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Empowering Self-Management: Unveiling the Impact of Artificial Intelligence in Learning on Student Self-Efficacy and Self-Monitoring

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A R T I C L E I N F O

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A B S T R A C T

Purpose: This article is going to provide insights to a complex connection between artificial intelligence in learning, student's self-management skills, and self-efficacy in educational sectors. This research objective surrounds the AI's impact on the learning experiences, of students by focusing on the existing gaps in previous research, primarily focused on the region of the Kingdom of Saudi Arabia. With the AI intervention, the understanding of the cognitive and motivational dimensions is influenced, as this research further explores the mediating role of self-efficacy in the relationship between AI and self-management. **Method:** This article pursues the research by using the methodology of structural equation modelling (SEM) with STATA-SEM, where data was collected from 239 students in the Kingdom of Saudi Arabia. The survey-based methodology was used to understand the student's views and thoughts related to AI, self-management, and self-efficacy. **Findings:** the main results from the research show that AI in education is connected to better management skills of students, and self-efficacy. However, this connection is influenced by the mediating role of self-efficacy in the learning process. The research also helps to discover the individual differences among the self-monitoring. This becomes the empirical evidence of the growing field of AI in the educational sector, offering insights into the AI affects the students' cognition and motivation in Saudi Arabia. **Originality/Implications:** this study plays a unique part as it builds an understanding of AI's influences on students learning in a particular type of culture and educational setting. The results are important for the teachers and policymakers, they can provide ideas on the implications that would improve both how students think and stay motivated in Saudi Arabia's learning settings.

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1. Introduction

Artificial intelligence (AI) has changed the learning and educational patterns followed globally, as it become the key player in revolutionizing, and reshaping the worldwide educational sectors (Kamalov, Santandreu Calonge, & Gurrib, 2023). This research is considered to be a study of the complex relationship between AI in learning and educational perspectives with the student's psychological constructs and outcomes. With the technological changes in educational institutions, teaching patterns, and learning methodologies, instructors, policymakers and researchers need to build an understanding of how AI affects student's thinking and motivation (Rane, Choudhary, & Rane, 2023). The study is mainly focused on the multiple impacts of AI on students' self-management ability, self-efficacy, and self-monitoring, contributing not only to the large vision to discover AI in education but also to make clear the context of diverse educational dynamics. When it comes to the transforming potential of AI in education, it can be observed that it has revolutionized education through tailored and flexible interventions, such as intelligent tutoring systems and adaptive learning platforms (Shaikh et al., 2023; Tandon & Tandon, 2020). Additionally, AI can affect the student's psychological characteristics and Meta-Cognitive abilities while delivering content (Alam, 2020). Hence the primary objective of this study is to gain insights, into the connection, between AI and students cognitive or psychological aspects. It aims to explore how AI influences students' self-management and self-confidence during the learning process. Through this investigation we can develop an understanding of how AI impacts students' cognition and motivation offering perspectives in the field of AI in education.

There has been a lot of literature that explores the use of intelligence (AI), in education through research (Alanzi et al., 2023). This research gives us insights into how AI can impact aspects of student learning. Many studies have focused on the effectiveness of AI driven tools in improving learning outcomes (Cheng, 2022). They have found that these tools can significantly reduce achievement and improve subject mastery (Wu et al., 2023). However, it's important to note that AI has the potential to bring about changes, beyond traditional academic measurements. Prior empirical studies have also looked into how AI affects students' motivation and cognitive abilities (Lin et al., 2022). Research has shown an upward trend between AI interventions or students' self-efficacy, indicating that tailored AI-assisted learning experiences lead to increased self-assurance and guilty verdicts in one's capabilities. (Chen et al., 2023). Further, additional research has examined the murky dynamics of AI's influence on the abilities of learners over self-regulation. Research concludes that AI-driven interventions are vital to nurturing students' autonomy and self-management amid the learning process. For instance, these interventions involve intelligent tutoring systems and adaptive feedback mechanisms (Mohammad et al.). These studies point out AI's potential as a scaffolding tool to assist students browse and determine their own learning pathways, in addition to its assure for a content delivery mechanism (Jaiswal & Arun, 2021). Also, actual data regarding the links between AI as well as student ability to self-monitor has come to light. Research indicates, AI-enhanced environments for education foster heightened awareness of metacognitive processes, as students interact using adaptive tools that provide immediate feedback and encourage reflection upon their academic performance (Kuleto et al., 2021). Collectively, these findings highlight the groundbreaking potential that AI has beyond its traditional function in content delivery as we traverse the empirical surfaces of AI in education (Thangavel, 2023). In order offer new insights to the developing conversation regarding artificial intelligence's influence on education, the research offered here broadens and enhances upon earlier empirical studies by exploring the intricate relationships between psychological concepts, learning outcomes, and AI in their learning environment.

There is an obvious understanding gap about the intricate links between artificial intelligence (AI), psychological theories, and specific student outcomes, despite the abundance of empirical studies exploring the integration of AI in education (Chen et al., 2020b). Essentially previous research has achieved significant strides in articulating how AI affects academic performance as well as subject proficiency (Pham & Sampson, 2022), that is still an apparent absence of studies that investigate the complex interactions between AI interventions and students' cognitive and motivational features. In order to deliver an improved comprehension of the holistic impacts of AI on student learning experiences, it is crucial to investigate the way AI influences learners' self-management capacity, self-efficacy, and self-monitoring while the learning process (Doroudi, 2023; Pham & Sampson, 2022). This is going to bridge the current empirical gap. Furthermore, nearly all of the empirical research that has already been conducted has a tendency to overlook contextual and cultural differences that might influence how AI integration manifests out in different educational contexts. Since the majority of research has been carried out within Western parameters, insufficient exists about the potential impacts of cultural quirks and AI's effects on results for students (Allen, McGough, & Devlin, 2021). This empirical gap emphasizes the need for further study that takes into consideration the unique cultural contexts where AI is applied, alongside discoveries that can be universally applied. The current study intends to bridge this gap by offering insights that are both globally applicable and cognizant about the particular educational context in which the analysis is being executed. Additionally, previous empirical research tends to focus on the direct and immediate impact of AI upon student learning, overlooking any of the mediating or moderating variables that might impact the results that have been observed. Currently there is a lack of analysis regarding factors that moderate the impact of AI, on student outcomes, such as variations in self-monitoring abilities as mediating variables, like student's self-efficacy (Mouta, Pinto-Llorente, & Torrecilla-Sánchez, 2023). To fill this knowledge gap and gain an understanding of how AI affects students' psychological characteristics and cognitive skills in learning applications this research aims to uncover the dynamics through which AI modifies these aspects.

