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INTEGRATING INFORMATION PROCESSING THEORY WITH ARTIFICIAL INTELLIGENCE FOR ENHANCED LEARNING OUTCOMES

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Abstract

This paper explores the transformative potential of integrating Information Processing Theory (IPT) with Artificial Intelligence (AI) to enhance educational outcomes. By examining key concepts of IPT and their application in general learning and AI-driven educational tools, this review highlights how personalized learning, cognitive load management, and immediate feedback mechanisms can be optimized. The study reveals that significant improvements in student engagement, comprehension, retention, cognitive load management, and feedback can be realized through the intersection of AI and IPT a positive indicator for improving learning outcomes. However, the study recommends addressing challenges such as data privacy, algorithmic bias, and equity while working with AI tools and proposes future collaboration research between cognitive scientists, AI developers, and educators crucial for developing effective educational tools. Further research should focus on understanding the nuances of human learning processes and how AI can be designed to support these processes.

Keywords: Artificial Intelligence; Cognitive Psychology; Information Processing Theory; Learning Outcome; and Method

INTRODUCTION

Cognitive psychology is a field of study that focuses on understanding the intricate processes involved in human cognition and mental processes. Cognitive psychology, the study of mental processes like attention, memory, perception, and problem-solving, has undergone significant evolution over the years. Among the foundational theories in this field is Information Processing Theory (IPT), proposed by George A. Miller and Richard Shiffrin in the 1960s (cited in Miller, 1956; Shiffrin & Atkinson, 1969). Since, the educational and learning theories have remained the cornerstone for the effective application of technology in education. According to Cardona et al. (2023), the foundational theories and principles that guide the development of AI-powered educational tools and systems include cognitive learning theory-which provides the basis for AI-based tutors that can adapt to individual student needs and learning styles; computer-supported collaborative learning (CSCL) principles-which support the creation of AI systems that facilitate and enhance student group work and collaboration; and the universal design for learning (UDL) framework-which informs the development of AI systems that can accommodate diverse student individual differences and learning needs. These theoretical foundations and design principles help shape the integration of AI in education, ensuring that the resulting tools and systems can effectively support and enhance student learning and engagement.

In the current state of AI application in education, it has proved effective in the teaching and learning arena. AI is useful for personalized and customized learning experiences tailored to individual students' needs and abilities Zawacki-Richter et al. (2019). It has also improved administrative and operational efficiency in educational settings (Holmes et al., 2023). Additionally, AI has enhanced student engagement by enabling more interactive and immersive learning experiences Luo (2024). Finally, AI has enabled the development of new teaching and learning methods that were not possible before. Thus, changing the whole experience of learning (Chen et al., 2020). However, the traditional educational methods which are still in practice often fail to address the current educational challenges related to the diverse needs of students, leading to issues like disengagement, uneven progress, and inadequate feedback (Husain, 2024), this is because the teacher stage's active role during instruction with the traditional methods like lecture method compared to the guiding, facilitating and sharing role the teacher partakes while implementing the current digital pedagogies (Almazova et al., 2020). Thus, the gap in these methodological implementations may result to low achievement of the learning outcomes. The new digital pedagogies based on AI seem to promise ground breaking impact in changing the education, however, there implementations still should be grounded on the educational and learning theories to obtain the best. This paper provides a comprehensive review of IPT, tracing its historical development, key concepts, theoretical underpinnings, applications, criticisms, and contemporary relevance. The paper further reviews how integrating IPT with artificial intelligence (AI) can address these challenges by creating adaptive, efficient, and personalized learning environments, thus achieving learning outcomes.

