	Positive
Song, Cuiping, Song, Yanping (2023) [191]	- To evaluate the impact of AI-assisted language learning on Chinese EFL students' writing skills. - To evaluate the impact of AI-assisted language learning on Chinese EFL students' writing motivation. - To provide evidence for the integration of AI-assisted writing tools in EFL classrooms. - To explore how AI-powered tools can cultivate and sustain students' enthusiasm and interest in the writing process.	AI-assisted language learning via ChatGPT enhances EFL students' writing skills and motivation.	Positive
Spain et al. (2021) [192]	- To induce data-driven policies for tutorial planning using reinforcement learning to provide adaptive scaffolding based on the Interactive, Constructive, Active, Passive framework for cognitive engagement. - To present the results of the policy analyses, including: - The best performing policies optimized learning gains by inducing an adaptive fading approach where learners received less cognitively engaging forms of remediation as they advanced. - Learners' prior knowledge impacted the type of scaffold that was recommended, showing an aptitude–treatment interaction.	Reinforcement learning can be used to induce adaptive scaffolding policies for personalized online training	Positive
St-Hilaire et al. (2021) [193]	- To compare the learning outcomes between two online learning platforms, Platform A and Platform B. - To assess the impact of the two platforms on participants' metacognition.	Interactive problem-solving exercises and personalized feedback on Platform B lead to better learning outcomes compared to lecture videos and multiple-choice quizzes on Platform A.	Positive

Table 1. *Cont.*

Authors	Study Objective	Main Findings	Outcome
Surjono (2007) [194]	- To empirically evaluate the effectiveness of an adaptive e-learning system (AES). - To compare the performance of students using the AES versus a non-adaptive system.	An adaptive e-learning system that personalizes learning and assessment based on student knowledge, learning styles, and multimedia preferences improves student achievement.	Positive
Vahid et al. (2020) [195]	- To use deep learning on single-trial EEG data to predict the presence of conflict, which is a measure of action control. - To identify the specific neurophysiological features related to attention and response selection processes that contributed to the prediction accuracy. - To demonstrate how AI approaches can be used to validate and develop the links between cognitive theory and the neurophysiology of human behavior.	Leveraging AI in e-learning using deep learning to predict action control from single-trial EEG data.	Positive
Valencia-Vallejo et al. (2018) [196]	- Self-efficacy. - Learning achievement. - Cognitive style (field dependence/independence).	Motivational scaffolding in e-learning environments improves self-efficacy and learning achievement, regardless of cognitive style.	Positive
Valencia-Vallejo et al. (2019) [197]	- Examine the effect of metacognitive scaffolding on academic self-efficacy, metacognition, and learning achievement in students learning mathematical content in an e-learning environment. - Determine if there are significant differences in metacognitive ability, academic self-efficacy, and learning achievement between students with different cognitive styles (field-dependent, intermediate, and field-independent) when learning mathematical content in an e-learning environment.	Metacognitive scaffolding in e-learning environments improves metacognition, self-efficacy, and learning achievement.	Positive
Vidanaralage et al. (2022) [198]	- Examine the behavior of schema congruent and incongruent participants when learning through video-based materials in a flipped learning environment. - Assess memory retention through immediate and delayed tests. - Analyze the emotional valence of participants during the study and test phases using AI-based emotion analysis.	Leveraging AI in e-learning of video-based learning and the role of schema and emotion in memory retrieval.	Mixed
Virós-i-Martin and Selva (2022) [199]	- Characterize the effects on a designer's learning when an AI assistant adapts to the designer's goals during design space exploration. - Compare the designer's learning when the AI assistant adapts to explicit learning goals versus when it does not adapt. - Conduct a preliminary study with 10 students to have them design earth observation satellite constellations while trying to learn about the design problem.	An AI assistant that adapts to the designer's learning goals improves the designer's learning in design space exploration, but may negatively impact task performance.	Negative

Table 1. *Cont.*

Authors	Study Objective	Main Findings	Outcome
Walkington (2013) [200]	- To investigate the impact of personalizing instruction to students' personal interests within an intelligent tutoring system (ITS) for secondary mathematics. - To compare the performance and learning outcomes of students who received personalized problems vs. normal algebra story problems.	Personalizing instruction to student interests within an intelligent tutoring system can promote faster, more accurate learning and transfer.	Positive
Wang and Liao (2011) [201]	- Propose an adaptive e-learning system for teaching English as a second language that considers various student characteristics. - Explore the learning performance of students using a data mining technique, specifically an artificial neural network, as the core of the proposed AL-TESL-e-learning system. - Set three different levels of teaching content for vocabulary, grammar, and reading to enable AL in the proposed AL-TESL-e-learning system. - Explore the feasibility of the proposed AL-TESL-e-learning system by comparing the results of a regular online course control group with the AL-TESL-e-learning system AL experiment group.	An adaptive e-learning system using data mining and artificial neural networks can improve student learning performance compared to a regular online course.	Neutral
Wang (2010) [202]	- To develop a web-based dynamic assessment system that combines the "cake format dynamic assessment" and "graduated prompt approach". - To investigate the effectiveness of the web-based dynamic assessment system (GPAM-WATA) compared to a normal web-based test (N-WBT). - To determine if the web-based dynamic assessment system (GPAM-WATA) improves e-learning effectiveness, particularly for students with low prior knowledge.	Web-based dynamic assessment using graduated prompts improves e-learning effectiveness, especially for students with low prior knowledge.	Positive
Wang et al. (2020) [203]	- To compare the learning impacts of individualized AL courseware to large-group classroom instruction in China. - To compare the learning impacts of individualized AL courseware to small-group classroom instruction in China.	ALS can lead to greater learning gains compared to large-group or small-group classroom instruction.	Positive
Wong et al. (2015) [204]	- To determine the impact of adaptive tutorials on perceived engagement of medical students with the learning materials. - To determine the impact of adaptive tutorials on the understanding of the appropriate use and interpretation of common diagnostic imaging investigations.	Adaptive tutorials improve medical students' understanding of diagnostic imaging compared to web resources.	Positive

Table 1. *Cont.*

Authors	Study Objective	Main Findings	Outcome
Yilmaz (2023) [205]	- To compare the efficacy of learning by a real-time intelligent instruction system versus learning with in-person human instructor-mediated training for teaching expert-level tumor resection skills. - To assess the performance of medical students who were randomly allocated to three feedback groups: (1) no real-time feedback, (2) real-time intelligent instruction, and (3) in-person human instruction.	Real-time AI instruction is more effective than human expert instruction for teaching expert-level tumor resection skills.	Positive
Younes (2021) [206]	- To identify the effect of using adaptive AI-enabled e-learning on developing digital content creative design skills among postgraduate students. - To measure the impact of adaptive AI-enabled e-learning on both cognitive achievement and practical performance of digital content creative design skills.	Adaptive AI-enabled e-learning environments can positively impact the development of digital content creative design skills.	Positive
Zhai et al. (2018) [207]	- To introduce biofeedback as a stimulus for learners to engage in retrospection regarding their learning behavior in an online self-directed learning context. - To investigate if biofeedback as a stimulus can significantly influence students' reading comprehension and cognitive hierarchy. - To examine how biofeedback affects students' cognitive taxonomies and reading abilities in light of different personal cognitive hierarchic levels. - To explore how biofeedback influences students' learning behavior in light of gender differences.	Biofeedback-based stimulated recall improves self-regulated online learning, with gender and cognitive taxonomy differences.	Positive
Zheng et al. (2021) [208]	- The study objectives are to propose a learning analytics-based personalized feedback approach and examine its effects on collaborative knowledge building, emotional status, co-regulated behavioral patterns, and cognitive load.	A learning analytics-based personalized feedback approach using deep neural networks can improve collaborative knowledge building and emotional status in online learning, without increasing cognitive load.	Positive
Zheng et al. (2024) [209]	- To examine the effect of an AI-empowered assessment and personalized recommendation approach to collaborative learning performance. - To specifically assess the impact on: - Collaborative knowledge building; - Cognitive engagement; - Socially shared regulated behaviors; - Group performance.	AI-empowered assessments and personalized recommendations can enhance online collaborative learning performance.	Mixed