There are many objectives of this research, but the main one is to right-and this real movement does not count for much these days and would often take the second, more insidious form: impiety toward prostitutes by letting them degrade themselves. This research is primarily--how AI impacts students' self-control in learning environments. Its chief aim is to figure out whether AI-driven interventions influence students' autonomy, punctuality, and general self-control in learning processes by applying advanced statistical methods. This aim is to provide evidence from real life suggesting how the AI tool works as a scaffold for students allowing them to plan their own learning pace. It expands upon the findings of previous research (Kuleto et al., 2021). Secondly, the study focuses closely at the link between their opinions about their own efficacy and artificial intelligence (AI) in the classroom. The aim of this study is to carry out an empirical evaluation of the manner in which learning experiences which are customized and flexible with the support of AI may improve students' self-belief, motivation, and confidence. The overall objective of strengthening our awareness of the motivational features of AI integration in education is in line with the intentions of this study (Wu et al., 2023). The study aims to shed light on the processes by which AI impacts students' perceptions regarding their competence by developing empirical connections within AI interventions and self-efficacy. This will ultimately be beneficial to improve educational practices that promote positive self-efficacy beliefs. In addition, examining the mediating function of students' self-efficacy for the relationship involving AI in learning and their ability for self-management is an essential objective of this study. This goal is to determine the underlying mechanisms by which AI interventions could indirectly impact individuals' self-management skills by influencing their belief in oneself. It accomplishes this by drawing upon philosophical models (Chen et al., 2020b). Understanding the complex cognitive and motivational processes at action during AI-mediated learning experiences needs a comprehension of this mediating pathway. In order to clarify the intricate interaction of elements affecting the influence of AI in education, the study also seeks to determine whether individual differences within self-monitoring abilities alleviate the relationship among AI in instruction and students' self-management features. The study expects to fill in empirical gaps and conduct a deeper examination of the complex impact of AI on student learning performance, with the help of these objectives.

2. Literature Review

These days, in the field of education, it's all about artificial intelligence according to the latest fads among students. How artificial intelligence changes the way students absorb knowledge, exercise abilities, and comprehend texts is of vital importance for education in the era of artificial intelligence (Yu & Lu, 2021). Most tangible, however, AI benefits personalized learning. AI is intelligent enough to change courses according to children's internal states of education--along with their flexibility for questions (Celik, 2023). This benefit to AI makes students follow a differentiated path online that matches their abilities and weaknesses at each step. What's more, AI can also facilitate the development of an immersive and interactive learning environment. For instance, in an immersive educational world people can climb trees, look at insects, or hear bird song, which creates new ways to learn about nature (Celik, 2023). At the same time, there are clear signs students today have entered their 'curiosity era'. They will be learning to use but the slightest hint of various technologies. Technologies like these enable students to try out hypotheses in a practical way and gain interest in theories that they simulate in practice (Pedró, 2020). AI-driven technologies can also provide immediate assistance for students. This helps students correct their mistakes and develop a growth mindset. Students make use of this immediate feedback loop to learn better because they can assess their progress and make informed decisions about their study methods (Zhang & Chen, 2021).

Although benefits of AI education are many, there exist some ethical and economic issues to be considered. However, it is important to approach these issues particularly the possibility of increasing discrimination in education with extreme caution. Further, reliance on AI may lead to the waning of some traditional teaching positions which poses questions about educators' roles in future classrooms (Channa et al., 2021). However, achieving a comprehensive and balanced learning experience is dependent on how AI's advantages are used while retaining the human aspects of education. Overall, artificial intelligence's effects on the student learning include numerous independent aspects like potential pros and cons (Yu & Nazir, 2021). As the technology advances, to achieve the goal of utilizing AI advantages and minimizing its risks educators, legislator must work together with society as a whole. AI has the potential to revolutionize education by complementing it with tools that are highly personalized, interesting and useful for every student in this changing world of knowledge (Dhawan & Batra, 2020).

To carry out a further investigation into the relationship between AI used in educational facilities and learners' ability for self-management, it is necessary to study how AI helps optimization of learning process (Li et al., 2021). One major advantage is that AI algorithms are adaptable; they can adjust the study aids according to individuals' performances by Analyzing each student. This merit of flexibility enables students to set and meet the learning needs in a classroom environment (Rastrollo-Guerrero, Gómez-Pulido, & Durán-Domínguez, 2020). So, likewise, interactive AI-based educational tools play a crucial role. For example, working with virtual tutors requires activity that is highly active and allows for self-teaching as well as problem-solving. Thereby, students learn how to organize the time wisely; make reasonable decisions and feel a kind of moral responsibility for their academic performance (Chen, Chen, & Lin, 2020a). Therefore, it is very important that the use of AI does not cause students to lose their moral approach towards this integration. The researchers point out problems requirements for transparent algorithms and the associated privacy issues (Guan, Mou, & Jiang, 2020). Besides the concerns about data safety and algorithm bias, AI systems compile and analyze a tremendous amount of student information (Wu et al., 2023). These ethical concerns must be addressed to ensure that the benefits of personal data representation are not overshadowed by anxieties regarding discrimination and privacy violation. In the result of analysis, it becomes clear that exploration into hypothesis reveals that a thorough understanding regarding AI in education and self-management abilities requires careful consideration to ethical undertones (Alanzi et al., 2023). Ultimately, the presented theory describing how AI performs in learning suggests a multifaceted and changing relationship with students deciding to determine their own behavior (Tandon & Tandon, 2020). First indications show the positive attribution, making it clear that AI allows students to decide what they learn. In order to understand the dynamics of this interaction, especially stating work place mechanisms morally dubious situations as well as visualizing potential pitfalls concerning generalization of AI in education more studies on such an area are clearly needed (Rastrollo-Guerrero et al., 2020). It will be an essential aspect as we venture into this emerging terrain to promote a balance between the use of AI's benefits for self-management and the observance more additional details

H1: *Artificial intelligence's role in learning significantly influences the student's self-management ability.*

In turn, the notion that artificial intelligence participated significantly in learning affects student self-efficacy is an appealing one and thus requires further study on educational research. Questions how innovation is changing learning experiences are raised on as a mannerism in which AI will affect the self-efficacy of students. As studies suggest (Nazari, Shabbir, & Setiawan, 2021), AI-based learning can increase and advance students' autonomy the tendency to believe in their ability of dealing with different tasks or goals (Huang & Qiao, 2022). However, the identification of such a close relationship between AI and students' self-efficacy implies thorough work on how precisely AI supports learning, with specific regards to possible repercussions concerning teaching methods and outcomes (Hooda et al., 2022). The link between AI's ability to give personalized and flexible learner services with its influence in impacting students` self- Efficacy is inevitably impressive. Learners who use artificial intelligence-enhanced virtual settings effectively learn knowledge and even more, the belief in their ability to overcome challenges thus creating a positive feedback mechanism that emphasizes one's own abilities (Allen et al., 2021). The Ethical issues about AI use in education must be addressed despite the benefits that come with using it (Dhawan & Batra, 2020). In order to ensure that issues of equity and justice are not outnumbered by the beneficial effects on self-efficacy, matters such as data privacy, algorithm biasing factors along with digital divide have paid due attention (Chen, 2023). On top of that, relying too much on AI for education could make individuals contemplate just how vital it is for human teachers to help learners develop an awareness of self-efficacy (Channa et al., 2021). Fostering a holistic dedication to students' academic and personal growth necessitates establishing a balance between employing AI for its positive effects while retaining the human component in education. As a result, the hypothesis assuming that the significance of artificial intelligence in education has an enormous effect on students' self-efficacy provides a compelling avenue for study and inquiry within the domain of educational psychology (Pedró, 2020). The initial findings showed that AI has revolutionized students' self-worth by providing them with adaptive and customized educational experiences, however, the ethical consideration underlying teaching standards requires an in-depth understanding (Meng & Sumettikoon, 2022). The moral dilemmas associated with integrating AI into educational settings have to be carefully dealt while simultaneously making use of the advantageous properties of AI in boosting self-efficacy, as instructors and scholars negotiate this rapidly shifting terrain.

