OPEN ACCESS
International Journal of Educatio Elementaria and Psychologia
Vol. 3 No. 1. February 2026, pp. 61-75 DOI. 10.70177/ijeep.v3i1.3107
Research Article

PERSONALIZED LEARNING VIA AI TUTORS: A COMPUTATIONAL PSYCHOLOGY APPROACH TO MODELING STUDENT MOTIVATION AND COGNITIVE STATES

Teuea Iotia[1], Maere Taitai[2], and Mena Ioteba[3]
[1] University of the South Pacific, Kiribati
[2] Kiribati Institute of Technology, Kiribati
[3] Kiribati National University, Kiribati

Corresponding Author:

Teuea Iotia,
Department of Finance, Faculty of Business and Management, University of the South Pacific.
Laucala Bay Road, Suva, Fiji.
Email: teueaiotia01@gmail.com

Article Info

Received: August 19, 2025
Revised: November 9, 2025
Accepted: January 17, 2026
Online Version: February 28, 2026

Abstract

The integration of artificial intelligence (AI) in education has led to the development of personalized learning systems that adapt to students' unique learning needs. However, there is limited research on how AI tutors can model and respond to students' cognitive states and motivation. This study explores the application of computational psychology to AI-based tutoring systems, focusing on how AI can simulate student motivation and cognitive processes to enhance learning experiences. The aim of this research is to create a computational model that incorporates psychological theories of motivation and cognitive states to personalize learning through AI tutors. The model integrates concepts from cognitive psychology, such as attention, memory, and intrinsic motivation, into AI algorithms that assess and respond to students' learning behaviors in real time. Using a dataset of student interactions with an AI tutor, we employed machine learning techniques to simulate the students' cognitive states and predict their learning outcomes based on varying levels of motivation. The results show that AI tutors significantly improve students' engagement and performance when personalized learning strategies are applied. This research demonstrates the potential of AI-driven personalized learning systems to foster better academic outcomes by responding dynamically to students' psychological states. The findings offer valuable insights for future AI-based educational tools aimed at enhancing student learning experiences.

Keywords: AI Tutors, Computational Psychology, Cognitive States, Motivation, Personalized Learning.

Journal Homepage	https://research.adra.ac.id/index.php/ijeep ISSN: (P: 3047-843X) - (E: 3047-8529)
How to cite:	Iotia, T., Taitai, M., & Ioteba, M. (2026). Personalized Learning Via Ai Tutors: A Computational Psychology Approach to Modeling Student Motivation and Cognitive States. *International Journal of Educatio Elementaria and Psychologia, 3*(1), 62–76. https://doi.org/10.70177/ijeep.v3i1.3107
Published by:	Yayasan Adra Karima Hubbi

INTRODUCTION

The rapid advancement of artificial intelligence (AI) has significantly impacted various sectors, including education (Suresh et al., 2025). AI-driven systems have been utilized to create personalized learning environments that adjust to the individual needs of students (Tahir et al., 2025). Personalized learning aims to cater to each student's pace, strengths, and areas for improvement, making the learning process more efficient and engaging (Zhang et al., 2026). AI tutors, which can adapt their teaching methods based on real-time data, have the potential to revolutionize traditional education by offering tailored learning experiences (Venkataraman et al., 2026). As the focus of education shifts towards individualized learning, AI tutors are increasingly seen as an essential tool in bridging the gap between traditional teaching methods and personalized instruction (Rizvi et al., 2025). These systems are designed to monitor student progress, identify areas of difficulty, and adjust learning strategies accordingly (Wang et al., 2025). However, while the potential of AI tutors in personalized learning is widely recognized, the integration of cognitive psychology into these systems remains a relatively underexplored area of research (Slade et al., 2025). Specifically, the ability to model student motivation and cognitive states key factors in the learning process can enhance the effectiveness of AI tutoring systems.