Table 1. *Cont.*

Authors	Study Objective	Main Findings	Outcome
Ziakkas et al. (2024a) [210]	- Improving the effectiveness of flight training by incorporating immersive technologies like VR and simulated air traffic control environments. - Developing technologies for dynamic real-time visualization, automatic pilot assessment, and adaptive training systems to improve the efficiency and efficacy of flight training. - Providing comprehensive insights into pilot performance and cognitive limitations to optimize the overall flight training lifecycle.	Use of AI and VR in flight training to provide personalized, adaptive training and assessment based on cognitive theories.	Neutral
Ziakkas et al. (2024b) [211]	- Improving the effectiveness and efficiency of flight training by incorporating immersive technologies like VR. - Developing dynamic real-time visualization, automatic human profile assessment, and training system adaptation technologies to optimize the flight training process. - Gaining complete insight into the cognitive limitations and performance of flight training participants to further optimize the training lifecycle.	Use of VR and AI-powered simulated environments to improve the effectiveness and efficiency of flight training.	Neutral
Zini and Fabio Le (2022) [212]	- To propose using reinforcement learning to automatically adapt the difficulty of computerized cognitive training exercises. - To illustrate a method to create difficulty-variation policies tailored to specific categories of trainee, and then refine these policies for individual trainees. - To present the results of two user studies evaluating the effectiveness of the RL-based adaptive training approach.	Reinforcement learning can be used to automatically adapt the difficulty of computerized exercises for personalized cognitive training	Positive

3.2. Search Strategy

The search terms were developed to cover the main topics of interest: e-learning, cognitive neuropsychology, artificial intelligence (AI), personalized learning (PL), and adaptive assessment (AA). The following keywords and their combinations were used:

- E-learning: "e-learning", "online education", "digital learning", "technology-enhanced learning".
- Cognitive Neuropsychology: "cognitive neuropsychology", "cognitive neuroscience", "brain-based learning", "neuropsychological assessment".
- Artificial Intelligence: "artificial intelligence", "AI", "machine learning", "ML", "intelligent tutoring systems", "adaptive learning".
- Personalized Learning: "personalized learning", "adaptive learning", "individualized instruction", "learner customization".
- Adaptive Assessment: "adaptive assessment", "computerized adaptive testing", "intelligent assessment systems".

Boolean operators such as "AND", "OR", and "NOT" were used to combine these keywords and ensure a comprehensive search:

("e-learning" OR "online education") AND ("cognitive neuropsychology" OR "cognitive neuroscience") AND ("artificial intelligence" OR "AI") AND ("personalized learning" OR "adaptive learning") AND ("adaptive assessment" OR "intelligent assessment")

3.3. Inclusion and Exclusion Criteria

Inclusion and exclusion criteria were developed with the aim of selecting studies that would be relevant to our research focus on AI in PL and AA. The inclusion and exclusion criteria for selecting the studies were as follows:

- Relevance to Study Focus: Explicitly investigated the role of AI in educational settings focused on PL and AA. We gave priority to studies for which the main theme was based on, or connected to, principles of cognitive neuropsychology combined with AI for PL and AA. Studies that did not focus on AI in education or studies conducted on AI alone without sharing pedagogical insights were omitted.
- Population Studied: We included studies focusing on learners at different levels, including K-12, higher education, and vocational training, and excluded those not focusing on learning environments. For example, AI applications focused on industry were beyond the scope of our review. For a due capturing of diverse learning needs, we also included studies targeting learners with cognitive or learning challenges.
- Study Type: Empirical studies, RCTs, and systematic reviews were favored since they provided the most robust evidence of the impact of AI on educational outcomes. Purely theoretical discussions or case studies were excluded unless they contained significant empirical data or practical applications. Non-peer-reviewed reports, conference abstracts, and white papers were also excluded to maintain quality and consistency.
- Language: Only papers published in English were considered. While this may introduce bias, the decision was made to ensure methodological rigor and accessibility for synthesis.

3.4. Justification for Exclusion

In total, 172 full-text studies were excluded at the data extraction stage. Common reasons for exclusion included:

- Lack of Empirical Evidence: Some were purely theoretical, while others did not include any empirical data to support the evidence being presented or stated.
- Irrelevance to AI in Education: Some of the studies had to be excluded, since, although they discussed AI, they did not relate it to its application to e-learning or AA.
- Insufficient Methodological Detail: Some studies that did not provide the design of the research, the studied population, or which AI tool was used were excluded in order not to delve into low-quality non-replicable research.

3.5. Quality Assessment

In that direction, and to ascertain the robustness and replicability of the included studies, a systematic quality assessment process was employed. Each study was evaluated for methodological rigor using the following criteria:

- Study Design: Priority was given to randomized controlled trials, longitudinal studies, and systematic reviews, which provided more reliable data on AI's impact on learning outcomes. Studies that lacked clear methodological design or had small sample sizes were excluded.
- Replicability: Only those studies were included which gave thorough methodological descriptions of the AI algorithms being used, and of what learning outcomes were measured. This would ensure that other researchers would be able to replicate the findings.
- Data Reporting: Due to a lack of complete data reporting or vague descriptions regarding the AI applications, such studies were excluded to base the review on high-quality and transparent research.

3.6. Synthesis and Analysis

We synthesized the findings by conducting a qualitative and quantitative analysis of the 85 included studies. The studies were analyzed for methodology, AI application, and impact on learning outcomes. We developed charts to visualize themes that occurred most frequently and the evolution of research methodologies over time (Figures 2–4). These visualizations helped highlight key trends in AI-powered PL and AA. Firstly, to analyze the methodology trends over time in the research papers reviewed, the process began by extracting and preprocessing the relevant methodology data from each study. This visualization revealed the evolution and shifts in methodological preferences over time, highlighting trends such as the increasing use of AI-driven methodologies in recent years, possibly reflecting the growing integration of AI in e-learning research (Figure 2).

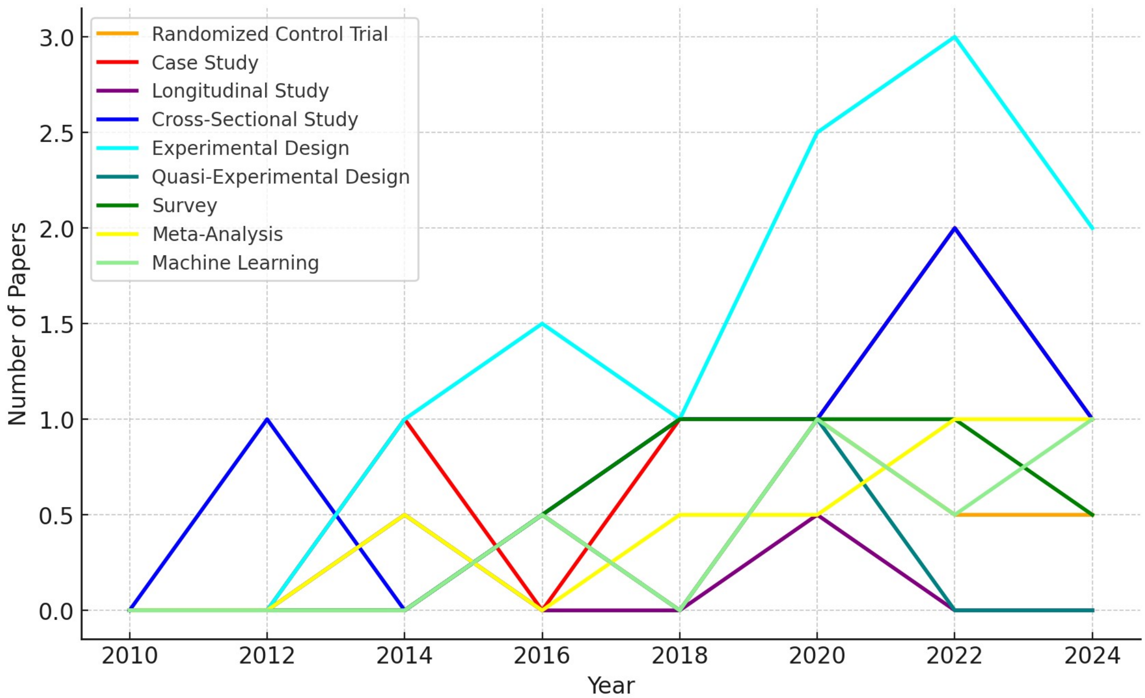

Figure 2. Evolution of research methodologies.