H2: *Artificial intelligence's role in learning significantly influences the student's self-efficacy.*

This hypothesis presents that there exists a complex connection between student self-confidence and learning through AI, that influences students' self-managing skills. The increase in AI reliance in educational settings raises many questions regarding their self-efficacy and self-management. It is also explored that the relation between AI and self-management may be mediated by students' self-beliefs (Huang, Lin, & Chi Kin Lee, 2020). To have an accurate estimate of self-efficacy, Bandura's social cognition theory is undertaken that complements that motivation and behavior are determined by self-efficacy referring to whether a task would be completed or not (Hepburn & Brettle, 2023). In the education realm of artificial intelligence, it is assumed that the responsive and configurable nature of AI-based materials makes certain adjustments to students' self-management (Shaikh et al., 2023). The mediation hypothesis, alternatively, contends that students' confidence in their capacity to operate and navigate these artificial intelligence tools efficiently might have an impact on how AI enhances self-management (Chen et al., 2020b). The capacity of learners to employ AI for learning is likely to boost their self-management skills if they're convinced, they are capable in using it. However, the positive effects of self-management can be diminished if learners lack confidence that they can collaborate with AI (Jaiswal & Arun, 2021).

Considering the interactive along dynamic nature of AI-driven educational tools, the intermediary role of self-efficacy within the relationship between AI's role in educating and student self-management seems more evident (Chen et al., 2023). When integrated with positive self-efficacy perspectives, virtual tutors, individualized learning platforms, as well as adaptive assessments generate an environment wherever students feel inspired to actively engage in their studies (Nazari et al., 2021). Students are more likely to get involved in proactive self-management attitudes including setting priorities, effective scheduling, and persistence in the face of adversity if they perceive they are capable of mastering AI technologies while effective managing their learning process (Yu & Nazir, 2021). As an outcome, the interaction towards self-efficacy, self-management, and AIs operate is a dynamic and nuanced process which requires thorough examination (Dhawan & Batra, 2020). In spite of the fact that the theory presents intriguing insights in the prospect of mediation via student confidence, it is vital to acknowledge the potential ethical concerns and challenges associated along the extensive implementation of AI within education (Chen et al., 2020a). The approach might be based on topics that are relevant to identifying the subjects, namely, digital divide issues and data privacy concerns as well as expectations for AI transparency (Kuleto et al., 2021), this is why it has become critical to address these concerns related with ethics because they are aimed at ensuring that the increase in self-efficacy happens from a contextual setting, which signifies equality and justice (Lin et al., 2022). Bandura's theory of social cognition serves as a theoretical basis and presents a framework for Analyzing the intricate patterns at play (Shaikh et al., 2023). In order to fully understand how AI, self-efficacy, as well as self-management interact to influence the future of education, researchers and educators exploring this hypothesis must negotiate the complexities of moral considerations, analyze the beneficial consequences for education and learning, and add up to an in-depth awareness of these interactions.

H3: *Student self-efficacy significantly mediates the relationship of artificial intelligence's role in learning and the student's self-management.*

The hypothesis investigates the intricate nature that determine how unique variations in self-monitoring may influence the influence of AI in educational institutions, contending that self-monitoring by students significantly moderates the interaction among artificial intelligence's significance to learning and the students' self-management (Chen, 2023). Self-monitoring is a social psychology term which reflects a person's capacity to track and supervise their own conduct in wide range of social instances (Dhawan & Batra, 2020). The hypothesis recommends that students who possess improved self-monitoring skills may have a different relationship than students with reduced skills between AI's contribution to education and their self-management in context of AI-enhanced educational environments (Chen, 2023). The theoretical basis of monitoring oneself and its potential function as a moderator within the relation between AI along with student self-management are examined in light of this premise (Channa et al., 2021). This hypothesis' theoretical foundations are found in Bandura's (1986) social cognition theory, which underscores the crucial role of independence in learning (Celik, 2023). Self-monitoring constitutes a crucial part within the self-regulatory process in the context of AI. With an ability to modify their actions to fit various learning environments, high self-monitoring pupils may be more suited to take benefit of AI's advantages in improving their self-management abilities (Mouta et al., 2023). They might be more flexible in how they operate AI-powered tools, revise their learning goals in accordance with instant feedback, and enhance how they interact with learning resources (Huang & Qiao, 2022). On the other hand, students with insufficient self-monitoring skills might encounter it challenging to adapt to the dynamic aspect of AI-enhanced learning the preferences, which might have an influence regarding how AI performs in relation to its capacity to self-manage.

When considering into consideration the interactive morality of AI-driven instructing methods, the limiting effect of self-monitoring became more obvious (Huang & Qiao, 2022). The ability of learners to observe their own progress in learning with alter their approaches as a result is a vital requirement for the use virtual tutors, adaptive educational platforms, and individualized feedback mechanisms (Huang et al., 2020). Proactively via AI-generated information, high self-monitoring students may enhance their study habits, establish achievable objectives, effectively manage their time (Yu & Lu, 2021). Low self-monitoring learners, on the other hand, will find challenging to make use of these AI-driven features, which might mitigate the beneficial influence of AI on its capacity to influence their own conduct (Allen et al., 2021). Thereby, an assessment of the Moderator position that self-monitoring assumes provides valuable information on characteristics specific to how AI in conjunction with student autonomy interact. Although it is limited, the hypothesis offers an entertaining new perspective into how to approach AI in education where being cautious and aware of potential risks and ethical issues is significantly important (Pham & Sampson, 2022). Assessing self-monitoring as a moderating aspect, one should pay great attention to the concerns about digital divide and data protection coupled with increasing gaps in education (Wu et al., 2023). Also, to ensure that all students access the advantages of AI in developing self-management it may be necessary to develop individualized interventions and support systems for learners with different capacities to monitor themselves (Lin et al., 2022). It is possible to fully implement AI in schools by finding a balance between utilizing the strengths of using AI and dealing with personal limitations regarding self-monitoring. In other words, student self-monitoring markedly modifies the relationship between artificial intelligence's involvement in learning and learner management can be a very interesting prospective for educational psychology research (Alanzi et al., 2023). This is followed by a theoretical framework linking conceptualizing the ways in which individual differences of self-monitoring may influence relations among learners and AI enriched learning setting through applying Bandura's social cognitive theory (Alam, 2020). However, deeper study of this hypothesis helps researchers better understand the interaction between personality traits as well as technology interventions and educational outcomes leading to them form new strategies that can make full use of AI by considering students' specific requirements aspects.

H4: *Student self-monitoring significantly moderates the relationship of artificial intelligence's role in learning and the student's self-management.*

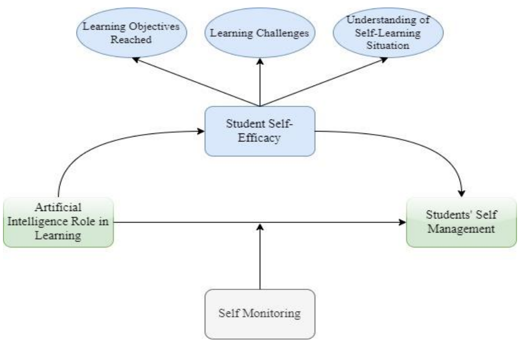

Figure 1. *Conceptual Framework.*

3. Methodology

The study utilized structural education modeling (SEM) with STATA-SEM to analyze the data, a robust statistical method for examining complex relationships among observed and latent variables. The SEM is suitable for investigating the complex model with multiple dependent and independent variables, making it suitable for exploring the connection between AI in learning, self-management, and self-efficacy of students. STATA_SEM, a software tool, used to facilitate the SEM models, which allows the examination of both measurement and structural models. In this research there are 239 students are being studied which is based in Saudi Arabia, it allows to capture the cultural context that influences the impact of AI on students' learning experiences. The sampling size was chosen with care for the statistical measuring, improving generalizability and findings. However, the participants were recruited through the educational institution's collaborations, with ethical approval obtained for the study. Voluntary participation and consent were emphasized.