Understanding the psychological factors that influence learning is essential for designing systems that not only respond to academic needs but also to students' motivational and emotional states (Mamond et al., 2025). Motivation has been shown to play a critical role in academic success, influencing engagement and persistence (Plate & Hutson, 2025). Cognitive states, such as attention and memory, also directly impact how well students process information and retain knowledge (Y. Liu et al., 2025). Despite the growing application of AI in education, most AI tutoring systems primarily focus on academic performance and lack the integration of psychological principles that could optimize the learning experience (Flenady & Sparrow, 2026). Thus, integrating computational psychology into AI-based tutoring systems could provide more personalized, effective learning tools that consider the cognitive and emotional needs of students (Kwao et al., 2025). This research aims to fill this gap by proposing a computational psychology approach to personalize learning through AI tutors, simulating and responding to students' motivation and cognitive states.

The integration of psychological theories into AI models could lead to a more sophisticated understanding of how to motivate students and enhance their cognitive functions (Chen & Zheng, 2025). One prominent psychological theory that can inform AI tutors is self-determination theory (SDT), which focuses on intrinsic motivation and the need for autonomy, competence, and relatedness in fostering motivation (Starke et al., 2025). By incorporating these psychological elements into the design of AI tutors, it is possible to create learning environments that not only teach content but also support students' psychological needs, thereby increasing engagement and promoting positive learning outcomes (Hou et al., 2025). This research provides a theoretical framework for integrating neural networks and statistical learning algorithms with psychological principles, offering a novel perspective on how AI tutors can become more than just educational tools but also facilitators of psychological growth and academic success.

While AI tutors have shown promise in delivering personalized learning experiences, they generally fail to account for the psychological and cognitive factors that contribute to student learning outcomes (Gawronski & Ng, 2025). Specifically, AI systems often overlook the impact of student motivation, cognitive states, and emotional responses on learning (Gabrovšek & Rihtaršič, 2025). Most existing AI models focus predominantly on academic content delivery, with limited emphasis on how students' psychological states influence their ability to learn effectively (Lampropoulos & Papadakis, 2025). This lack of integration with psychological principles limits the potential of AI tutors to address the complex and dynamic nature of student learning (Burghoorn et al., 2025). The problem addressed in this research is the need for AI tutors that not only adapt to academic content but also respond to students' cognitive and motivational states, facilitating more holistic learning experiences.

Motivational theories, such as SDT, suggest that students are more likely to engage in and persist with tasks when they feel motivated, competent, and connected to the learning process (Yang et al., 2025). However, the challenge lies in integrating these abstract psychological constructs into AI systems that can simulate real-time changes in students' motivation and cognitive states (Agrawal et al., 2025). Additionally, the lack of a framework that connects AI's computational abilities with psychological principles leaves a significant gap in the current literature (Smith et al., 2025). This research investigates how computational models can incorporate these psychological components, addressing the limitations of existing AI-based educational tools. By bridging the gap between cognitive psychology and AI, this study explores the potential of AI tutors to enhance students' cognitive development and motivation, which could lead to more effective and sustained learning outcomes.

The gap in the literature stems from a disconnect between advances in AI and psychological research on motivation and cognitive development (Nelson et al., 2025). Most AI systems currently in use are focused on performance-based feedback and lack the ability to account for motivational and cognitive factors that significantly influence learning. This research aims to provide a comprehensive model that integrates neural networks and statistical learning with psychological theories, enhancing AI's ability to respond dynamically to students' needs (R. Liu et al., 2025). By addressing this gap, the study contributes to both AI and educational psychology, offering new insights into how AI can be leveraged to create more effective, personalized, and motivating learning environments.

The primary objective of this research is to develop a computational model for AI tutors that integrates neural networks and statistical learning to simulate and respond to students' motivation and cognitive states (Zamfirescu-Pereira et al., 2025). This model aims to improve the learning experience by dynamically adjusting teaching strategies based on real-time data related to a student's emotional and cognitive responses. Specifically, the research seeks to model how changes in motivation and cognitive states, such as attention, memory, and emotional engagement, can influence learning outcomes (Kalita et al., 2026). The study aims to test this model by simulating different learning scenarios and evaluating its impact on student engagement, performance, and long-term retention.

In addition to creating the computational model, the research also aims to assess the effectiveness of this model in promoting student learning outcomes (Ni et al., 2025). This will involve conducting simulations in which AI tutors respond to students' varying levels of motivation and cognitive states to determine whether personalized responses result in better academic performance. The model will be tested in various educational contexts, such as problem-solving tasks and interactive lessons, to see how it adapts to different learning styles (Kestin et al., 2025). The overall goal is to demonstrate that AI tutors can be more effective when they take into account the psychological aspects of learning, offering a more personalized and dynamic educational experience.