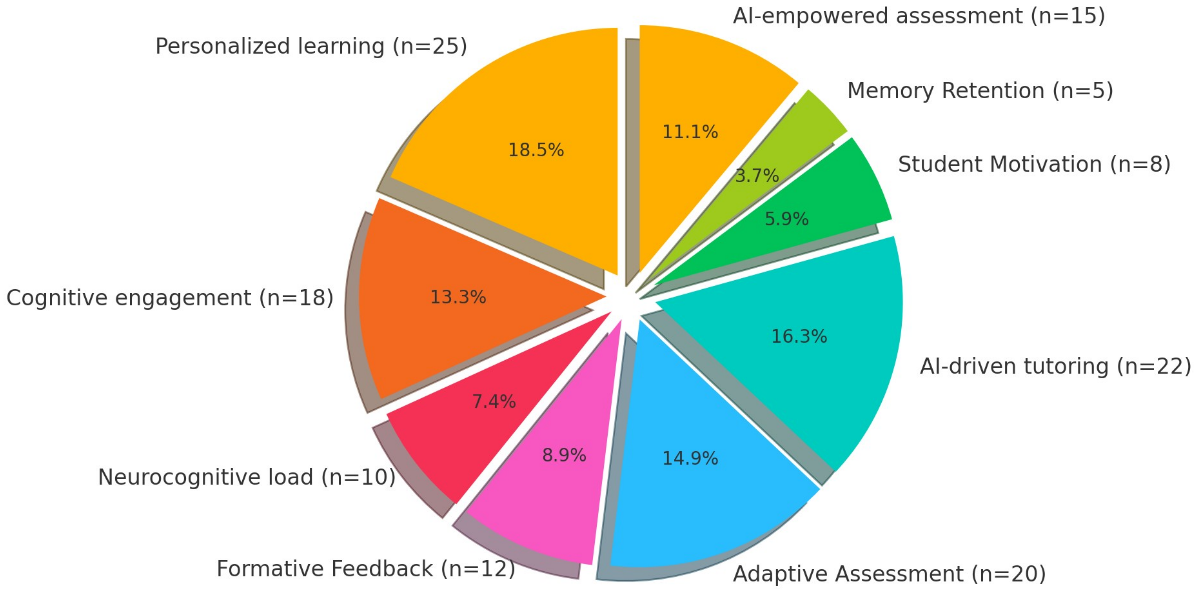

Figure 3. Distribution of objectives across AI-driven studies focused on PL and AA.

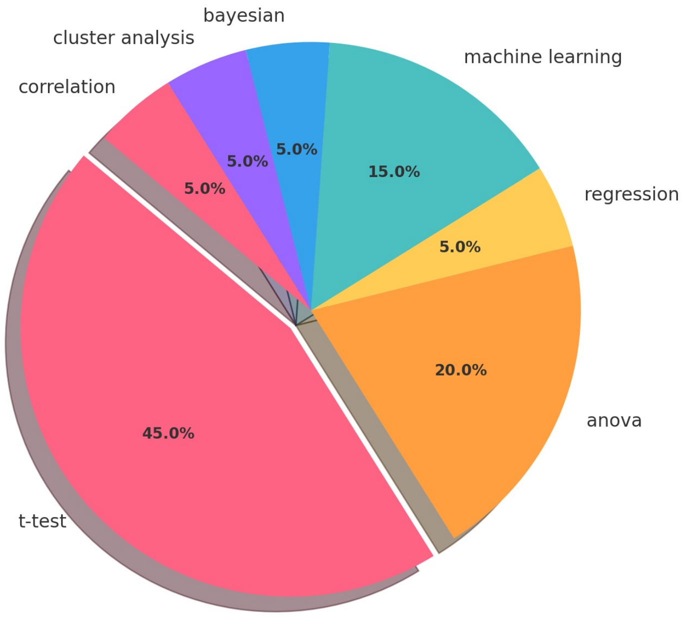

Figure 4. Overview of methodological statistical approaches.

4. Results

The present systematic review was focused on 85 research papers dealing with the role of AI in PL and AA. To gain insight into the focus areas of these studies, we analyzed the primary objectives across the reviewed literature. Figure 3 illustrates the three most frequent research objectives: "PL", "AI-Driven Tutoring", and "Adaptive Assessment", showing the rising focus on adapting educational experiences with the help of AI technologies. Each slice represents a specific objective, with the size of each segment corresponding to the proportion of studies addressing that objective. The objectives include "PL" (n = 25), "AI-Driven Tutoring" (n = 22), and "Adaptive Assessment" (n = 20), which were the most frequently explored topics. Lesser-explored objectives included "Memory Retention" (n = 5) and "Student Motivation" (n = 8). The visualization highlights the prominence of personalized approaches and adaptive technologies in recent AI research in e-learning.

To analyze the distribution of statistical techniques used in the research papers, a pie chart was created to provide a visual summary. This chart categorizes and displays the various statistical methods applied across all the studies reviewed, offering a clear representation of their prevalence. More specifically, the creation of this pie chart involved identifying the different statistical techniques employed, such as descriptive statistics, regression analysis, ANOVA, factor analysis, and ML-based statistical models, among others. Each technique was tallied across research papers to determine its frequency of use. The resulting pie chart shows the proportion of each statistical method, providing an at-a-glance understanding of which techniques are most used in the field (Figure 4).

The pie chart (Figure 5) summarizing the distribution of research outcomes across all 85 studies provides a comprehensive overview of the findings categorized into positive, negative, mixed, and neutral outcomes. This chart visually represents the overall effectiveness and impact of the interventions, methodologies, and tools examined in the reviewed papers.

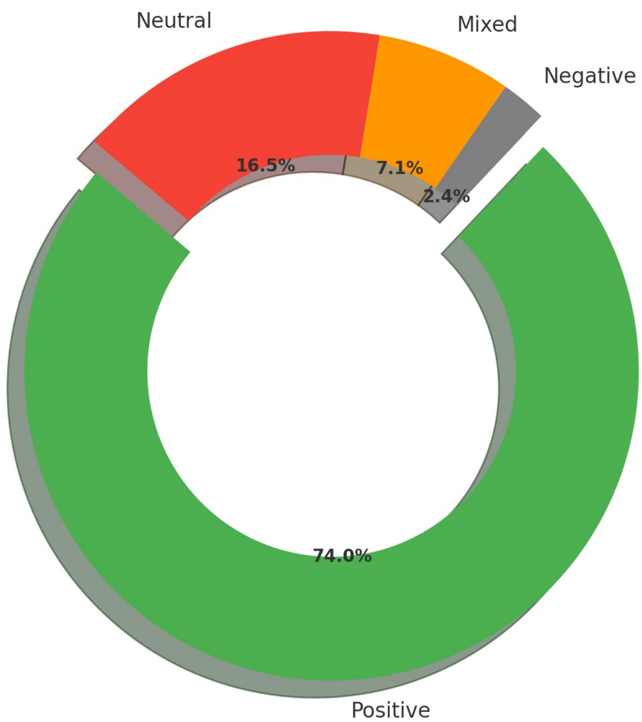

Figure 5. Distribution of research outcomes across 85 e-learning studies.

Each study's outcome was classified based on the reported results. A study was labeled as "positive" if it demonstrated a favorable outcome or supported the hypothesis, "negative" if the results did not support the hypothesis or showed adverse effects, "mixed" if the outcomes were partially supportive or had both positive and negative elements, and "neutral" if the study found no significant effect or remained inconclusive.

The pie chart displays these categories as proportional segments, allowing for an immediate understanding of the overall research landscape. The dominance of positive outcomes in the chart might suggest that many of the interventions or methodologies explored are effective or beneficial in the context of e-learning and AI integration. Mixed outcomes indicate areas where results were less clear or context-dependent, while neutral and negative outcomes highlight challenges or limitations encountered in the research. The following section analyzes the research questions according to the studies examined, highlighting how principles from cognitive neuropsychology, PL, and AA have been leveraged by AI systems to enhance learning experiences.

4.1. RQ1: How to Leverage the Principles of Attention and Perception to Create an AI System That Can Better Personalize Learning?

The multidimensional method of the personalization of learning is considered one which can incorporate the principles of attention and perception into an AI system. This may be driven by ideas of AL, emotion management, mechanisms of feedback, cognitive aspects, technological tools, and collaborative approaches that AI systems may help by constructing more interesting and effective educational experiences. In managing the emotional state of learners, several factors may be considered to enhance learning to its fullest capacity. Micro-Break Activities, supported by AI-based decision-making frameworks, enable the learner to manage their emotions, such as anxiety, to refocus and improve their performance [130,140,192,201]. If adaptation of the learning schedule is related to mood or time of day, this can have an impact on performance. The AI system may schedule the tasks at more appropriate times and offer the learner some personalized reading to get them in a good mood if necessary [157]. Engagement Metrics can monitor interaction levels, using data to adjust learning experiences and re-engage students when attention wanes [139]. Affective Reinforcement Learning uses emotional and engagement cues to personalize educational content, which may enhance learning outcomes [182]. These strategies can help learners remain engaged and emotionally balanced, both important for learning. Timely and relevant feedback is a prime ingredient in effective learning. Continuous, adaptive feedback supports learners in maintaining attention and understanding material more effectively. Formative Feedback and Assessment tools [178], together with Real-Time Feedback systems like EEG-Based Neurofeedback, provide immediate actionable insights that substantially improve learning performance [160]. AI-powered tutors, using Intelligent Feedback Mechanisms, offer automated, metric-based feedback, at times outperforming traditional expert instruction [143].