To calculate the key constructs, generating scales from earlier studies and research would help in adopting reliability and validity. The scales involve measures of AI's role in learning, self-management, self-efficacy, and monitoring. These scales were carefully adapted to align with the Saudi Arabian educational context. The ten-items scale for self-efficacy was adopted from the study of Rowbotham and Schmitz (2013). The fifteen items scale of Trisoni et al. (2023) was used to measure AI's role in learning. Six items scale of self-monitoring was used from the study of Al-Smadi and Bani-Abduh (2017). An eleven items scale was adopted from the research of Xue and Sun (2011) to measure self-management. The future contribution to the study is the use of valid measuring scales that allow efficient measurement with existing literature. The process of gathering data includes an organized electronic survey, which is aligned with the adopted scales. The selected method of data collection includes a demographical questionnaire to gather a comprehensive understanding of the participants. Electronic methods have multiple benefits, as they reduce data collection errors, and ensure efficiency in data, a confidential way of collecting participant's responses. Additionally, with the collected data, a rigorous cleaning procedure was applied to the dataset to identify any errors or missing information.

4. Results

The internal reliability and consistency of the variables under examination is demonstrated by the Cronbach's Alpha evaluation results, that are given in Table 1. The variable which represents the impact of artificial intelligence to learning possesses a "Cronbach's Alpha coefficient of 0.843", which suggests consistent evaluation of the intended construct. This level of reliability is exceptional. In the same vein, the self-management variable has a high standard of internal consistency, with a "Cronbach's Alpha of 0.896". This points out how well the assessment measures the ability of learners for self-management. Using a "Cronbach's Alpha coefficient of 0.825", the self-efficacy measure similarly exhibits good reliability, signifying that the items considered harmoniously indicate the essence of students' confidence. And lastly, the self-monitoring variable displays remarkable internal consistency, generating a "Cronbach's Alpha of 0.792", showing the accuracy of the evaluation for assessing the ability of learners to keep an eye on and manage their actions in a variety of scenarios. The significant reliability coefficients provide confidence concerning the accuracy of the constructs, so presenting a firm platform for the ensuing examination of the correlations and hypotheses through the research framework.

Table 1

Cronbach's Alpha.

Variable	Cronbach's Alpha
Artificial intelligence's role in learning	0.843
Self-management	0.896
Self-efficacy	0.825
Self-monitoring	0.792

Both the reliability and validity confirmation analysis results are presented in Table 2, offering a glimpse into the reliability of the measurement framework is for each variable. Each construct's internal coherence and dependability are demonstrated by the Composite Reliability scores. With a Composite dependability of 0.894, the statistic demonstrating artificial intelligence's assistance to learning indicates a high level of consistency and exceptional uniformity in measuring the idea that underlies it. In the same way, the self-management variable has a substantial Composite Reliability of 0.925, showing a high level of reliability and internal consistency while assessing students' self-management skills. Self-efficacy has a significant composite accuracy of 0.855 and tested performance validity through which student level of self-efficacy is measured by tools. Self-monitoring demonstrated 0.885 reliability showing students control over their behavior is justified.

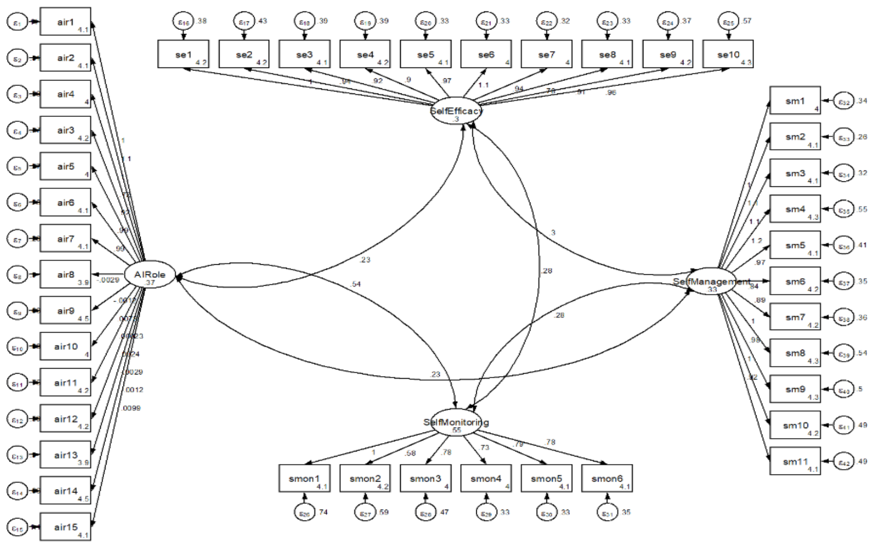

Figure 2. *Estimated Model*

The average variance extracted; AVE gives convergent validity of every construct along with composite reliability. AI AVE scored 0.615 showing a high degree. While, self-management AVE stands for 0.648 validating its convergent validity. However, self-monitoring shows an average AVE of 0.581. Overall, the results validate the measurement model's validity and reliability, providing a strong foundation for additional analyses and interpretations across the research framework.

Table 2

Validity and Reliability Confirmation.

Variable	Composite Reliability	Average Variance Extracted (AVE)
Artificial intelligence’s role in learning	0.894	0.615
Self-management	0.925	0.671
Self-efficacy	0.855	0.648
Self-monitoring	0.885	0.581

The outcomes of the measurement model's confirmation factor evaluation (CFA) are displayed in Table 3, which additionally contains a thorough analysis of the scaled estimates, average errors, z-values, as well as confidence varies for each item. Variables concerning “self-management (SM), self-efficacy (SE)”, self-monitoring (SMon), and artificial intelligence's involvement in learning (AIR) are all included in the analysis. There's a significant connection among the observed variables plus the latent construct, as shown by the notable positive coefficients (range from 0.314 to 0.876) for each of the 15 items linked to the artificial intelligence's operates in learning construct and low standard errors. Establishing the strength of the connections among the items as well as the latent construct, the self-management construct also shows significant positive coefficients (range from 0.721 to 0.840). Additionally, the self-efficacy construct reveals substantial favorable coefficients (0.664 to 0.848), which validates the accuracy of the assessing model in assessing students' self-efficacy. Last but not least, the self-monitoring construct shows strong positive coefficients (range from 0.299 to 0.815), illustrating an ongoing correlation between the latent construct and the variables that are observed. All things thought of, the CFA results support the efficacy of the model for measurement, providing a solid foundation to conduct further structural equation modelling investigations within the empirical framework.