Understanding Information Processing Theory

Information Processing Theory emerged in the 1960s as a response to the limitations of behaviourism in explaining complex cognitive processes. At that time, behaviourism dominated psychology, focusing on observable behaviours and stimulus-response associations. However, it struggled to account for higher-order cognitive functions like memory and problem-solving (Neisser, 2014). George A. Miller and Richard Shiffrin proposed IPT, which postulates how people perceive the situation around them, how they take knowledge into memory, and how they can later on remember what they learned. The information processing model (IPM) likened the human mind to a computer with input, processing, and output processes, thus, processing information through a series of stages that is through sensory register or memory, short-term or working memory (STM), and long-term memory (LTM) (Miller, 1956; Atkinson & Shiffrin, 1968). Shiffrin and Atkinson (1969), acknowledged that storage and retrieval are antagonistically opposite in their working process, mirroring one another.

According to Miller, (1956); Atkinson and Shiffrin (1968); sensory memory briefly stores information from the environment, lasting only about 0.5-3 seconds and capable of holding around four items. It relies on attention; unattended information is lost and does not enter short-term memory. The sensory register processes this information, with the best-understood registers being iconic (visual) and echoic (auditory). Less is known about tactile, olfactory, and gustatory registers. The information our senses pick up from the environment is fleeting and easily forgotten if we don't actively focus on it. For instance, the light reflected off a coffee cup reaches our eyes, but unless we consciously direct our attention to it, that visual impression rapidly disappears. Sensory memory, which includes both visual (iconic) and auditory (echoic) impressions, has several key characteristics: Representation - sensory memory maintains a representation or imprint of the sensory input, like an image or sound. Capacity - sensory memory can hold a large amount of information, but only for a brief period. Duration - the duration of sensory memory is very short, lasting just fractions of a second to a few seconds before the information fades. Forgetting - the primary reason sensory memories are quickly forgotten is due to the natural decay or degradation of the sensory trace over time, not necessarily any active removal or replacement of the information. Our senses constantly pick up a wealth of environmental data, but unless we focus our attention on it, that raw sensory information vanishes rapidly from our conscious awareness due to the inherent transient nature of sensory memory.

Miller; Atkinson and Shiffrin moreover mention that short-term memory (STM), also known as working memory, is where conscious processing occurs. STM is the interaction point between new stimuli and existing knowledge, enabling active processing. Strategies like rehearsal and chunking, therefore, can expand STM's capacity, which is typically limited to 5-9 items for about 15-30 seconds. Forgetting in STM is mainly due to interference. Our perception and understanding of the world around us involve a dynamic interplay between the short-term storage of immediate sensory information and the retrieval of relevant long-term memories. For example, when we visually focus on a coffee cup, that specific perceptual input is temporarily held in our short-term memory. However, to truly comprehend the cup in a broader context - such as recognizing it as "my cup that I poured coffee into three hours ago" requires accessing and integrating related details stored in our long-term memory banks. Which is a rearrangement of the information considering prior existing experiences (Bartlett, 1932). This seamless blending of immediate sensory awareness and recalled background knowledge allows us to construct a richer, more coherent interpretation of the objects and situations we encounter. The cup is not just a visual stimulus, but an item imbued with personal significance and a particular history, all of which emerges from the interplay between short-term perception and long-term recollection. In essence, our moment-to-moment experience is an amalgamation of the sensory data unfolding before us and the comprehensive understanding we have developed over time through learning and memory. This dynamic interplay between the present and the past shapes how we perceive, comprehend, and make sense of the world.

Baddeley and Hitch (1974) proposed an alternative working memory model to further explain STM processes as in Figure 1. Over time, IPT has been refined and integrated with other models, such as Baddeley and Hitch's Working Memory Model, which introduced separate components for different types of information processing (Baddeley and Hitch 1974 as cited in 2000). Baddeley and Hitch's (1974) model of working memory provides a more detailed and dynamic understanding of short-term memory (STM) than previous models, such as the multistore model proposed by Atkinson and Shiffrin (1968). Their model posits that short-term memory is not a single, static store but rather a system comprised of multiple components that work together to process and temporarily hold information.