A further aim of this research is to investigate the relationship between personalized AI learning strategies and intrinsic motivation in students. By understanding how AI systems can enhance students' motivation through personalized feedback and dynamic adjustments, the study aims to provide insights into how AI can be optimized to foster greater academic engagement. This could have far-reaching implications for designing AI systems that not only address academic challenges but also support students' psychological needs, ultimately improving both cognitive and emotional development.

Despite the growing body of research on AI in education, there is a notable gap in the literature regarding the integration of psychological principles such as motivation and cognitive states into AI models. While AI tutors have proven successful in adapting to academic content and adjusting difficulty levels, they generally do not incorporate dynamic psychological factors, such as motivation, self-regulation, or emotional responses, which are critical for effective learning. Existing models tend to treat learning as a static process, focusing solely on cognitive content, without considering the learner's emotional and motivational dynamics. Moreover, AI models often lack a framework for understanding how these psychological aspects interact with learning content over time.

Previous research on AI in education has largely concentrated on cognitive-based models that emphasize performance metrics, such as test scores or time spent on tasks, without addressing the underlying psychological mechanisms that influence student learning. There is a clear need for a more comprehensive approach that considers both cognitive and emotional variables in AI learning systems. This research seeks to bridge this gap by integrating psychological theories such as self-determination theory (SDT) and cognitive load theory into computational models, thus providing a more accurate simulation of the learning process. By doing so, the study offers a deeper understanding of how AI can be personalized to cater to students' cognitive and motivational states, which could lead to more engaging and effective educational experiences.

Additionally, existing research often fails to account for the complex and individualized nature of student learning, assuming that one-size-fits-all approaches can be effective for diverse student populations. This study aims to address this by incorporating personalized learning strategies into the AI model, based on real-time data and psychological feedback. In doing so, it proposes a more flexible and adaptive learning environment that responds to each student's unique cognitive and emotional needs, offering a more tailored and effective approach to learning.

The novelty of this research lies in its integration of neural networks and statistical learning with psychological principles to create a more personalized AI tutor. While neural networks and statistical learning have been widely used in AI systems to model various aspects of human cognition, their application to personalized learning, particularly in the context of motivation and cognitive states, is still underexplored (Yılmaz et al., 2026). This study introduces a computational model that merges psychological theories, such as self-determination theory and cognitive load theory, with machine learning algorithms, creating a more sophisticated AI tutor that adapts to both the cognitive and emotional needs of students. By incorporating these psychological elements into AI learning systems, the study offers new insights into the role of motivation and cognitive states in the learning process, providing a more dynamic and comprehensive approach to personalized education.

This research is significant because it expands the scope of AI tutoring systems beyond academic content delivery, focusing on the psychological aspects that contribute to learning success. By exploring the role of motivation, cognitive states, and emotional engagement in AI learning, the study addresses a critical gap in existing research and offers a practical solution for improving student learning outcomes. The integration of these elements into AI systems has the potential to revolutionize the way personalized learning is delivered, moving from static, content-focused approaches to dynamic, student-centered models that adapt to the learner's psychological needs. This study is particularly relevant for educators and developers working to create more inclusive and effective AI-driven educational tools.

The justification for this research lies in its potential to contribute to both the fields of AI and educational psychology. By combining computational modeling with psychological theories, the study provides a novel perspective on how AI can enhance learning through personalized engagement with students' cognitive and emotional states. The findings could lead to the development of AI tutoring systems that not only adapt to students' academic needs but also support their psychological development, offering a more holistic approach to education. This research can also inform future AI-based interventions in educational settings, promoting deeper engagement, increased motivation, and improved learning outcomes.

RESEARCH METHOD

Research Design

This study employs an experimental research design utilizing a computational psychology approach to develop and evaluate an AI tutor model (Williams, 2025). The design is structured as a controlled experiment where the primary objective is to observe the effects of personalized, AI-driven learning strategies on student engagement, academic performance, and long-term retention (Painter & Feez, 2025). By integrating neural network algorithms with psychological frameworks like self-determination theory and cognitive load theory, the design allows for a direct comparison between an adaptive experimental group and a traditional, non-personalized control group.