Combining AI-driven feedback with human input may provide comprehensive guidance tailored to individual needs [142]. Individualization can also reach beyond these groups by adapting content according to a person's cognitive and thinking style. For example, an initial assessment of user preferences can serve as a ground for content adaptation [165,181]. Further considerations of cognitive style might, for instance, be that field-dependent learners need more guidance while field-independent learners require more freedom [197]. Other forms of personalization will also be supported by technological tools. AI-enabled recommendation agents can facilitate content personalization in videos to increase engagement and improve learning outcomes [153]. Cognitive Graphs provide visualizations of students' cognitive structures that can support them in developing metacognitive reflection and insight [176]. Integrating biofeedback monitoring physiological states may enable the real-time adaptation of instructional strategies for a more personalized experience [207]. An adaptive system will be even more powerful if it includes different learning styles. For example, using the VAK model may provide all possible options for adapting visual, auditory, and kinesthetic modalities. It is expected that Activity Theory Principles will allow predictions to be made about learning outcomes and provide students with relevant experience based on their activities. SRL strategies are likely to motivate learners to better govern the processes of learning and, correspondingly, increase the level of learning outcomes. This could provide real meaning and context to otherwise abstract ideas. In fact, problem-solving time and accuracy have been found to increase because of learning materials matched to student interests [200]. Interactive and Adaptive Content, such as quizzes embedded within videos, can ensure students understand concepts before progressing, helping to maintain engagement [159].

Neurophysiological measures can further enhance learning outcomes by optimizing cognitive performance. Neuroadaptive Training adjusts task difficulty based on cognitive workload, optimizing learning efficiency. Neurofeedback for Cognitive Enhancement, utilizing EEG-based feedback, supports the self-regulation of brain activity, potentially improving attention and working memory. Monitoring neurophysiological states, as in the ANLS, has been shown to significantly enhance learning performance. Additionally, AI can facilitate collaborative learning by forming heterogeneous groups that maximize cognitive diversity, fostering critical reflection and improving learning outcomes [177]. Integrating Social Cognitive Theory may promote social engagement and interaction, contributing to a more supportive learning environment [131]. Real-time data and predictive analytics are viewed as key enablers in reaping full effectiveness from PL. Predictive Analytics can forecast academic performance for informing the design of PL strategies [161].

Empowered by AI, the assessments could employ multi-modal data fusion techniques that estimate and react to cognitive loads by adapting the learning environment to the state of the learner [128]. Such data-driven methods, complemented by simulator training, can offer functional experiences in support of perceptual learning [151]. VR combined with AI for Skill Training have been applied to create immersive environments personalized to the learning path of an individual—a promising step towards the effective development of skills [210]. To be widely accepted and effective, AI systems should be friendly for the student users. It has been shown that adaptive AI-enabled e-learning maintains student motivation, and it is an important factor in optimizing attention—an extremely perishable cognitive resource [206]. Reinforcement learning has been applied to develop adaptive training that dynamically adjusts itself as a reaction to learners' improvement towards the optimization of engagement and learning outcomes. The AI systems would be continuously able to adapt to individual student needs, and research evidence in healthcare demonstrates intervention tailored to patient needs, a principle that may be generalized into education. Predictive algorithms may reduce cognitive load and improve perception by forecasting learners' needs [145].

While individual adaptation is important, it is equally critical for optimizing learning trajectories. Individualized adaptive training appears to result in promising findings within areas such as professional sports and gaming [179]. Kept within their zone of proximal development through real-time feedback and offered adaptively challenging content, attention and efficiency might be maximized. Individualized scaffolding, with support provided from real-time analytics, can provide informed and timely support, which has been shown to significantly enhance SRL by maintaining the focus of learners.

Various deep learning approaches have been conducted to analyze comprehensive learning patterns regarding individual adaptations that enhance perception and retention. By understanding how learners process information, AI systems may adjust content delivery to better focus and engage learners. Through different studies, it has been observed that web-based PL systems, driven by machine learning, show better student achievement, hence indicating the potential of AI to continuously adapt to and predict the needs of learners [190]. Affective factors also create engaging and effective learning experiences. Affect-aware feedback has become a crucial part of PL, since emotional states have a great impact on the learning process itself [146]. AI will learn from these affective hints to adapt the learning experience. This process will use attention and perception to maximize learning. Matching cognitive style with assessment may reduce cognitive overload and increase focus on relevant tasks. Formative self-tests tailored to individual needs can enhance learning efficiency [126]. Electrophysiology and hyperscanning research provide insights into brain activity during learning, which AI systems can use to adapt learning environments based on real-time cognitive data [134]. Immersive technologies, such as VR and AI, offer opportunities to engage the learners' perceptual systems in new ways. Applications reported include enhancements in diagnostic skills, along with more stimulating environments for learning [147]. AI systems that integrate schema and affect attention and memory retrieval might enable perceptual learning, indicated by [198]. Attempts to adapt the learning environment to different cognitive styles, based on factors such as cognitive ability, have been reported to lead to improved learning outcomes [183]. Brain stimulation integrated with video games has produced results on far-transfer learning that could be used by AI systems to craft learning experiences according to personal, attention-, and perception-sustaining cognitive strengths. This review, therefore, suggests that AI systems, having regard to attention and perception, could lead to significant changes in PL experiences. The strategies discussed herein, from those related to emotion management and adaptive feedback to the cognitive and technological tools described, outline how AI can contribute to making educational settings appealing and effective. As AI continues to evolve, native abilities for personalization in learning through optimization of perception and maintenance of focus have a high likelihood of raising the bar regarding what is possible in personalized education.

4.2. RQ2: How to Leverage the Principles of Language Systems in the Brain to Create an AI System That Can Better Personalize Learning?

More than anything, the potential for PL enhancement in language acquisition is considerable, considering recent developments in AI. Understanding how these language systems function in the human brain might allow AI to tailor the experience to each learner. Here is a description of how emotional and cognitive adaptation, PL, feedback and assessment, cognitive style adaptation, engagement and motivation, technological integration, and long-term adaptation can help in effective AI-driven language learning. Emotions are a crucial part of language processing and learning. AI approaches that can estimate and regulate learners' emotional states can favorably impact language learning. For instance, AI-powered decision models could assess the emotional state of learners and select appropriate activities for them, which could mitigate anxiety or negative feelings to maintain focused attention and the fluent use of language [140]. Furthermore, aligning content presentation with students' moods and times of maximum productivity can have the effect of maximizing learning efficiency [157].

Neurofeedback techniques thus offer promising methods for emotional and cognitive adaptation. The regulation of brain activity associated with language functions by means of EEG-based neurofeedback may improve working memory and attention, those critical factors for language learning. Techniques such as breathing exercises may further enhance cognitive skills and thereby contribute to improved language comprehension and production. PL scenarios are also critical for making language learning experiences revolve around an individual's preferences, thus being in close resonance with natural language processing by the human brain. Adaptive scaffolding extends reinforcement learning as learners make progress, maintaining cognitive engagement [192]. Adaptation of content presentation by prior knowledge and to the learners' individual preferences may also ensure that the learner receives the proper material at the right moment, thus satisfying continuous assessment and instruction provided by ALPs [203].

Formative feedback is key to continuous improvement in any language. AI-driven formative feedback and on-the-spot error correction have been found to facilitate more rapid language processing and internalization [178]. Similarly, virtual tutors or chatbots may now offer automated feedback and support with cost-effective alternatives to human-tutored courses [138]. Individualized feedback, together with interactive problem-solving exercises, may further enhance metacognitive skills that lead to a deeper comprehension of language. Deep neural network-based classification techniques applied to discussion transcripts can enable, for example, AI-based personal feedback on optimally processing language [208]. Language-based content can be further adapted based on individual cognitive and thinking styles. Cognitive style can, for example, be measured early in the learning process and AI can adapt the instructional materials based on these cognitive styles. Multimodal learning methods, such as the VAK model, engage different parts of the brain, enhancing comprehension and recall [163].

Semantic network analysis can help optimize language learning by assessing changes in knowledge structures and enabling AI to tailor content to align with learners' existing cognitive patterns. Tools such as the Natural Semantic Network can help provide relevant personalized content, which has been shown to increase engagement and performance [175]. Personalized content, including AI-powered video recommendations and practice exercises, can further enhance learner engagement and performance by targeting relevant topics [149,150]. In language learning, explicit goals by learners should be considered to realize optimal results. AI systems that generate iterative, learner goal-based hypotheses may facilitate targeted feedback, improving language comprehension and use [199]. Through motivational scaffolding, i.e., by using supportive language to enhance self-efficacy, learners may also be helped to conquer challenges [196]. Immersive technologies like VR offer dynamic and real-time language training environments that allow contextualized suggestions and feedback [211].