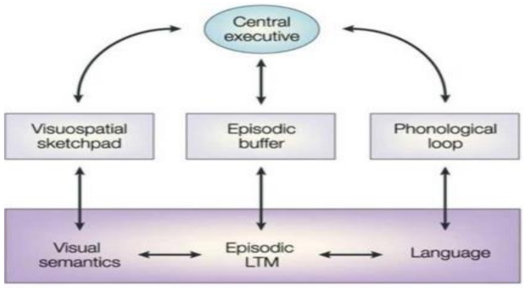

Figure 1. Show the Alternative Working Memory Model (Baddeley & Hitch, 1974)

The key conclusions about short-term memory based on Baddeley and Hitch's working memory model include the following: Multicomponent Structure: Working memory consists of multiple components, including the central executive, the phonological loop, the visuospatial sketchpad, and later, the episodic buffer. Each component has a specific role in processing and temporarily storing different types of information. Central Executive: This is the control system that directs attention and coordinates the activities of the other components. It does not store information but manages cognitive tasks. Phonological Loop: This component handles verbal and auditory information. It consists of the phonological store (which holds sounds) and the articulatory rehearsal process (which refreshes the memory traces). Visuospatial Sketchpad: This component processes visual and spatial information, helping in the creation and manipulation of images and spatial layouts. Episodic Buffer: This integrates information from different sources and is crucial for creating a coherent episodic memory. Dynamic Process: The model emphasizes that short-term memory is a dynamic and active process rather than a passive store. It involves continuous manipulation and updating of information, which is essential for complex cognitive tasks like learning, reasoning, and comprehension. Capacity and Limits: While traditional views of short-term memory often focus on a limited capacity (e.g., 7±2 items), the working memory model suggests that capacity may vary depending on the component and the nature of the tasks being performed. The phonological loop and visuospatial sketchpad have their own capacity limits, which can be affected by factors such as rehearsal and chunking. Interaction with Long-Term Memory: The model acknowledges that working memory interacts closely with long-term memory. Information is not only temporarily held in working memory but also retrieved from and encoded into long-term memory, highlighting a more integrated view of memory processes.

The working memory model has broad implications for understanding a range of cognitive tasks and conditions. It provides insights into how individuals perform tasks that require simultaneous processing and storage of information, and it helps explain difficulties in cognitive functioning observed in various psychological and neurological conditions. Thus, Baddeley and Hitch's working memory model revolutionized the understanding of short-term memory by presenting it as a complex, multifaceted system crucial for a wide range of cognitive functions.

According to Baddeley and Hitch (1974); Squire (2004), long-term memory (LTM) is the stage where information is stored and recalled over long periods, from hours to years. Long-term memory (LTM) as encompassing declarative, procedural, and episodic memory, the following conclusions can be drawn about LTM: Diverse Types of Memory: LTM is not a monolithic store but comprises different types of memory, each serving distinct functions like: Declarative Memory: This involves factual information (e.g., "knowing that" Kampala is the capital of Uganda) and is further divided into semantic memory (general knowledge) and episodic memory (personal experiences). Procedural Memory: This involves skills and actions (e.g., "knowing how" to drive a car) and is typically less conscious and more automatic compared to declarative memory. Episodic Memory: This involves specific personal experiences and events, providing a sense of time and context (e.g., remembering your first day of elementary school).

Duration and Stability: LTM stores information over extended periods, ranging from hours to a lifetime. This duration highlights the stability and persistence of long-term memories, although they can still be subject to forgetting and distortion over time. Storage and Recall: LTM encompasses everything we know and can do, meaning it includes both the storage and retrieval processes. Successful recall from LTM depends on the encoding strength and the presence of effective retrieval cues. Encoding and Consolidation: Information must be encoded into LTM, a process that can involve various strategies such as rehearsal, elaboration, and the use of mnemonic devices. The consolidation process, which can take place during sleep, helps stabilize memories for long-term storage. Brain Structures Involved: Different types of LTM are associated with distinct brain regions. For example, the hippocampus is crucial for forming new declarative and episodic memories, while procedural memory involves the basal ganglia and cerebellum. Interdependence with Short-Term Memory: LTM interacts with short-term memory (or working memory). Information often moves from short-term to long-term memory through processes like rehearsal and encoding. Similarly, LTM is accessed and used during tasks that involve working memory. Role in Identity and Learning: LTM plays a critical role in shaping our identity and enabling learning. Episodic memories contribute to our personal narrative, while declarative and procedural memories are essential for acquiring knowledge and skills. In general, LTM is a complex and multifaceted system that stores and allows recall of information over long periods. It is crucial for learning, skill acquisition, personal identity, and the performance of everyday activities.