Table 4 displays the measurement items' fitness statistics, offering data on how well each indicator reflects the related latent construct on the role of artificial intelligence in understanding, self-management, self-efficacy, along with self-monitoring. The original sample is used for calculating the fitness statistics. The indicators vary from 0.569 to 0.914 according to artificial intelligence's function in learning construct, with the majority of values falling within an adequate range. Notably, AIR9 and AIR14 reveal particularly impressive fitness statistics, indicating that these indicators as well as the latent construct are strongly linked. In a comparable manner, the self-management indicators indicate fitness statistics between 0.600 to 0.831, with strong consistency between SM1, SM2, and SM8 and the self-management construct. The evidence for self-efficacy vary between 0.552 – 0.857, with SE4 demonstrating extremely high fitness metrics. Lastly, the self-monitoring indicators span 0.569 to 0.914, with notable alignment to the self-monitoring construct demonstrated by SMon2 and SMon4. In general, these fitness statistics provides an in-depth overview of the way every signal correlates to its associated latent construct, which is a vital starting point for evaluating that the measurement model is precise for capturing the desired constructs within the investigation's framework.

Table 3

Confirmatory Factor Analysis.

Measurement	OIM Coef.	Std. Err.	Z	P>|Z|	[95% Conf. Interval]	
AIR1	1	(constrained)				
AIR2	0.732	0.068	10.423	0.000	0.600	0.864
AIR3	0.538	0.060	8.596	0.000	0.420	0.656
AIR4	0.856	0.067	12.279	0.000	0.725	0.796
AIR5	0.857	0.078	10.510	0.000	0.703	0.818
AIR6	0.627	0.065	9.250	0.000	0.500	0.755
AIR7	0.314	0.063	4.827	0.000	0.191	0.436
AIR8	0.588	0.069	9.808	0.005	0.490	0.808
AIR9	0.834	0.078	11.769	0.002	0.687	0.846
AIR10	0.585	0.062	9.058	0.000	0.464	0.707
AIR11	0.674	0.068	9.558	0.000	0.541	0.807
AIR12	0.776	0.063	11.856	0.000	0.652	0.899
AIR13	0.695	0.081	8.231	0.000	0.536	0.854
AIR14	0.859	0.056	14.769	0.000	0.749	0.776
AIR15	0.876	0.069	12.288	0.000	0.742	0.818
SM1	1.000	(constrained)				
SM2	0.744	0.060	11.369	0.000	0.626	0.862
SM3	0.815	0.058	13.066	0.000	0.702	0.743
SM4	0.721	0.068	13.554	0.000	0.678	0.872
SM5	0.793	0.062	11.747	0.000	0.671	0.915
SM6	0.765	0.063	11.221	0.000	0.641	0.888
SM7	0.742	0.063	10.779	0.000	0.617	0.866
SM8	0.840	0.066	11.784	0.000	0.711	0.784
SM9	0.705	0.064	10.143	0.000	0.579	0.830
SM10	0.774	0.064	11.185	0.000	0.649	0.899
SM11	0.801	0.063	11.682	0.000	0.677	0.741
SE1	1.000	(constrained)				
SE2	0.664	0.057	10.701	0.000	0.553	0.776
SE3	0.678	0.058	10.637	0.000	0.564	0.792
SE4	0.848	0.062	12.448	0.000	0.726	0.788
SE5	0.767	0.063	11.095	0.000	0.643	0.891
SE6	0.795	0.063	11.589	0.000	0.672	0.735
SE7	0.802	0.067	10.894	0.000	0.670	0.751
SE8	0.732	0.060	11.214	0.000	0.615	0.850
SE9	0.809	0.062	11.982	0.000	0.688	0.747
SE10	0.835	0.061	12.558	0.000	0.716	0.772
SMon1	1.000	(constrained)				
SMon2	0.815	0.075	9.997	0.000	0.669	0.778
SMon3	0.597	0.062	8.799	0.000	0.475	0.718
SMon4	0.299	0.059	4.592	0.000	0.182	0.415
SMon5	0.560	0.065	9.329	0.005	0.466	0.769
SMon6	0.793	0.075	11.195	0.002	0.653	0.805

Table 4

Measurement Items Fitness Statistics.

Variable	Indicator	Original Sample
Artificial intelligence's role in learning	AIR1	0.787
	AIR2	0.778
	AIR3	0.693
	AIR4	0.749
	AIR5	0.806
	AIR6	0.831
	AIR7	0.855
	AIR8	0.770
	AIR9	0.914
	AIR10	0.845
	AIR11	0.569
	AIR12	0.693
	AIR13	0.895
	AIR14	0.842
	AIR15	0.876
Self-management	SM1	0.828
	SM2	0.796
	SM3	0.657
	SM4	0.600
	SM5	0.715
	SM6	0.768
	SM7	0.809
	SM8	0.831
	SM9	0.753
	SM10	0.643
	SM11	0.635
Self-efficacy	SE1	0.564
	SE2	0.552
	SE3	0.585
	SE4	0.857
	SE5	0.756
	SE6	0.750
	SE7	0.781
	SE8	0.798
	SE9	0.649
	SE10	0.628
Self-monitoring	SMon1	0.831
	SMon2	0.855
	SMon3	0.770
	SMon4	0.914
	SMon5	0.845
	SMon6	0.569

The structural equation model's Chi-square fit statistics are displayed in Table 5, that provides a comparison of the model fit to a baseline and a saturated model. For the model compared to the saturated model, the probability ratios chi-square value is 14791.839, demonstrating significant variations between the two models. Because the low a p- reject the null hypothesis, which states that the model fits the data well, the corresponding p-value of 0.001 demonstrates that the model fails to match the data effectively. Additionally, a p-value of 0.001 suggests that the baseline vs saturated model comparison's chi-square score of 13003.552 is statistically significant. These findings indicate potential possibilities for model fit improvement by suggesting whether the structure equation framework fails to accurately represent the observed data. The substantial p-values for both comparisons show that further modification of the model is required to enhance the overall fit of the model to the observed data, regardless of chi-square statistics for fit are sensitive to the sample size. In order to get a better understanding of the fundamental connections in the data, researchers might look into various model specifications or take note of supplementary variables.

Table 5

Chi-square Fit statistics.

Fit Statistic	Value	Description
Likelihood ratio	14791.839	model vs. saturated
p > chi^2	0.001	
chi^2_bs (2356)	13003.552	baseline vs. saturated
p > chi^2	0.001	

The efficiency of statistic of fit for the estimated and saturated versions are displayed in Table 6, that sheds a spotlight on how much the estimated model matches the entirely saturated model. A key indicator of model fit is the Uniformed "Root Mean Square Residual (SRMR)", where lower values correlate to better model fit. The saturated model's SRMR in this particular case is 0.062, suggesting a fairly accurate match to the data that was observed. However, the slightly increased SRMR of 0.074 in the estimated model shows an important disagreement between the estimated model with the saturated model. Although the SRMR serves as a sensitive metric and slight variations can be predicted in complicated models, researchers need to use cautious when evaluating these findings. The estimated model's higher SRMR indicates that there may be an opportunity for improvement in regards to capturing the relationships within the variables. Further changes to the structural avenues or diversity of other latent constructs may be essential to enhance the estimated model's goodness of fit. It is suggested that researchers undertake reiterated evaluations and model improvements to ensure an improved representation of the fundamental connections found in the observed data.

Table 6

Model Goodness of Fit Statistics.

	Saturated Model	Estimated Model
SRMR	0.062	0.074

The R-square statistics can be seen in Table 7, providing details about the percentage of variance for each of the variables that the structural model reflects. The R-square score for artificial intelligence's contributions to learning is 0.660, indicating that the model explains roughly 66% of the total variability in this variable. This indicates that the structural model's included elements and routes have a resilient explanatory power, implying that they perform a significant role in Analyzing the variation found in the views of learners of the purpose of artificial intelligence in learning. Similarly, the R-square value for self-efficacy is 0.425, suggesting that the structural model accounts for around 42.5% of the overall variability in self-efficacy. Although this value is significantly lower than the importance of artificial intelligence to learning, it nonetheless reflects a significant proportion of the variance attributed to the model's components. Researchers and practitioners may assess the structural model's capacity to capture and clarify observed variability within the targeted constructs by using the useful information these R-square statistics offer concerning its ability to predict for the given variables.