Interactive AI tools offering personalized feedback on aspects like grammar, vocabulary, and coherence would further help improve language skills. It has also been shown that AI-assisted tools, including ChatGPT, can positively influence writing skills and motivation. Interactivity and personalized feedback have thus become crucial variables for effective language learning [191]. Biofeedback mechanisms allow the continuous monitoring of physiological states related to attention and affective engagement. This may enable AI to adapt instructional strategies based on real-time student responses and offer a more customized approach to learning [207]. Long-term language learning requires ongoing adjustment. Personalization of language learning across several sessions will contribute to meeting the dynamic needs of the learners. Systems that provide progressive scaffolding of learning experiences can develop language competencies over time [141]. Incremental rehearsal and peer-assisted learning strategies, also characterized by repetitions of exposure to new vocabulary or concepts, may further support language acquisition within a collaborative environment [148].

Conclusively, with deep-seated integration of AI in state-of-the-art educational technologies, significant strides may occur in personalized language learning. An understanding of how the systems of language work in the brain could conceivably support the continuous updating of learning experiences by AI-driven systems in view of the learner's emotional state, cognitive style, and learning objectives. This is done through continuous feedback, neuroadaptive technologies, and immersive environments, creating truly dynamic learning experiences that will be personalized to respond to changes in learners' needs. The current AI development in education has the potential to continue improving language acquisition, engagement, and long-term retention to improve educational outcomes.

4.3. RQ3: How Can the Principles of Reasoning and Problem-Solving Processes in the Brain Be Leveraged to Create an AI System That Can Better Personalize Learning?

The cognitively based principles of reasoning and problem-solving are applied to PLSs. Further embedding AL technologies, real-time feedback mechanisms, emotional engagement methodologies, interactive content, data-driven approaches, scaffolding, and social learning techniques can constitute the development of an AI system that realizes highly personalized and effective learning experiences. Core strategies in AI-driven educational systems include personalized and AL. Adaptive scaffolding and fading techniques dynamically adjust task complexity with the goal of optimizing cognitive engagement. Moreover, PL scenarios tailored according to individual preferences and aligned with natural cognitive processes might result in improved achievements in reasoning and problem-solving. Cognitive graphs can further support PL paths as learners progress, ensuring that the delivery of content remains relevant to the learner's needs, promoting better cognitive processing and mastery of problem-solving skills [176,189,203]. Research has proven a correlation between AL technologies and improved learning outcomes via continuous assessments and adaptive instructional content with significant efficiency gains [201].

For optimal learning, content personalization is crucial. For example, research has demonstrated that problem-solving tasks relevant to individual students' interests are solved with greater speed and accuracy, thus making abstract constructs more relevant. Similarly, AL platforms that dynamically adapt content based on prior knowledge and preferences have associated benefits for improved engagement and learning outcomes. AI-powered formative feedback tools will help in sustaining engagement and improving problem-solving skills through timely and actionable insights [178]. Dynamic assessment systems, which modify task difficulty based on learner performance, offer constant challenges and stimulate reasoning processes. Explainable AI, which can display personal and understandable feedback, has also proved effective in improving learning outcomes [155]. AI-powered tutors which provided automated audiovisual feedback have shown clear gains in performances. Real-time intelligent instruction has illustrated that timely feedback and error correction improve problem-solving abilities.

In addition, effective reasoning and problem-solving capabilities can be further enhanced by managing learners' emotional states. Emotion and sentiment management frameworks that assess and respond to the mood of learners may reduce anxiety and improve concentration. Neuroadaptive training and EEG-based neurofeedback apply real cognitive workload measures to adjust the difficulty of a task appropriately to keep learners from being overwhelmed or under-challenged. With emotional intelligence, the AI systems will be able to provide support and resources in the most favorable ways for the emotional needs of the learners. Research has shown that mood and time of day may impact student performance, and perhaps considerations of task adjustment could help in maximizing the effectiveness of learning.

Interactive and engaging content is important for maintaining learners' interest and developing their problem-solving skills. Tools such as interactive exercises and gamification can increase learners' focus and engagement [149,187]. Video-based feedback has been shown to enhance understanding and retention, while adaptive tutorials that adjust content based on learners' responses increase engagement and comprehension [180,204]. Interactive videos with embedded quizzes that adapt according to performance further enhance learner engagement and understanding [159]. AI-powered recommendations and data-driven methods may lead to PL that meets personal needs. ML algorithms analyze cognitive data and find the points where learners are struggling and intervene appropriately. Predictive analytics may forecast performance in solving a particular problem and inform PL strategies to ensure appropriate times when the support must be given. The integration of biofeedback mechanisms, which track and react to the physiological states of the learners, will enable personalized instruction strategies and improve their engagement and performance [153].

Scaffolding techniques provide structured support to help learners develop problem-solving skills. Metacognitive scaffolding, which supports the planning, monitoring, and evaluation of activities, improves metacognitive abilities and learning outcomes [197]. Motivational scaffolding and attention-based review mechanisms can help keep learners engaged and focused, particularly during complex reasoning and problem-solving tasks [168,196]. Studies have also highlighted the cost-effectiveness of automated courses through virtual assistants that provide immediate feedback and support for problem resolution [138]. Social and collaborative methods improve problem-solving by interacting and supporting peers. AI systems can support heterogeneous group formation to foster cognitive diversity in collaborative problem-solving activities [177]. Application of the principles of social cognitive theory in AI systems fosters interactive supportive learning environments that improve critical thinking and problem-solving skills [131]. AI-driven social robots with affective cues have also been demonstrated to optimize engagement within collaborative learning environments [182].

Specialized techniques, like VR, make this either immersive or personalized. Students in a virtual environment experience real-time problem-solving and instantaneous feedback that helps them build practical skills and cognitive processes. ALS uses various model-based reinforcement learning methods to create differential tasks according to needs and stages of progress towards enhancing reasoning. Research has also shown that EEG-based systems for monitoring attention and comprehension, in conjunction with interactive video feedback, can individualize problem-solving approaches by dynamically changing the difficulty of tasks as a function of learners' cognitive states. All these strategic dimensions amalgamate to bring in higher levels of PL, mapping on the principles of reasoning and problem-solving in the brain. An adaptive and personalized AI-driven learning system can employ real-time feedback, emotional and cognitive engagement, interactive content, data-driven approaches, scaffolding, social learning, and specialized technologies to bring efficiency to PL experiences. These will lead to higher and more engaging learning that is efficient and more personalized for each learner.

4.4. RQ4: How Can the Principles of Memory Storage and Retrieval, along with Numeric Cognition in the Brain, Be Leveraged to Create an AI System That Can Better Personalize Learning?

The process can work out the principles of memory storage and retrieval, and numeric cognition, to enhance AI-based PL systems. A few techniques of AL, along with mechanisms for personalized feedback and engagement, can help construct the best learning environments by considering the cognitive and emotional parameters of the learner. This discussion synthesizes research-based strategies into one cohesive approach for the improvement of AI-driven learning systems. AL and feedback systems dynamically balance levels of cognitive engagement through reinforcement learning by providing adaptive scaffolding and fading techniques to optimize memory storage and retrieval. The internalization of information in the learners is facilitated by formative feedback and continuous assessment. Therein, AL strategies can focus on remediation or continuity based on learners' progress to ensure the delivery of content that is necessary for cognitive processing.

Long-term retention requires adaptive space education and cognitive tracking. Adaptive space education, which adjusts spacing intervals and repetitions of learning material according to the learner's knowledge level, has been shown to improve long-term retention [158]. Cognitive structure visualization and knowledge retention tracking over time help identify areas requiring revision. Content delivery, tailored to learners' prior knowledge and preferences, enhances engagement and learning outcomes. Research has shown that AL technologies and personalized teaching are in line with the cognitive processes responsible for memory storage and recall [163,203]. Customized content delivery and interactive experiences also lead to deeper levels of engagement and retention. Matching content to learners' preferred learning modality—visual, auditory, or kinesthetic—significantly improves learning outcomes [187]. Numeric interactive exercises that engage learners in active problem-solving processes enhance memory and cognitive skills [149]. Tailoring content to student interests and experiences "grounds" abstract concepts and increases the speed and accuracy of problem-solving [200]. AL systems that adjust the complexity of numeric problems based on the performance of each learner ensure that each gets an appropriate challenge [189]. Personalized video recommendations go on to further enhance engagement and learning outcomes [153].

The emotional state and degree of involvement are important factors in the effectiveness of storing and recalling information. AI-driven decision frameworks detect learners' emotions and inject micro-break activities into the learning process to sustain favorable emotional states for the memory processing of learned material [140]. Activities can be optimized with respect to learners' moods and productive times [157]. Attention-aware review mechanisms can reinforce key concepts effectively [168]. Interactive and fun numeric activities trigger attention that further enhances retention, hence more effective learning.