One of the seminal contributions of IPT was Miller’s concept of “chunking,” which refers to organizing information into meaningful units to enhance memory capacity (Miller, 1956). Preparing and presenting simple and interesting instructional materials ease processing and hance retentions of knowledge. Additionally, Shiffrin and Atkinson's "modal model" of memory delineated the flow of information from sensory input to LTM storage (Shiffrin & Atkinson, 1969). The retention of information for long time is expected in the long-term memory, this can be achieved through teaching or learning in multiple modes, especially presenting information in both visual and verbal modes. This is clearly shown in Paivio (1971 as cited 1991) dual coding theory which proposed that memory for images differs from memory for words, introducing the dual coding hypothesis. This hypothesis suggests that seeing an image results in both the image and its label being stored in memory, and extends this idea to other senses, such as associating the smell of an orange with its label. Additionally, some researchers identify control processes in thinking and learning, known as metacognition. Metacognition involves strategies like drawing pictures to understand complex topics or mentally summarizing text to ensure comprehension. The dual coding theory is a result of the implication of information processing theory for supporting academics through enhancing instructional design and presentation and thus, supporting learning.

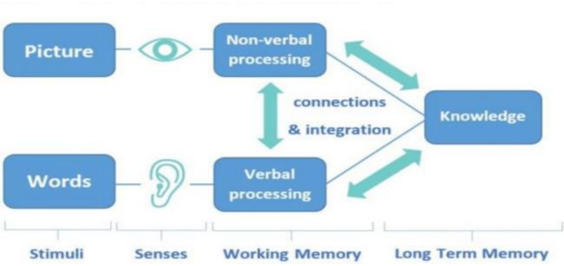

Figure 3. Shows the Dual Coding Model of (Paivio, 1971 as cited in 1991)

Information Processing Theory (IPT) Criticisms

Despite its foundational role in cognitive psychology, IPT has faced criticisms and challenges. It has been accused of oversimplifying human cognition and neglecting the influence of emotions, motivation, and individual differences (Anderson, 1995) for example, the theory's idea that rehearsal is necessary for long-term memory encoding fails in cases like trauma, where memories can form automatically. Subsequent research has led to revisions and refinements of the original model, incorporating insights from neuroscience and artificial intelligence (Sternberg, 2020). Many find the computer analogy unappealing and inaccurate, as no computer program can fully replicate human cognition's complexity. These models also neglect fundamental developmental changes, such as the shift from concrete to abstract thinking, and overly focus on internal processes, ignoring environmental influences and external stimuli. Additionally, the theory does not adequately consider the impact of emotions or behaviours on cognition or account for individual and cultural differences.

Information Processing Theory (IPT) Application Domains

Applications of IPT extend to various domains, including education, where it has influenced teaching strategies to accommodate the limitations of STM and enhance encoding processes for long-term memory retention (Anderson, 1995). In technology, IPT principles have informed the design of user interfaces and information systems to optimize human-computer interaction (Sternberg, 2020). In classrooms, teachers often use worksheets for student practice. However, incorporating more senses can enhance encoding. For example, students could act out new vocabulary words. In higher education, using multiple modes of information is beneficial. If hands-on experiences aren't feasible, instructors might use or create video tutorials. Multi-modal learning engaging multiple senses increases the likelihood of memory retention. Encoding involves actively working with new information to store it in the brain, like using the acronym ROYGBIV to remember the colour spectrum. Frequent practice of recalling information strengthens memory. Cognitive load, discussed in cognitive load theory by Sweller (1988), which refers to, how cognitive resources are used during learning. Overloading students with too much information can hinder comprehension and task completion. To help students process information effectively, teachers and instructors should consider activities that optimize cognitive performance. Such as effective instructional design, and use of new technologies. Thus, the recent application of new technologies like artificial intelligence (AI) in education seems to hold a promise in solving the pedagogical problems experienced in the field.