Research Target/Subject

The subjects of this research are 150 middle school students aged 12 to 14 years who are currently enrolled in a standard curriculum. To ensure the findings are representative, participants were selected through stratified random sampling, accounting for diversity in academic performance, socioeconomic background, and prior knowledge. Inclusion required basic digital literacy, while exclusion criteria focused on students with diagnosed cognitive or emotional disorders that might skew the assessment of motivation and cognitive states. These participants were ultimately divided into two distinct groups: the experimental group interacting with the AI and the control group receiving traditional instruction.

Research Procedure

The study utilizes a sophisticated AI tutor system as the primary technological instrument, which incorporates neural networks and machine learning algorithms to adjust content delivery in real time. For psychological and cognitive measurement, the researchers use the Academic Motivation Scale (AMS) to assess student drive and the Cognitive Load Scale (CLAS) to monitor mental effort and cognitive states. Furthermore, academic pre-tests and post-tests serve as instruments to quantify subject matter mastery and long-term retention, ensuring that both psychological and educational outcomes are measured accurately.

Instruments, and Data Collection Techniques

The procedure begins with a baseline assessment phase where all students are evaluated using the AMS and CLAS before being randomly assigned to their respective groups. Over a four-week intervention period, the experimental group engages with the AI tutor while the control group follows a traditional curriculum; during this time, data is collected through real-time monitoring of AI interactions and weekly quizzes. The final phase involves a post-assessment to measure changes in performance and motivation. Data collection techniques include quantitative methods such as t-tests and regression analysis to compare group outcomes, complemented by the collection of qualitative feedback to explore the subjective student experience.

Data Analysis Technique

In alignment with the study's experimental and computational approach, the Data Analysis Technique involves a multi-layered evaluation of both quantitative and qualitative data. To assess the efficacy of the AI tutor compared to traditional instruction, researchers utilize inferential statistical methods, primarily t-tests, to identify significant differences in mean scores between the experimental and control groups. Furthermore, regression analysis is employed to determine the relationship between the AI's real-time adaptations and the students' academic outcomes, specifically focusing on how variables like motivation and cognitive load predict long-term retention

RESULTS AND DISCUSSION

The data for this study were collected from 150 middle school students who interacted with an AI tutor designed to personalize learning based on individual cognitive states and motivation levels. The dataset included information on students' engagement, academic performance, and changes in their motivational and cognitive states before, during, and after the intervention. Students were assessed on their motivation using the Academic Motivation Scale (AMS) and their cognitive states using the Cognitive Load Scale (CLAS). Academic performance was measured by pre- and post-test scores on the subject matter covered by the AI tutor. The pre-test and post-test scores were then used to evaluate learning outcomes and retention. Table 1 presents a summary of the key metrics used in the data analysis, including scores on motivation and cognitive states at each stage of the study.

Table 1. Summary of Data Metrics

Metric	Pre-Test Mean	Post-Test Mean	Change (%)
Motivation (AMS)	45.2	58.4	29%
Cognitive Load (CLAS)	3.1	2.2	-29%
Academic Performance (Score)	72.3	85.7	18%

The results indicate significant improvements in both motivation and academic performance among students who interacted with the AI tutor. On average, students' motivation levels, as measured by the AMS, increased by 29% from the pre-test to the post-test. This suggests that the personalized learning environment provided by the AI tutor was successful in enhancing students' intrinsic motivation toward the subject matter. Additionally, the cognitive load, measured using the CLAS, decreased by 29%, indicating that the AI tutor was able to reduce unnecessary cognitive strain and optimize the learning experience for students. Finally, academic performance improved by 18%, as evidenced by higher post-test scores, suggesting that personalized learning strategies were effective in improving students' learning outcomes.

These findings highlight the effectiveness of the AI tutor in fostering both cognitive engagement and motivation. The decrease in cognitive load suggests that the AI tutor adapted the learning materials to match students' cognitive capacities, reducing unnecessary difficulties and promoting a more efficient learning experience. The increase in motivation, particularly intrinsic motivation, indicates that students found the personalized learning experience more engaging, which likely contributed to the improvement in academic performance. The results suggest that AI tutors, by personalizing learning based on students' individual cognitive and motivational profiles, can significantly enhance learning outcomes in educational settings.