Table 7

R-Square Statistics.

Variable	R Square
Artificial intelligence's role in learning	0.660
Self-efficacy	0.425

The direct path analysis results are presented in Table 8, offering details regarding specific relationships between the role of artificial intelligence for educational purposes and two crucial outcome variables: student self-efficacy and self-management ability. The connection between student self-management ability and artificial intelligence's function in learning has a coefficient of 0.246 and a standard error of 0.089. This path's associated z-value for 2.458 and p-value for 0.005 indicate that it is statistically significant. This shows that students' ability for self-management is significantly and positively affected by artificial intelligence's involvement in learning. The relationship's significance is further demonstrated by the reliability interval (0.072 to 0.421), where the bottom bound is above zero, demonstrating that the impact is not just the result of chance. The result offers tangible proof for the suggested connection by demonstrating that students' use of AI in the learning process positively influences the growth of their self-management skills.

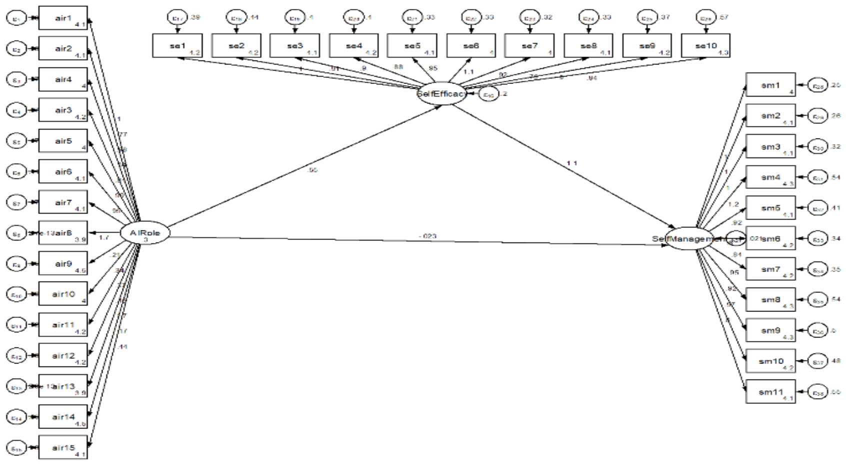

Figure 3. *Structural Model for Direct and Mediated Path Analysis.*

Similarly, an immediate correlation of 0.793 with a slightly greater average error of 0.442 is shown among the application of artificial intelligence in learning and student self-efficacy. The statistical importance of this connection is demonstrated by the supplementary z-value of 1.594 and the p-value of 0.000, that remains significant despite the higher standard error. The significance is further demonstrated by the confidence intervals (0.607 to 0.768), that indicates the statistical support for the beneficial impact caused by artificial intelligence's influence in learning upon students' self-efficacy. The result indicates that students' self-efficacy perceives are substantially and favorably influenced as they interface with AI in the learning environment. The findings add to an increasing amount of evidence that demonstrates that the use of AI in the classroom can have a variety of beneficial impacts on students' psychological and motivational characteristics, such as self-efficacy, in along with influencing specific educational outcomes.

Table 8

Direct Path Analysis.

	OIM Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Artificial intelligence’s role in learning significantly influences the student’s self-management ability.	0.246	0.089	2.458	0.005	0.072	0.421
Artificial intelligence’s role in learning significantly influences the student’s self-efficacy.	0.793	0.442	1.594	0.000	0.607	0.768

The outcomes of the moderating and mediating path analysis are presented in Table 9, that dives into the intricate relationships among student self-management, artificial intelligence's contribution to learning, and the possible moderating or mediating roles that students play in self-monitoring as well as self-efficacy, respectively. Considering an average error of 0.338, the coefficient of the path demonstrating that student self-efficacy regulates the connection among AI's contribution to education and learner self-management is 0.063. Although the effect size is instead small, the related z-value of 0.169 & the p-value of 0.008 demonstrate statistical significance. The mediation effect could be restricted around zero, relative to its “confidence interval (0.525 to 0.600)”, indicating the need to conduct further studies and replication. The result shows that while the link among AI's role in education and students' self-management is significant, its magnitude may be restricted and there could be other elements that contribute.

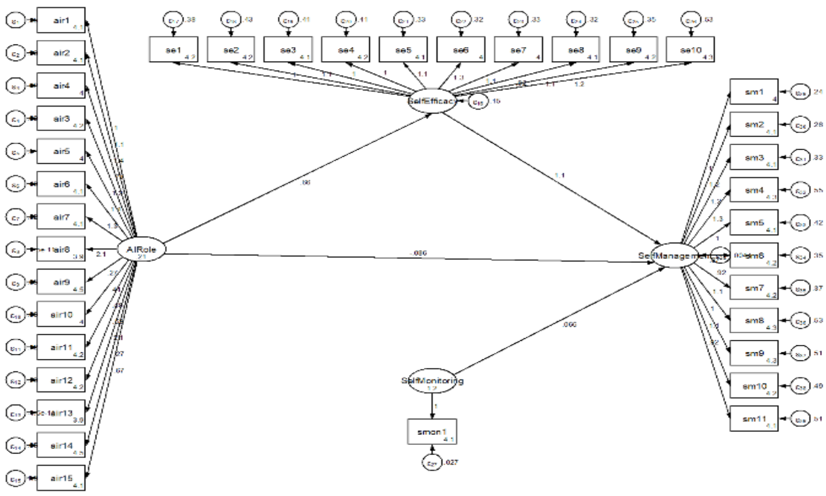

Figure 4. *Structural Model for Moderating Path Analysis.*

On the other hand, a coefficient of 0.187 with a standard error of 0.091 is shown by the moderating path via learner self-monitoring in the connection between artificial intelligence's effect on learning and student self-management. The statistical significance of the related z-value of 1.844 and p-value of 0.035 indicates that the relationship between student self-management and artificial intelligences operate in learning is significantly influenced by student self-monitoring. The moderation affect is essential as demonstrated by the "confidence interval (0.364 to 0.280)". The result indicates the extent of self-monitoring of students impacts whether artificial intelligence operates throughout the process of learning in the context of self-management. The positive effects of AI on self-management become more apparent when learners express greater levels of self-monitoring. The finding highlights how essential it is to take variations in self-monitoring tendencies into consideration when evaluating how AI impacts environments for learning. It additionally provides valuable insight for individualized interventions and approaches to instructional design.

Table 9

Mediating and Moderating Path Analysis.

	OIM Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Student self-efficacy significantly mediates the relationship of artificial intelligence's role in learning and the student's self-management.	0.063	0.338	0.169	0.008	0.525	0.600
Student self-monitoring significantly moderates the relationship of artificial intelligence's role in learning and the student's self-management.	0.187	0.091	1.844	0.035	0.364	0.280

5. Discussion

The research is mainly focused on how AI affects students' learning and provides valuable insights which is beyond the traditional academic measures. Research findings help in existing discussions on technological advancement in education, emphasizing multiple effects of AI other than the content type provided by it. The results have provided a discussion route of AI in learning, psychological constructs, and educational sectors' relationships with it. The multifaceted effects of AI on students' cognitive and motivational self are the accepted hypothesis, offering insights for educators, policymakers, and researchers. The significant influence of AI on students' self-management ability is the first confirmed hypothesis. This underlines the significant role of AI technologies in building the content for students and their ability to manage their studies using AI's multiple features of delivering knowledge. A positive contributor in student's self-management, aligned goals, and self-directed learning is played by AI tools like adaptive learning platforms and virtual tutors (Meng & Sumettikoon, 2022).