The Artificial Intelligence (AI) in Education and Information Processing Theory (IPT)

The educational landscape is undergoing a profound transformation, driven by the rapidly advancing field of Artificial Intelligence (AI). AI is proving to be a game-changer, offering innovative solutions that cater to the diverse needs of students and educators alike.

Fundamentally, AI is designed to emulate and surpass human intelligence, encompassing a wide range of technologies such as machine learning, planning systems, expert systems, natural language processing (including chatbots powered by Generative Pretrained Transformers), cognitive computing, robotics, and automation (Khosravi et al., 2023). These cutting-edge AI-driven tools and systems are being seamlessly integrated into the educational ecosystem, revolutionizing the way we approach learning and teaching. The introduction and advancement of AI-powered technologies have empowered instructors to perform their duties with unprecedented efficiency and effectiveness. Moreover, these technological innovations are not limited to the classroom; they are also transforming various academic sectors, streamlining administrative processes and enhancing overall institutional effectiveness (Chen et al., 2020). Beyond the conventional image of powerful supercomputers, AI is now manifesting in more tangible and interactive forms, such as intelligent robots and supporting systems. These AI-driven solutions are revolutionizing the learning experience, from early childhood education to higher learning institutions, by adapting to the unique needs and preferences of each student (Chen et al., 2020). In essence, the integration of Artificial Intelligence in education is ushering in a new era of personalized learning, improved administrative efficiency, enhanced student engagement, and the development of ground breaking pedagogical methods. As this technological revolution continues to unfold, the educational landscape is poised for a transformative and innovative future. Its therefore highly recommended that the AI models designed to support education should be aligned with the educational goals Cardona (2023).

The ongoing advancements in Artificial Intelligence (AI) are profoundly reshaping the landscape of education, offering innovative solutions that are tailored to the unique needs and preferences of both students and educators. At the heart of this transformation lies the recognition that simply replicating human intelligence is not enough. By drawing insights from the principles of Information Processing Theory (IPT), AI systems can be designed to more closely emulate the nuanced and dynamic nature of human learning processes. This synergistic approach unlocks new possibilities for improving educational outcomes. Consider, for instance, the case of adaptive learning platforms. These AI-powered systems are capable of continuously assessing the student's existing knowledge, understanding, and cognitive processing capabilities. Based on this, they can then dynamically adjust the difficulty and content of the learning materials to provide the optimal level of challenge for each individual learner. By aligning the AI-driven learning experience with the principles of IPT, the educational system can better cater to the unique needs and learning styles of each student. This personalized and adaptive approach fosters deeper engagement, improved knowledge retention, and ultimately, more meaningful and effective learning outcomes. The integration of AI with the foundational principles of information processing theory represents a powerful intersection, unlocking new frontiers in educational innovation and student success. As this synergistic approach continues to evolve, the future of learning promises to be more personalized, adaptive, and transformative than ever before.

Innovative AI Applications Guided by Information Processing Theory (IPT)

As the field of education continues to evolve, a remarkable convergence has emerged between the cutting-edge capabilities of Artificial Intelligence (AI) and the foundational principles of Information Processing Theory (IPT). This synergistic union holds the promise of revolutionizing the way we approach the art and science of teaching and learning.