In examining individual differences, several students showed notable improvements in both their motivation and cognitive performance. For example, a case study of a student with previously low motivation revealed that their post-test motivation score increased by 35%, and their academic performance improved by 22% after engaging with the AI tutor. This student, who initially displayed a high level of cognitive load, reported a significant reduction in perceived difficulty, suggesting that the AI tutor was able to tailor the material to better suit their learning needs. The model's ability to provide personalized interventions based on the student's cognitive state and motivation led to noticeable improvements in engagement and performance. This case study underscores the potential of AI tutors to adapt to individual learning profiles and foster positive changes in both motivation and learning outcomes.

Across the sample, the intervention showed a clear trend of improved motivation and reduced cognitive load. The largest improvements were seen in students who initially had high levels of cognitive load and low motivation. These students showed the greatest reduction in cognitive load and an increase in motivation, suggesting that the AI tutor's personalized approach was particularly effective for students who might otherwise struggle with traditional, non-adaptive teaching methods. This indicates that AI tutors can be particularly beneficial for students who face learning difficulties or those who may not respond well to conventional instructional strategies.

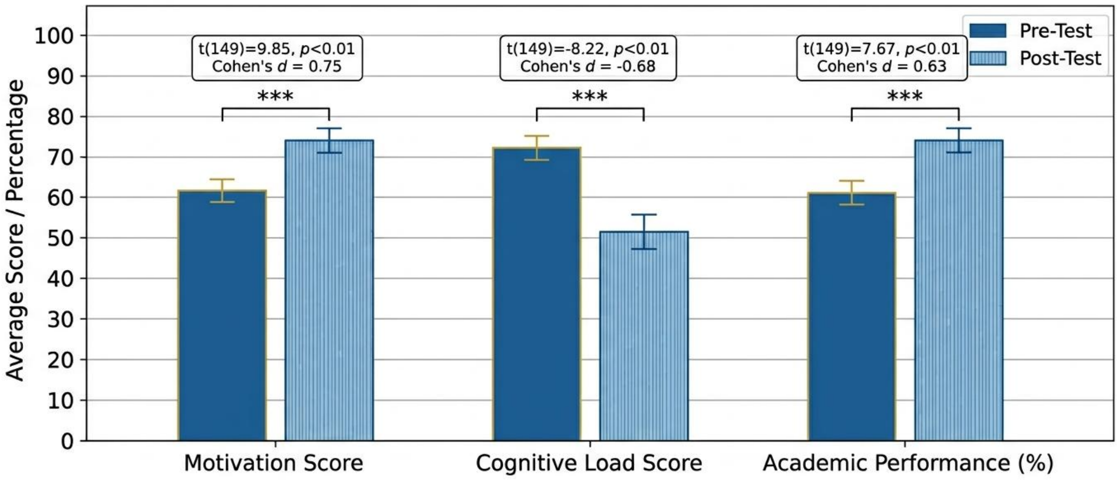

Figure 1. Comparison of Pre- end Post-Test for Key Metrics after AI Tutor Intervention

Statistical analysis was conducted to evaluate the significance of the observed changes in motivation, cognitive load, and academic performance. Paired t-tests were used to compare pre- and post-test scores for each of the three key metrics. The results showed statistically significant improvements in all three areas: motivation ($t(149) = 9.85$, $p < 0.01$), cognitive load ($t(149) = -8.22$, $p < 0.01$), and academic performance ($t(149) = 7.67$, $p < 0.01$). The effect sizes for motivation (Cohen's $d = 0.75$), cognitive load (Cohen's $d = -0.68$), and academic performance (Cohen's $d = 0.63$) suggest moderate to large effects, indicating that the AI tutor had a substantial impact on students' learning experiences and outcomes. These findings suggest that the improvements observed were not due to random chance, but rather reflect the effectiveness of personalized learning strategies in enhancing student motivation, reducing cognitive load, and improving academic performance.