There is evidence that teaching learning materials according to students' cognitive and thinking styles enhances memory retention and numeric cognition. Artificial intelligence systems can estimate the learners' favorite cognitive style and adapt tasks to that, bringing personalization into the learning process, and thus catering to different learners with different cognitive capabilities. This adaptation helps in enhancing memory retention and numeric problem-solving skills. Numeric cognition can be optimized by individualizing problem-solving tasks to the learner's current knowledge and by gradually raising task difficulty. It enhances learners' numeric concept acquisition and improves their numeric information storing and retrieval capabilities [203]. The use of performance metrics in assessments will allow specific feedback to be given and targeted adjustments to be made to optimize numeric cognition [128]. Collaborative learning activities that employ social learning principles further enhance problem-solving skills by allowing learners to capitalize on peers' strengths [177]. Interactive videos with embedded quizzes adapt to learner performance, enhancing engagement in numeric tasks [159]. AL paths that track knowledge retention over time enable timely reviews and provide continuous assessment, enabling personalized instruction [152,201]. Advanced technologies, including AI-driven feedback systems, neurofeedback, and immersive virtual reality, ensure the persistence of memory storage and numeric cognition. AI systems that implemented metric-based approaches for formative feedback showed gains in performance outcomes [144]. Adaptive space education systems, providing optimization of spacing intervals and repetitions, improve the efficiency of learning and retention [158].

Neurofeedback systems, which monitor the state of the mind in real-time, improve the capability of memory retention and numeric problem-solving [160]. Furthermore, training based on VR and AI technologies, which provide dynamic environments with contextualized recommendations and real-time feedback, enhance this process [211]. It has been shown that integrating motivational scaffolding into e-learning environments can heighten confidence in learners about their memory and numeric abilities. Including elements like goal setting, the tracking of progress, and rewards enhances engagement with tasks [196]. Affective reinforcement learning, wherein content would be adapted to emotional and engagement cues, may lead to better learning outcomes [182]. Emotion recognition systems support a positive learning environment, promoting memory retention and cognitive engagement [129]. Cognitive assessment tools and explainable AI methods provide necessary feedback on the process of storage and retrieval of information in the students' memory, thereby facilitating the customization of learning tasks accordingly. Specifically, explainable AI methods provide insights on learning outcomes to support focused interventions. Chronometric cognitive assessment techniques assess temporal patterns of the retrieval of information and allow instructional approaches to be customized to learners' cognitive processes. Multimodal content caters to different media formats for various cognitive styles, which enhances memory and numeric cognition. Interactive tools with personalized feedback provide reinforcement to the memory through repeated practice and engagement. The use of video-based feedback and other forms of multimedia also increase interest and comprehension. By applying different types of media, AI systems can better engage learners and support the facilitation of memory. Therefore, the integration of memory storage and retrieval principles with numeric cognition into the AI-driven PL systems means an overall robust framework for optimizing educational outcomes. The AI-driven systems dynamically adjust the reinforcement learning and personalized feedback, cognitive engagement level, and provide educational content relevant to each learner's needs. This approach surely enhances memorization and problem-solving abilities. Including adaptive space education, neurofeedback, and multimodal contents strengthens these systems. Furthermore, motivational scaffolding and affective reinforcement establish a positive learning environment, supporting cognitive engagement in ways that make learning more effective. In further developing AI technologies, the role of addressing cognitive and emotional dimensions in PL becomes a core aspect of educational innovation shaping more customized and effective learning outcomes.

4.5. RQ5: How to Leverage the Principles of Affective, Motivational, and Meta-Cognitive Processes in the Brain to Create an AI System That Can Better Personalize Learning?

Theories of affective, motivational, and metacognitive processes can be used to develop new ways through which AI enhances PL. If combined, these principles will enable AI learning environments to help learners be more motivated and self-regulated. Because emotional states are important determinants of effective PL, the recent use of AI-based decision frameworks focusing on the assessment of emotions and introduction of micro-break activities has provided evidence that emotional states may be better regulated with an overall improvement in learning outcomes. Research indicates that maintaining a positive emotional state while reducing anxiety may increase motivation, drive, and overall learning effectiveness [140]. AI-driven feedback systems were also found to provide feedback that maintains positive emotions in a manner like human instruction and reduces negative emotions. AI-powered feedback and assessment lie at the heart of optimizing learning processes. These tools can really amplify the level of involvement in behavior, emotion, and cognition. Feedback being continually adaptive and timely motivates learners to develop more productive metacognitive strategies [178]. Real-time feedback mechanisms, which provide immediate corrections and suggestions, further enhance learning and both affective and motivational states. The application of reinforcement learning dynamically adjusts levels of cognitive engagement and could serve effectively to support motivational and metacognitive processes. Adaptive fading, where the cognitive load is reduced as learners progress, maintains optimal cognitive engagement and fosters self-regulation. Adaptive e-learning systems, which offer content adapted to learners' needs and preferences, may enhance the affective and motivational processes, especially when the remedial or continuity strategy is focused on the AL strategy based on the progress achieved by the learner.

Integration of learning styles within PL scenarios is particularly relevant for improving affective and motivational outcomes. The consideration of personal preference during the learning process creates a conceptual consonance with the brain's natural motivational mechanisms, enhancing general engagement and learning results. Structuring content with respect to the students' interests improves problem-solving speed and accuracy because the ability to relate to abstract concepts is enhanced. Personalized recommendations of videos using AI enhance engagement with the learning process.

The adaptation of learning tasks to the current state of learners in cognitive and emotive respects will employ efficient learning. For example, demanding tasks are scheduled in peak times, while mood-enhancing content or breaks during times of low productivity maintain a positive affective state. Neurofeedback and physiological measures can support affective and metacognitive processes. EEG neurofeedback systems monitor the learner's brain activities instantaneously and provide video interactions based on the current state of the learner's mind. Biofeedback mechanisms related to attention and emotional engagement help the AI system to interactively adapt the instructional approach in real time [207], thereby dynamically adapting content and difficulty levels based on the cognitive and emotional states of learners.

Collaborative learning environments also benefit from the functionalities enabled by AI towards group formations based on cognitive diversity. Drawing on the principles of social learning, AI systems analyze data on the behavior and performance of the students and, hence, have the chance to congregate heterogeneous groupings that maximize collaboration and learning consequences. Social constructivist approaches also support metacognitive skills development in a considerable way, where learning arises through interaction either with knowledgeable peers or AI systems. Furthermore, interactivity could be enhanced with interactive and engaging content such as videos with embedded quizzes or gamified learning elements that keep up the learner's interest and motivation throughout the learning process.

For improving meta-cognitive strategies, integration of tools like self-assessment quizzes, reflective prompts, and progress tracking would be possible. These activities would enable learners to plan, monitor, and evaluate their learning processes. The continuous adaptive scaffolding should foster goal setting, reflections on one's understanding, and self-regulation of strategies. Cognitive graphs and real-time analytics could create PL pathways aligned with emotional and motivational needs. AI-empowered assessments providing recommendations will further enhance cognitive engagement and the socially shared regulation of learning behaviors. Dynamic training environments, such as VR, offer feedback and recommendations contextually. Because of this, learners could have their motivation preserved while the metacognitive processes could be scaffolded [210]. On the other hand, ML algorithms that analyze cognitive data may offer targeted intervention if the learners fail in an affective, motivational, or metacognitive process [172].

Scaffolding motivation in e-learning environments could lead to greater self-efficacy and more engaged learners. AI systems with goal setting, progress tracking, and rewards enhance the learners' interest in, and persistence with, learning tasks. Blended adaptive e-learning systems, combined with simulator training, could provide practice exercises for supporting development in both metacognitive skills and motivation. A blended approach to feedback, exhibiting AI-generated feedback together with human feedback, provides comprehensive and personalized guidance about metacognitive skills. Real-time adaptation features adjust the difficulty of the content based on the learners' affective and motivational states, keeping them challenged but not overwhelmed, to maintain a positive attitude toward learning [202]. Emotional Intelligence plays an important role in AI systems when dealing with students' affective states, directly influencing motivation and learning processes. AI systems that score and respond to students' emotional responses can make available individualized resources that improve motivation and engagement. Interactive exercises with feedback for individual responses provide students with the opportunity to correct their mistakes in real time, providing metacognitive support. This feedback is even more effective if it is delivered through multimedia.

AI systems can also control user expectations to enhance users' performance and satisfaction. For instance, the realization of AL models will adapt the task difficulty and type according to learner performance to maintain an optimal level of challenge to better support engagement and motivation. Long-term personalization makes personal learning experiences for individuals continue to adapt to the progress and needs of learners while reassuring their affective and motivational states through time.

Overall, engaging affective, motivational, and metacognitive processes in AI-driven PL systems provides a potentially potent framework for improving learner engagement, self-regulation, and overall learning outcomes. An AI system could capture, in real time, every moment of a learner's emotional and cognitive states and feedback, challenges, and support at optimally matched levels. This would make for highly motivating, dynamic, personalized development that builds self-efficacy toward full development. Neurofeedback, AL strategies, and collaborative learning models extend the influence of these systems to make the learning experiences engaging and effective. With further developments in AI, personalization for the affective and cognitive needs of learners will feature as a core axis in innovations within education.