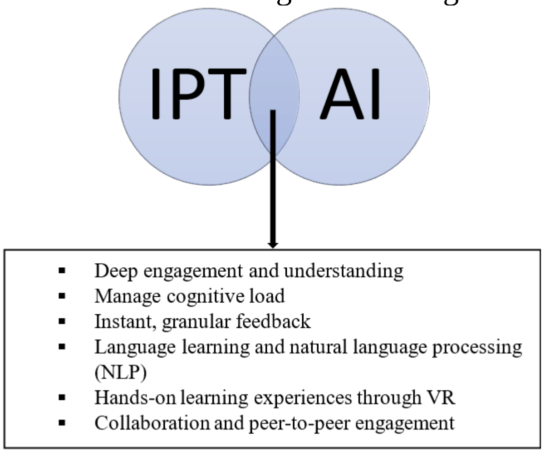

Figure 4. Fusion of IPT and AI as a New Frontier in Personalized, Adaptive, and Data-driven Learning

At the heart of this transformative alliance lies a deep understanding of how the human mind processes and assimilates information. IPT has long emphasized the highly personalized nature of cognition, recognizing that each individual learner brings a unique set of strengths, weaknesses, and preferred modes of learning to the table. Harnessing the power of AI, we now have the means to translate this holistic understanding of the learner into truly personalized educational experiences as demonstrated in figure 4 above. Imagine a world where AI-powered adaptive learning platforms continuously assess a student's performance, adjusting the content, pace, and level of challenge to match their evolving needs. This personalized approach not only fosters deeper engagement and understanding but also helps manage cognitive load, breaking down complex information into manageable, digestible segments. But the benefits of this AI-IPT fusion extend far beyond personalization. IPT also highlights the crucial role of immediate, meaningful feedback in the learning process. AI-driven educational tools can now provide students with instant, granular feedback on their assignments, quizzes, and assessments, empowering them to identify and rectify their mistakes in real-time. This dynamic cycle of learning and feedback can dramatically enhance knowledge retention and overall academic performance.

Moreover, the data-driven insights unlocked by AI can transform the way we approach educational planning and intervention. By analysing vast troves of educational data, AI can uncover patterns, trends, and anomalies that might otherwise go unnoticed, equipping educators with the intelligence they need to refine their teaching strategies and address areas of concern proactively. The integration of AI and IPT also holds immense promise in the realm of language learning and natural language processing (NLP). AI-driven tools can facilitate seamless language translation, automated essay scoring, and conversational agents that can engage students in natural, intuitive dialogue breaking down barriers and making abstract concepts more accessible. But the true power of this synergy lies in its ability to create truly immersive, hands-on learning experiences. AI-powered simulations and virtual reality (VR) environments can transport students into dynamic, real-world scenarios, allowing them to apply their knowledge and hone their problem-solving skills in engaging, practical contexts.

Finally, IPT's recognition of the social dimensions of learning finds a natural ally in AI's capacity to foster collaboration and peer-to-peer engagement. AI-enabled tools can connect students for group projects, discussions, and study groups, cultivating a vibrant, interconnected learning ecosystem that mirrors the rich social tapestry of the real world. As we continue to navigate the rapidly evolving landscape of education, the fusion of Artificial Intelligence and Information Processing Theory stands as a beacon of hope a transformative alliance that holds the power to unlock new frontiers in personalized, adaptive, and data-driven learning. By embracing this synergy, we can empower students to thrive in the ever-changing world of knowledge and discovery, preparing them for the challenges and opportunities that lie ahead.

Challenges and Ethical Considerations in Fusing IPT and AI

Integrating Information Processing Theory (IPT) with Artificial Intelligence (AI) in education promises significant advancements but also brings several challenges and ethical considerations that need to be addressed to ensure successful implementation and equitable outcomes.