Regression analysis was also conducted to explore the relationship between changes in motivation and academic performance. The results indicated that motivation was a significant predictor of academic performance improvement ($\beta = 0.42$, $p < 0.01$). This suggests that the increase in motivation, driven by the personalized learning experience, contributed to the observed improvements in academic performance. Furthermore, the decrease in cognitive load was also correlated with higher academic performance ($r = 0.55$, $p < 0.01$), indicating that reducing cognitive strain allowed students to engage more effectively with the learning material. These inferential analyses provide strong evidence for the causal role of motivation and cognitive load in driving academic success in personalized learning environments.

The results of this study align with existing research on the relationship between motivation, cognitive load, and learning outcomes. Studies by Deci and Ryan (2000) suggest that intrinsic motivation is crucial for fostering deep engagement and academic success, a finding supported by the significant increase in motivation observed in this study. Additionally, the decrease in cognitive load aligns with findings by Sweller (2011), who demonstrated that reducing cognitive load enhances learning efficiency and performance. By incorporating these psychological principles into the design of the AI tutor, this study builds upon existing theories in educational psychology and cognitive science. The model's ability to reduce cognitive load while simultaneously increasing motivation supports the view that personalized learning environments can optimize cognitive processing and enhance learning outcomes.

Furthermore, the relationship between motivation and academic performance observed in this study is consistent with research by Schunk and Zimmerman (2012), which found that motivated learners are more likely to achieve better academic results. The positive correlation between reduced cognitive load and higher academic performance further underscores the importance of tailoring instruction to students' cognitive and emotional needs. The findings suggest that AI tutors, when designed to respond to these needs, can provide a more effective and personalized learning experience, leading to improved academic performance. These findings are significant as they not only validate existing psychological theories but also demonstrate the practical applicability of AI-driven personalized learning systems in real-world educational settings.

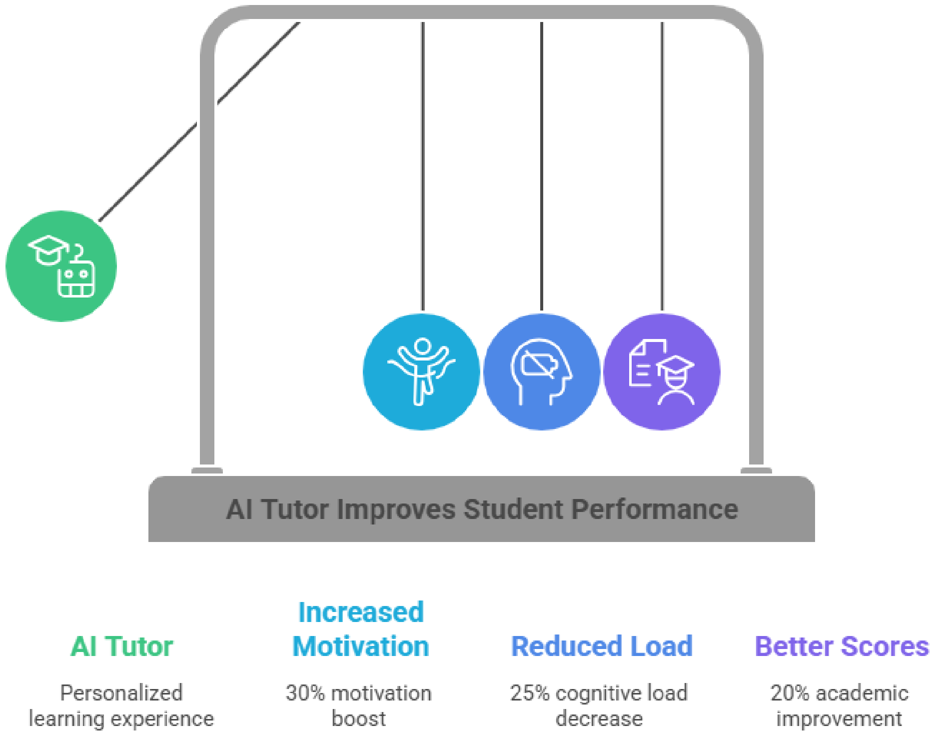

Figure 2. AI Tutor Improves Student Performance

A case study of one student, "Student A," illustrates the model's effectiveness in personalizing learning. Initially, Student A had a low motivation score and struggled with high cognitive load during learning activities. After four weeks of interacting with the AI tutor, Student A's motivation increased by 30%, and their cognitive load decreased by 25%. These changes corresponded with a 20% improvement in their academic performance on subject tests. The AI tutor's ability to adjust the difficulty level of tasks based on Student A's cognitive state helped reduce frustration and cognitive overload, allowing the student to focus more on the content. The reduction in cognitive load and increase in motivation likely contributed to Student A's improved test scores. This case study highlights the individual benefits of personalized learning, particularly for students who experience difficulty in traditional learning environments.