4.6. The Integration of AI, PL, and Cognitive Neuropsychology in E-Learning Systems

The functionality of the education system, due to technologies such as machine learning, neural networks, and natural language processing, analyzes student performance data, predicts further learning needs, and makes dynamic adjustments to optimize learning. AI powers the intelligent tutoring systems of ALEKS and Carnegie Learning, whereby real-time adaptation can be done on each performance by students. PL simply customizes learning experiences to fit each learner's unique needs and abilities. AI enhances PL by constantly analyzing students' progress and accordingly adapting the learning path, which might allow students to proceed at their own pace. Cognitive neuropsychology focuses on how the learner processes information, stores it, and retrieves it. AI systems also make use of cognitive principles, such as cognitive load theory and memory retrieval. This ensures that AI-powered systems, such as NeuroNation and iSTART, utilize cognitive performance for managing cognitive load, enhancing memory retention, and regulating attention.

The points of intersection of the components mentioned above suggest embedding AI in PLSs, where live data and AI-driven analytics create adaptive environments that optimize student engagement and outcomes. Additionally, AI tools utilize cognitive principles when improving learning by the adjustment of content based on cognitive states such as attention and cognitive load. PL systems automatically adapt to each learner's individual cognitive profile by selecting appropriate instructional materials based on each learner's cognitive strengths and capacities. The full integration of AI and PL brings further advances from cognitive neuropsychology whereby state-of-the-art systems like Affective AutoTutor adapt content and emotional feedback based on the learner's cognition state and emotional engagement. This also highlights how AI-driven education has the potential to offer not only personalized content, but also optimized content with respect to cognitive and emotional states that will further enhance learning outcomes. The Venn diagram below (Figure 6) illustrates the key intersections between Artificial Intelligence (AI), PL, and cognitive neuropsychology in the context of e-learning. Each circle represents a critical component that, when integrated, forms the foundation for advanced AI-driven educational systems. The overlapping areas highlight how these elements work together to create adaptive, personalized, and cognitively aligned learning environments.

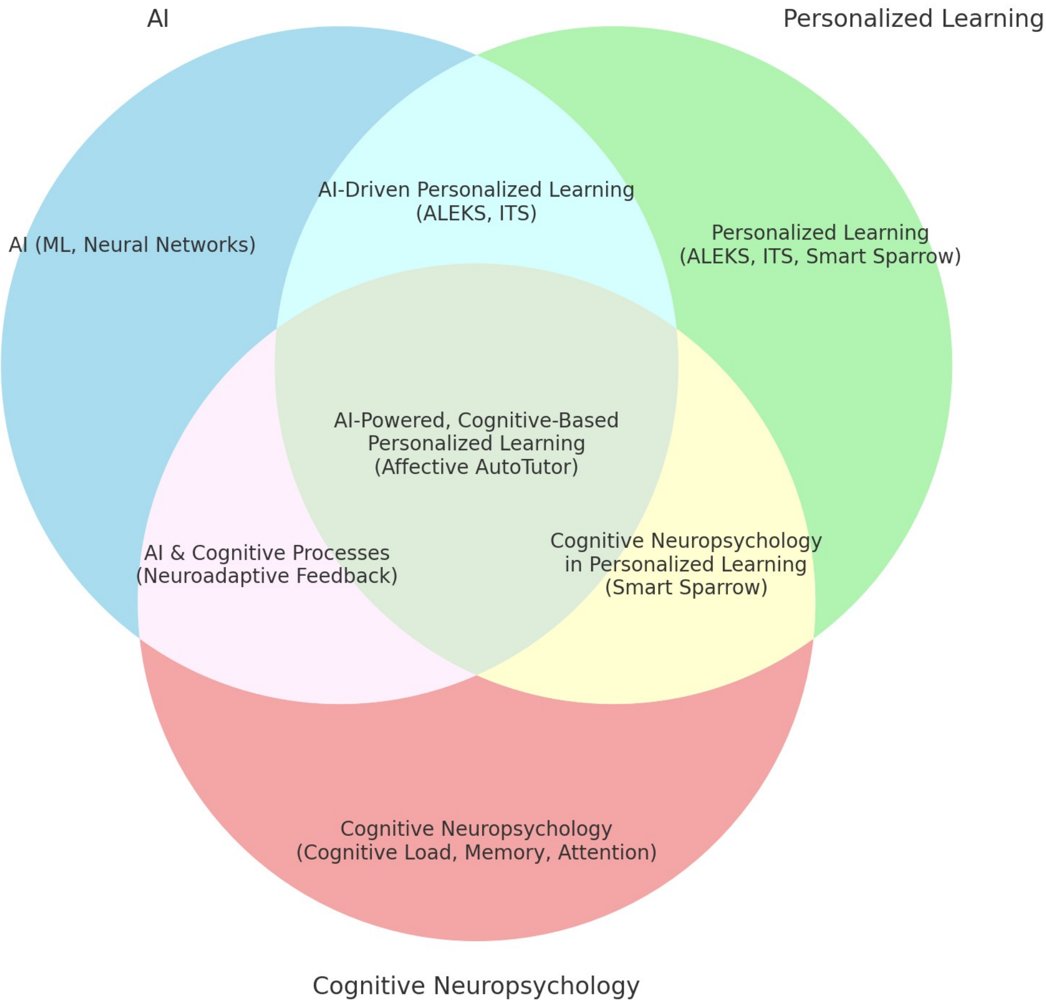

Figure 6. Analytical intersections of AI, PL, and cognitive neuropsychology in e-learning systems.

5. Discussion

This review has systematically examined the role of artificial intelligence (AI) in e-learning, specifically in enhancing PL and AA through cognitive neuropsychology principles. By synthesizing the results of 85 studies, we found significant evidence supporting AI's transformative role in education, particularly in improving student engagement, learning outcomes, and the efficiency of assessment strategies. The findings of this review align with, and expand on, existing theories of PL, cognitive neuropsychology, and AA. AI-driven systems, by leveraging these theoretical frameworks, can provide PL experiences tailored to the needs of individual learners. This section will focus on the key areas of AI's impact and their broader implications for educational theory and practice.

5.1. Real-World Applications of AI in PL and AA

Real-world applications of PL and AA, with the integration of AI, have already been able to show measurable improvements in educational outcomes. There are two major implementations of AI: intelligent tutoring systems and adaptive learning platforms (ALPs), both of which improve student engagement and performance by tailoring the educational experience to individual needs.

5.1.1. Intelligent Tutoring Systems (ITS)

ITS are highly effective in delivering content that dynamically adapts to the individual learner's progress, learning style, and cognitive capacity. These systems dynamically manage content delivery by providing feedback that automatically changes according to the learner's pace. For example, in mathematics education, ITS have shown promise in improving student performance by delivering PL materials tailored to each student's cognitive strengths and weaknesses [116]. ITS offer a more focused approach, and their individualized nature enables students to go at their own pace and thus maintain retention and engagement.

5.1.2. Adaptive Learning Platforms (ALPs)

Another successful application of AI is the ALPs which have already been used both at K-12 and the higher education level. The system continuously modifies the educational content in accordance with the way the student interacts with the platform. For instance, one such ALP used in prep courses at universities continuously modifies the learning material in accordance with understanding and progress shown by students. These dynamic content modulations have been most successful in mathematics, as this subject is often very complex and requires different ways of instruction. ALPs have been found to increase student engagement through personalized challenges and feedback based on the learner's real-time performance, keeping them motivated and on track [116,117].

5.1.3. Adaptive Assessment Techniques

In AA, it has been possible to apply AI in the real-time modification of question difficulty based on previous answers provided by the learner. Examples include Bayesian mastery modeling applied in professional assessments such as GRE and GMAT. These AAs allow for a more accurate measure of the learner's abilities by dynamically changing the difficulty of the questions based on the student's performance evidence [213,214]. Because the system reacts to a student's strengths and weaknesses, the assessment experience is personalized and very effective at precisely measuring his knowledge. This approach allows the high stakes testing environment to provide tailored assessments, hence making the process more reflective of the skill level of each candidate.

5.1.4. Neuroadaptive Systems

AI has also been successful in neuroadaptive training systems, particularly in high-stakes environments such as flight simulation. The system adjusts learning tasks in real time based on the activity of the brain and cognitive workload, hence making the training efficient. While a person is undergoing flight training, for instance, systems like these track the state of the brain and modulate the difficulty of the simulation. Such personalized adaptation can help optimize learning because training does not become too easy or too overwhelming, thus enhancing the rate at which skills are learned and improving their retention, according to [215].