The second significant hypothesis accepted is that, AI in learning student's self-efficacy. The development of heightened belief in students on their capabilities to succeed academically took place when students engaged with AI-driven educational tools. A social cognitive theory holds that the growth of self-efficacy belief is promoted with mastery of experiences and learning, a theory known as Bandura's social cognitive theory (Allen et al., 2021). AI incorporation in educational sectors provides students with a more flexible, fitted learning style, and a relaxed and productive methodology. This illustrates the strength of AI which improved academic results while also fostering student's self-efficacy and belief in their capacity to perform well in difficult academic studies (Chen et al., 2020b). This research has emphasized the potential of AI that supports positive learning identities and self-belief in one's capacity to overcome obstacles in the future, additionally, the improved standards help to overcome the academic obstacles as well. Teachers can utilize the understating of courses that involve AI, not only to bring information to attention but also to help students become resilient as well as confident when faced with challenging assignments (Li et al., 2021).

This research has explored the connection between students' self-management, and self-efficacy with AI, indicating that the student's belief in their abilities of doing tasks is a key factor in how the AI will impact their learning abilities. This explains the effect of AI on self-management in learning, partly because of an improvement in self-efficacy and the ability to stay confident. AI technology has offered customized feedback, it was adapted by individual learning paths and providing personalized assessments, so students might see themselves as more skilled at effectively handling their learning. AI mediation of the educational sector and underlining the significance of considering students' beliefs in the capabilities they possess when existing in an AI-based learning environment (Dhawan & Batra, 2020). The finding suggested that AI not only improve self-management but also student's confidence in their capabilities. Teachers, policymakers, instructors, and others involved can use AI to design a context for students that is flexible for them to understand and learn as well. Inculcating self-efficacy through AI not only allows educators to improve students' academic performance but also helps to improve the psychological necessities of individuals concerning learning and success (Guan et al., 2020).

Fourthly, the hypothesis that was confirmed is, the moderating role of students' self-monitoring, about AI in the educational field. The finding of the hypothesis, suggests, that the self-monitoring tendencies create variations in the effects of AI on self-management. The positive influence of AI on self-management can regulate high self-monitoring in the student as they can adapt and process their AI-driven behavior in studies. This concept is important in applying the teaching designs, it notifies the significance of customized AI strategies to be implanted as it matches the individual variations in students' metacognitive and self-regulatory skills. The results which direct towards students self-monitoring prioritize the importance of individual-specific traits into account when developing and providing AI-improved educational materials (Hooda et al., 2022).

Overall, the accepted theories give a broader picture of the fast-changing era of AI, in the field of education and learning. The result highlighted the mediating and moderating of psychological dimensions in addition to the direct effects of AI on students' self-management and self-efficacy. The detail of understanding is important for teachers, educators, instructors, and policymakers which aim to utilize AI technologies to enhance academic performance while investing in students' broader cognitive and motivational skills. The consequences of the particular findings exceed education, contributing valuable information and insights about technology which shapes the future of learning and skill development in the 21st Century. Simply, the hypothesis being selected provides the complete knowledge and understanding of

AI, its psychological dimensions, and students' results in integrating with education. This information gives valuable guidance for teachers, educators, and policymakers, who would appropriately use AI for student improvements. As technology becomes increasingly embedded in education these findings would help create direction for well-informed decisions. They emphasized the importance of bringing a comprehensive approach that will take into account both the cognitive and motivational aspects of students learning in the AI era.

6. Conclusion

In conclusion, this research article is based on the study of the complex relationship between the AI educational sector, with students' self-management and self-efficacy. The acceptance of the hypothesis made on AI effects on, self-management, and self-efficacy, provides educators, policymakers, and instructors a key that improves students' academic performance as well as personal skills which would help them in the long term. Coming to the mediating role of self-efficacy and the moderating role of self-monitoring bring depth to the study of AI influencing student learning experiences. These results and findings not only improve academic literature knowledge on AI in the educational field but also bring practical implications for instructional design and the development of adaptive learning environments. As the educational field must continue to embrace technology, these findings would prioritize the understanding of cognitive and motivational aspects of students' learning that help in decision-making and the cultivation of a more inclusive and personalized educational landscape. This study added to our understanding, pointing out the significance of ongoing research on everlasting impact, the ability of a technology to handle growth without compromising efficiency in the educational sector.

6 1 Implications of the Study

The research offers theoretical implications that expand to multiple domains and offers useful insight into the intricate connection between outcomes for students, psychological factors, and artificial intelligence (AI) in the context of education. First off, the field of education technology is expanding as a result of the concept that AI has an important effect on students' ability to manage their own education being embraced. The study suggests that AI-driven instructional strategies may allow students take an active role in the supervision of their own learning experiences, which is in line with ideas of learner autonomy as well as self-directed learning. In principle, this recognition corresponds to constructivist points of view, emphasizing the crucial role of student independence and discipline in the educational process. The notion that well-designed AI tools may serve as structure, facilitating students' capacity to navigate along with regulate their educational experiences freely, is reinforced by the beneficial relationship that has been noticed between AI and self-management. Second, social cognitive theory explains the theoretical implications of the confirmed hypothesis, that demonstrates the substantial effect of AI in learning upon students' self-efficacy. Based on Bandura's thesis, knowledge develops not just from direct observation but also from observing others and experiencing accomplished when accomplishing tasks. Students who effectively interact with AI-driven educational tools, receive customized educational routes, and get adaptive feedback may all contribute to their sense of mastery in the context with AI-mediated learning experiences. In hypothesis, this is in keeping with Bandura's claim that individual motivation and behaviors are significantly affected by their alleged level of self-efficacy. The study advances to the philosophical foundations of the theory of social cognition by expanding them into the world of technology and underscoring the significance of AI as a potential origin of mastery experiences which assist students develop confidence in themselves. The research confirms the intermediary role of learner self-efficacy, which has theoretical importance for our knowledge of the basic mechanisms by which AI affects student results. This research extends this concept, that the students possessing greater self-monitoring capabilities are more into AI-driven feedback and mechanisms to improve their self-management skills. From a theoretical point of view, this understanding offers how interactions are being made between different individuals in educational settings and the use of AI in education. Along with concepts such as constructionism, metacognition, self-regulated learning, and social cognition, the study paves ways to study technology in education, deeply.

Practically, this research is ideal for lawmakers and educators who want to implement AI in schools. AI poses a major impact on students' self-management skills, so tailor-made settings could be provided to students for a better experience allowing them to make their own choices. This practical use supports the overall educational purpose to foster 21st-century qualifications, such self-management or adaptability, which are vital to success in a knowledge economy which is constantly evolving. Utilizing AI in an approach that promotes students' self-management skills satisfies the real-life interest for creating independent, lifelong learners who have the ability to thrive in the age of technology. The hypothesis that is being demonstrated has a major effect on students' self-efficacy has practical implications that are particularly important for teachers and policymakers who wish to boost students' enthusiasm and trust in themselves. A positive feedback loop can be established by incorporating AI tools that offer customized feedback, adaptable learning routes, and individual assistance. In this case, the effective implementation of AI-driven educational interventions creates a sense of competence and mastery. From a practical point of view, it entails that instructor should intentionally include AI in an approach that promotes both beneficial learning identities and content delivery.