Challenges

Data Privacy and Security: The use of AI in education often requires the collection of vast amounts of personal data from students. Ensuring the privacy and security of this data is paramount. Mishandling or breaches of data can lead to serious privacy violations (Eynon, 2013). Educational institutions must implement robust data protection measures and comply with relevant regulations such as the General Data Protection Regulation (GDPR) and the Family Educational Rights and Privacy Act (FERPA) (Schwartz et al., 2019). Algorithmic Bias: AI systems are only as good as the data they are trained on. If the training data contains biases, the AI can perpetuate or even exacerbate these biases, leading to unfair treatment of certain groups of students (Baker & Hawn, 2021). Continuous monitoring and updating of AI algorithms are necessary to ensure they promote fairness and do not reinforce existing inequalities. Cognitive Load Management: While AI can help manage cognitive load by tailoring content to individual students, there is a risk of either under-challenging or overloading students if the AI does not accurately gauge their cognitive state (Kalyuga, 2009). It is crucial to develop sophisticated models that can accurately assess and adapt to students' cognitive needs in real time. Technical Challenges: Implementing AI-driven educational tools requires significant technical infrastructure and expertise. Many educational institutions, especially in under-resourced areas, may lack the necessary technology and skills to effectively deploy and maintain these systems (Holmes et al., 2019).

Ethical Considerations

Equity and Access: Ensuring equitable access to AI-driven educational tools is a major ethical concern. Students from underserved communities might not have access to the necessary technology or internet connectivity, exacerbating existing educational inequalities (Reich & Ito, 2017). Efforts must be made to bridge the digital divide and ensure that all students benefit from AI-enhanced education. Informed Consent: Students and their guardians must be fully informed about how their data will be used and the implications of AI-driven learning systems. Obtaining informed consent is crucial to maintain trust and transparency (Williamson, 2017). Transparency and Accountability: The decision-making processes of AI systems should be transparent. Educators and students should understand how these systems work and the basis for the recommendations or decisions they make. Additionally, there should be clear accountability mechanisms in place for decisions made by AI systems (Luckin et al., 2016). Autonomy and Agency: While AI can provide personalized learning experiences, it should not undermine the autonomy and agency of students. It is essential to ensure that students remain active participants in their learning process and are not reduced to passive recipients of AI-generated content (Holmes et al., 2019). Ethical Use of AI: AI in education should be used ethically, ensuring that it enhances the learning experience without manipulating or exploiting students. Developers and educators must consider the long-term implications of AI on student development and well-being (Holmes et al., 2019).

METHOD

The research method employed in this study involves a comprehensive literature review. This approach was chosen to gain a deep understanding of the existing knowledge base, theories, and empirical findings related to the topic of integrating Information Processing Theory (IPT) with Artificial Intelligence (AI) in education. The literature review method provides a systematic approach to understanding the integration of IPT and AI in education. By rigorously selecting and analysing relevant articles, this study aims to contribute valuable insights and highlight areas for future research and development.

RESULTS & DISCUSSION

This study critically and comprehensively reviewed the literature on IPT, its historical development, key concepts, theoretical underpinnings, applications, criticisms, and contemporary relevance. Further, the study reviewed how the integration of IPT with AI improves learning outcomes. The critical review of the literature found that IPT emerged in the 1960s as a response to the limitations of behaviourism in explaining complex cognitive processes. Meaning IPT developed due to the existence of a problem that cannot be adequately solved by the available educational and learning theories, therefore, it filled the gap of mental human cognition processes that were not catered to in the behaviourism theory of learning that existed earlier. According to Neisser (2014) behaviourism theory struggled to account for higher-order cognitive functions like memory and problem-solving. Therefore, Miller and Shiffrin 1960 (cited in Miller, 1956; Shiffrin & Atkinson, 1969) postulate how people perceive the situation around them, how they take knowledge into memory, and how they can later on remember what they learned. IPT emphasises key ideas in cognitive psychology that is memory and problem-solving. For example, according to Koch et al. (2020), neuroimaging techniques such as functional magnetic resonance imaging (fMRI) have provided insights into the neural correlates of memory encoding, retrieval, and forgetting, supporting the theoretical framework proposed by IPT. How human memory can effectively and efficiently be used to address problems is the top agenda of IPT. Longitudinal studies have investigated the developmental trajectory of information-processing abilities from childhood to adulthood, shedding light on the stability and plasticity of cognitive processes over the lifespan (Korzeniowski et al., 2021).