The following Figure (Figure 7) illustrates the impact of AI on learning pathways, which is a result of the diverse mechanisms of AI that ensure PL experiences. Integrating personalized content delivery, management of cognitive load, and real-time analytics on learning provides feedback to adapt to the needs of the learner. AI-powered PL makes changes to educational pathways by tailoring content to the strengths and weaknesses of the learner and through interaction with the content. ALPs fine-tune the process of learning to meet the performance and learning style of each student, offering a better feel for personalization. They also regulate cognitive overload, keeping it from under-challenging or overwhelming, meaning it automatically adjusts task difficulty in real time. The AI systems analyze learner behaviors, such as task completion time and errors, in search of optimal cognitive engagement to improve learning efficiency. Additionally, analytics in learning enable AI to keep track of the behavior and progress of a student, thus, they suggest the places where extra support might be necessary. This information is used by the automated assessment to fine-tune learning pathways by offering more help when it is needed and scaling it back as the proficiency level of a student rises. The Figure visually sums up how AI constantly adapts to the cognitive and emotional needs of the learner through optimized engagement and outcomes from personalized real-time feedback and intervention.

Figure 7. AI's impact on learning pathways through personalized content, cognitive load management, and learning analytics.

5.2. *Cognitive Neuropsychology in AI-Enhanced Learning Systems*

Principles of cognitive neuropsychology such as handling cognitive load and answering emotional states further enhance personalization in learning environments. The monitoring of cognitive and emotional states through biometric data adjusts difficulty and the type of instructional content in AI systems, thereby optimizing learning experiences.

5.2.1. Cognitive Load Management

Cognitive load refers to the amount of mental effort being used in working memory. AI-driven systems that monitor cognitive load, using tools like electroencephalography (EEG) or other physiological signals, can adjust learning tasks in real-time to suit the learner's mental state. For instance, when the system detects high cognitive load—indicating that a task may be too difficult or that the student is fatigued—it can simplify the task or provide additional support. Conversely, when cognitive load is low, suggesting that the learner is under-challenged, the system can introduce more complex tasks to keep the learner engaged and avoid under-stimulation [215]. This dynamic adjustment ensures that learners remain within their optimal cognitive zone, where they can achieve the best learning outcomes.

5.2.2. Emotion-Based Adaptation

Affective computing is the ability of systems to perceive and respond to human emotions. This has been a very important feature of AI-enhanced learning systems. For instance, facial recognition or voice-based platforms detect the signs of frustration, boredom, or excitement of learners. Based on such emotional signals, AI can adapt the learning environment, such as by using motivational messages or simplifying the task at moments of frustration of the learner, or gamifying when the learner is bored [216]. These systems work on the back of strong interlinkages between emotional states and cognitive processes of memory and attention to make sure learners remain emotively balanced and engaged for optimized learning.

5.2.3. Neuroadaptive Training

In high-intensity environments, such as medical training or flight simulators, neuroadaptive systems are required to maintain an optimal cognitive state. These systems adjust task difficulty while continuously monitoring real-time brain activity through non-invasive neuroimaging techniques, such as functional near-infrared spectroscopy (fNIRS) or EEG, to match a learner's cognitive workload. For instance, if the trainee experiences cognitive overload in a particular task, the system may decelerate the speed of the simulation or provide supplementary guidance. Such on-the-fly adjustment not only results in better learning but also prevents cognitive burnout, such that the trainee is able to maintain high performance over extended training periods [217].

5.3. Educational and Practical Implications

The findings of this review have major implications for educators, policy makers, and e-learning platform developers. While AI systems continue to be integrated into education, the need is felt for new models and strategies in education that integrate the use of AI in the development of 21st-century skills. AI-enhanced PL and AA require a paradigm shift in traditional pedagogical approaches, for example, through educators embracing AI to optimize educational experiences. Educators should move to adopt the use of AI tools that offer PL pathways because such systems can bring tremendous improvement in student outcomes by tailoring instruction to individual needs. The instructional design should be done in such a way that the continuous assessment and adaptation capability are availed by AI in constructing learning experiences so that every student moves forward at his own pace and receives the support he needs if he is having difficulties. Policymakers and educational administrators should thus lay down guidelines concerning the use of AI in education: "Equity issues will need to be addressed, including bias in data use, misuse of algorithms and protection of student data", since only then will the AI system be truly effective if it is designed to be fair and inclusive of all students in the exercise of equal access to AI-driven learning tools [218–224].

5.4. Ethical Considerations in AI-Driven Educational Systems

Despite the obvious benefits involved in AI in education, its integration into education brings to life several critical ethical issues that have to be considered if the goal of using these technologies responsibly is to be realized. These concerns involve, among other things, the possibility of algorithmic bias, privacy concerns, and equity questions regarding access to AI-powered learning tools. AI systems using historical data to inform their decision-making processes might carry over pre-existing biases. For example, AI algorithms that are trained on data containing biases due to past discriminations will replicate those biases, whether in learning recommendations or updates of assessment. Given this, AI system architecture should contain intrinsic bias detection and correction mechanisms. Fairness metrics, including demographic parity, become quite necessary to reduce the risks. Regular auditing of bias in algorithmic outputs, combined with the execution of fairness metrics like demographic parity, can help mitigate these risks.

AI-powered learning systems often require the collection of large amounts of sensitive data, including biometric data like brain activity or emotional state. Keeping this information private will be crucial for student privacy and to avoid the potential misuse of such data. In this respect, educational institutions should implement strict data protection mechanisms and deal securely and transparently with personal information related to students. Furthermore, regarding such collection and processing, informed consent would have to be obtained from students and guardians as well, which, in any case, is necessary for obtaining confidence in systems using AI in general. The AI learning systems, in this regard, should be designed in a way that will guarantee equal opportunity and access for all students. The unequal educational opportunities notion may further be exacerbated where some students cannot attend schools with the requisite technological infrastructures necessary to participate in AI-based interventions effectively. Policymakers and educators must deal with the issue of unequal access to these devices and make sure the operating algorithms are non-discriminatory and adaptive to the students' varying learning abilities.

5.5. Future Directions and Research

The technological trends in AI, cognitive computing, and e-learning are changing rapidly. As identified in our systematic review, it helped us to extract meaningful and emerging patterns from the domain of e-learning. From an instructional design perspective, this review offered a holistic perspective on AI in e-learning systems, i.e., PL and AA. The consequences of our review in education are cognitive neuropsychology, AI in e-learning, and adaptive pedagogy and assessment. This review also allowed potential practical implications to be discussed. With the rapid development of AI technologies in education, several avenues have opened for future research and development.

Future empirical studies will be needed to establish the long-term impact of AI-driven PL systems and AAs on diverse student populations. Future studies should be conducted on a large scale, focusing on longitudinal surveys of the impact AI has on enhancing students' engagement in learning, improving learning outcomes, and enhancing cognitive development. These should further establish the scalability of AI-driven learning systems across diverse educational contexts and explore how these systems can adapt to different cultural and socio-economic settings.

As AI systems become more integrated into education, testing and analyzing methods to reduce bias in these systems can help make them more inclusive. For this, researchers will have to develop algorithms for AI systems that are understandable, explainable, and free of all forms of discriminatory biases to ensure fairness and equity in learning experiences for all learners.

The ethical implications of AI in education, particularly concerning data privacy and consent, must be thoroughly explored. Research should examine how AI systems can be designed to protect students' privacy while still providing valuable PL experiences. Additionally, ethical frameworks for the responsible use of AI in education should be developed to guide policymakers and educators in implementing AI-driven systems.

6. Conclusions

This comprehensive review concludes with the transformative potential of AI in the e-learning environment using PL and AA. By analyzing 85 carefully selected studies, the paper showed that AI-driven systems can remarkably improve student performance, engagement, and motivation by providing educational experiences tailored to every individual's needs. Also, amidst all the encouraging results, some of the major concerns highlighted in this review pertain to issues of equity, scalability, and security. As AI continues to evolve, these kinds of limitation must be addressed through empirical research and ethical considerations. Hence, further efforts will be made to bridge the gap between cognitive neuropsychology principles and practical applications of AI and, in time, ensure that AI-enabled PL environments are not only effective but also equitable.

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Abbreviations

AI	Artificial Intelligence
PL	Personalized Learning
AA	Adaptive Assessment
AL	Adaptive Learning
ITS	Intelligent Tutoring Systems
ML	Machine Learning
VR	Virtual Reality
SRL	Self-Regulated Learning
ALP	Adaptive Learning Platform
ALS	Adaptive Learning Systems
EEG	Electroencephalogram
ANLS	Adaptive Neuro-Learning System
fNIRS	Functional Near-Infrared Spectroscopy
PLATO	Practical Learning Authoring Tool
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
HMM	Hidden Markov Model
LMS	Learning Management System
ADDIE	Analysis, Design, Development, Implementation, and Evaluation
VAK	Visual, Auditory, Kinesthetic
VLE	Virtual Learning Environment

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