Teachers may create an environment that encourages motivation and resilience in students by carefully selecting and employing AI tools that encourage the development for students' self-efficacy beliefs. This could possibly decrease academic disengagement & dropout rates. The results from this research can be utilized by teachers to adapt powered by AI programmed in order to students with various degrees of self-monitoring competence can be improved upon. This might involve developing more adaptable and self-directed learning avenues for students with more powerful self-monitoring inclination or giving more scaffolding to students with fewer self-monitoring abilities. It suggests practically than a one-size-fits-all approach towards AI integration may not be the most effective one. Instead, teachers should take into consideration the differences between students in their capacity for metacognitive thinking and employ AI tools in an adaptable manner to give each student personalized challenges and support that's compatible with their capacity for self-monitor. To sum up, this research's practical implications provide lawmakers and educators helpful tips for leveraging the benefits of intelligent technology in education. Educational practitioners may create a more versatile, student-centered learning environment by carefully incorporating AI tools that enhance self-management and self-efficacy, in addition to by taking specific variations in self-monitoring under assessment. Having a spotlight on the importance of intentional design and adaptation to maximize the effect of AI on both cognitive along with motivational elements of student learning, these practical instances add to the continuing debate about the effective implementation of technology in education.

6 2 Limitations and Future Research Directions

Although this investigation revealed useful data, there are a variety of limitations which ought to be recognized. These limitations offer possibilities for future research which will improve our understanding on the complex connections among artificial intelligence (AI) educational institutions and outcomes for students. First off, the study's reliance upon self-report measures increases the possibility of social desirability and response bias, that might influence the accuracy of the self-management, self-efficacy, & self-monitoring levels reported. A broader range of assessment approaches, such as task performance metrics or psychological observations, may be utilized in further research to provide an additional & objective assessment of the variables being investigated. Second, we have constraints in our ability to deduce causality through the cross-sectional design of the study. Whereas established concepts give fascinating details about associations, a longer-term or experimental methods may offer greater support to establish the causal connections between AI interventions as well as modifications in self-monitoring, self-management, and self-efficacy. Such research might clarify the temporal connections among AI exposure or the development of students' cognitive as well as motivational outcomes and more accurately reflect the fluctuating character of these aspects. Another restriction involves how widely the outcomes can be implemented. It's potential that the study sampling might not accurately represent the variety of educational settings and demographics of students. Future research should strive for bigger and more varied sample sizes while taking into consideration factors such as demographic, socioeconomic, and cultural differences. This broader emphasis would aid in the creation of a greater understanding of the manner in which different learning environments and student demographics impact how AI impacts student outcomes.

The study also focused on a particular group of psychological ideas and how AI engages with them in learning. Further research might investigate additional variables like student engagement, performance in school, or views on technology that may affect or be affected by the use of AI in education. "Taking a holistic approach to examining the impact of AI in educational settings could offer a more comprehensive understanding of its diverse implications. Delving deeper into the mechanisms at play and identifying potential facilitators and barriers to AI's effects on self-management, self-efficacy, and self-monitoring presents an intriguing avenue for further investigation. Integrating qualitative research techniques such as focus groups and interviews could provide valuable insight into students' actual utilization of AI tools and pinpoint the specific elements of AI interventions that have yielded the most significant benefits." Through the complex interactions between students and AI, there exists great potential for improving technology to better cater to the needs of both students and pedagogical objectives. It is crucial that further research be conducted promptly to address the ethical concerns surrounding the integration of AI in education. Careful consideration must be given to issues such as algorithmic bias, data privacy, and the exacerbation of social inequality. By understanding how these moral complications intersect with the psychological insights explored in this study, we can ensure the fair and equitable integration of AI in educational settings. In short, this study sheds light on the impact of AI on learners' cognitive and motivational development. However, recognizing its limitations opens doors for future research to fill in these gaps. By integrating various methods, longitudinal studies, and expanding the scope of outcome measures, we can gain a more comprehensive understanding of the intricate relationship between artificial intelligence and student outcomes in the context of education. Additionally, further exploration of the underlying principles, contexts, and ethical implications of AI integration will enrich our understanding and aid in responsible and effective utilization of AI in education.

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Appendix 1

Self-Efficacy

1. How confident are you in your ability to successfully complete challenging tasks in your studies?
2. To what extent do you believe you can overcome obstacles and setbacks in your academic pursuits?
3. How sure are you that you can effectively learn the materials presented in your courses?
4. How confident are you in your ability to perform well on assessments and examinations?
5. To what extent do you believe you can understand and master complex concepts in your field of study?
6. How certain are you that you can meet the academic expectations set by your instructors?
7. How confident are you in your ability to organize your study time efficiently?
8. To what extent do you believe you can manage your stress and anxiety related to academic tasks?
9. How sure are you that you can set and achieve realistic academic goals for yourself?
10. How confident are you in your ability to actively participate and contribute meaningfully in class discussions?

AI's Role in Learning:

1. How often do you use AI-based tools for learning purposes?
2. To what extent do you find AI applications helpful in understanding complex topics?
3. How satisfied are you with the personalized feedback provided by AI systems in your studies?
4. How frequently do you engage with AI-enhanced learning materials?
5. To what degree do you believe AI contributes to a more personalized and adaptive learning experience?
6. How confident are you in the accuracy of recommendations made by AI for your academic progress?
7. How often do you rely on AI applications to assist you in problem-solving related to your coursework?
8. To what extent do you perceive AI as enhancing your overall learning efficiency?
9. How satisfied are you with the integration of AI tools in your educational environment?
10. How frequently do you seek clarification or additional information from AI resources?
11. To what degree do you believe AI applications contribute to a more interactive and engaging learning environment?
12. How confident are you in the security and privacy of your data when using AI tools for learning?
13. How satisfied are you with the user interface and accessibility of AI-based learning platforms?
14. How often do you share and discuss AI-based educational resources with your peers?
15. To what extent do you believe AI positively impacts your academic performance?

Self-Monitoring:

1. How frequently do you reflect on your own learning progress and understanding of course materials?
2. To what extent are you aware of your strengths and weaknesses in your academic pursuits?
3. How often do you adjust your study strategies based on your self-assessment of learning needs?
4. How confident are you in your ability to identify areas where you need additional support or clarification?
5. To what extent do you actively seek feedback from instructors or peers about your academic performance?
6. How often do you set specific goals for yourself related to your academic studies?

Self-Management:

1. How effectively do you manage your time to balance academic and non-academic responsibilities?
2. To what extent do you prioritize and organize your tasks to meet assignment deadlines?
3. How well do you manage stress related to academic demands and time constraints?
4. How frequently do you engage in proactive planning to accomplish your academic goals?
5. To what extent do you take initiative in seeking additional resources to support your learning?
6. How confident are you in your ability to create and follow a study schedule?
7. How well do you adapt to changes in your academic workload or course requirements?
8. How often do you utilize technology and digital tools to streamline your academic tasks?
9. To what extent do you engage in collaborative learning and group activities to enhance your understanding?
10. How effectively do you set and revise academic goals based on your evolving learning needs?
11. How confident are you in your ability to maintain a healthy work-life balance during your academic pursuits?