IPT is widely applied in areas such as the technology user interface designs and information systems for human-computer interaction. The neural mechanisms underlying information processing could enhance our understanding of how cognitive processes are instantiated in the brain (Sternberg, 2020). IPT in the classroom, for managing student learning through well-prepared multi-modal instructional designs, according to Khalil and Elkhider (2016) instructional design theories support the selection and preparation of effective instructions that ease learner cognition. The current applications of IPT are in the development of artificial intelligence (AI) models such as the cognitive functions and intelligent systems models, which mainly support the cognitive aspects of learning. This shows the wide relevance of cognitive theories in the development of AI models that support learning. This finding agrees with a study by Cardona et al. (2023), which found that the foundational theories and principles that guide the development of AI-powered educational tools and systems include cognitive learning theory, computer-supported collaborative learning (CSCL) principles, and the universal learning design (UDL) framework. Additionally, Computational modelling approaches have been used to simulate information processing mechanisms in the human brain, further elucidating the underlying processes and mechanisms proposed by IPT (Friston, 2022). Among the issues with IPT is the oversimplification of human cognition and neglecting the influence of emotions, motivation, and individual differences, noted by Anderson (1995) IPT oversimplifies human cognition and neglects the role of emotions, motivation, and individual differences, inaccurate computer analogy the human brain, neglects fundamental developmental changes, especially external ones but only focuses on internal changes, not adequately considering the impact of emotions or behaviours on cognition or account for individual and cultural differences. This means, however great the relevance of IPT in wide fields, it's inadequate in addressing some of the issues it puts forth. Another significant finding of the study further reveals that the integration of IPT and AI fosters active engagement and understanding, manages cognitive load, instant feedback, language learning, and natural language processing, and provides hands-on experience through virtual realities, collaboration, and peer-to-peer engagement. This shows the effectiveness of IPT in fostering the development of the current AI models such as cognitive functions and intelligent systems models, thus supporting its application in education. The finding complies with the study by Cardona et al. (2023), which found cognitive learning theory a foundational guide for the development of AI-powered educational tools and systems. Further, Chen et al. (2020) suggest that the identification of educational theory is fundamental in adopting artificial intelligence in education. Thus, through the integrative approach of intersecting educational theory and technological implementation, positive pedagogical changes can be realised in education. Thus, enhancing learning outcomes.

CONCLUSION

Information processing theory has had a profound impact on the field of cognitive psychology, providing a framework for understanding how the mind processes information. Its emphasis on mental operations and information-processing mechanisms laid the groundwork for research in memory, attention, perception, and problem-solving. While IPT has its limitations, it remains relevant in contemporary cognitive psychology, shaping our understanding of cognition and informing research in various domains. Further, integrating IPT with AI in education has the potential to revolutionize learning outcomes. However, addressing the associated challenges and ethical considerations is crucial for ensuring that these technologies are implemented in a way that is fair, equitable, and beneficial for all students. Robust data protection, continuous monitoring for biases, equitable access, transparency, and maintaining student autonomy are key factors that must be prioritized.

Moreover, educators should focus on understanding the interconnectedness between the existing educational and learning theories or develop new educational theories to harness the development of teaching and learning in the new artificial intelligence era. This is because educational theories support the effective implementation of new technologies without causing further problems regarding the existing issues in the education realm such as inequality, equity, and injustice. Thus, future studies should focus on identifying emerging technologies such as future advancements in AI, such as more sophisticated natural language processing and machine learning algorithms, and how they can be implemented through the guidance of the existing educational theories or the development of new educational theories. Further, through interdisciplinary research: Collaboration between cognitive scientists, AI developers, and educators is crucial for developing effective educational tools. Research should focus on understanding the nuances of human learning processes and how AI can be designed to support these processes. Through these approaches the education stakeholders can realize effective achievement in the learning outcomes in the current AI era.

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