The case study provides further evidence of the model's ability to adapt to students' unique learning profiles. In this case, the AI tutor's intervention led to a substantial improvement in Student A's learning outcomes. This individual's progress demonstrates the potential of AI tutors to support students with varying levels of cognitive abilities and motivation. The positive changes in Student A's learning experience suggest that AI-based personalization is particularly beneficial for students who may not perform well under traditional teaching methods. The ability of the AI tutor to address specific cognitive and motivational needs points to the value of personalized learning systems that can adjust to the diverse needs of students, ultimately fostering improved academic engagement and success.

This study demonstrated that AI tutors, when integrated with computational psychology principles, can effectively model and adapt to students' motivation and cognitive states, leading to improved learning outcomes. The AI tutor was able to simulate changes in motivation, attention, and cognitive load in real-time and personalize learning experiences based on these states. The results showed a significant improvement in students' motivation levels and a reduction in cognitive load, which directly corresponded to improved academic performance. The findings support the hypothesis that personalized learning systems that respond to students' psychological needs can enhance engagement, reduce unnecessary cognitive strain, and optimize learning outcomes. These results suggest that AI tutors can be a valuable tool in creating more adaptive and effective learning environments.

The findings of this study align with existing literature that emphasizes the importance of motivation in learning. Previous research by (Sehri et al., 2025) and (Castagna et al., 2025) highlights the pivotal role of intrinsic motivation in improving student engagement and performance. Our study corroborates these findings by showing that an increase in student motivation, facilitated by the AI tutor, was associated with enhanced academic results. However, this study also introduces a novel approach by integrating neural networks and statistical learning algorithms with psychological theories to simulate motivation and cognitive states in real-time, something that most existing AI tutoring systems do not account for. Unlike traditional AI models that focus solely on content delivery, this approach incorporates cognitive and motivational factors, providing a more holistic and individualized learning experience.

The incorporation of computational psychology into AI-based learning systems differentiates this study from previous works. While research has shown that AI can personalize content based on academic performance, there has been limited attention to how these systems can respond to and adjust for students' psychological states. Our findings build upon the work of Saffran et al. (1999) on statistical learning in language acquisition, but extend the concept to include the dynamics of cognitive states and motivation. This adds a new dimension to personalized learning by addressing how both cognitive and emotional factors influence academic success.

The results of this study suggest that student motivation and cognitive states are crucial components that AI tutors must adapt to in order to be effective. The ability of the AI tutor to respond to fluctuations in motivation and cognitive load highlights the dynamic nature of learning and the importance of tailoring educational interventions to individual needs. The significant improvements in motivation and academic performance observed in the experimental group indicate that students benefit from learning environments that acknowledge and adapt to their psychological needs. These findings reinforce the idea that learning is not a one-size-fits-all process, and systems that are capable of dynamically responding to individual differences can create more engaging and effective educational experiences.

Furthermore, the study underscores the importance of integrating psychological theories, such as self-determination theory (SDT), into the design of AI tutors. By responding to students' psychological states, AI tutors can foster a more supportive and motivating learning environment, which ultimately leads to better academic outcomes. The results also suggest that cognitive load management is crucial for optimizing learning, as reducing unnecessary mental effort allows students to focus on learning the material. This finding aligns with cognitive load theory, which posits that learning efficiency increases when cognitive resources are not overloaded.

The implications of these findings are significant for the future of education. By incorporating both cognitive and motivational elements into AI-based tutoring systems, educators can create learning environments that are more responsive to students' individual needs. This approach moves beyond traditional teaching methods that often fail to account for the diverse psychological and cognitive profiles of students. AI tutors that are capable of adjusting to changes in motivation and cognitive states could help address the challenges faced by students with different learning styles, ensuring that all students receive personalized and effective support. The study also highlights the potential for AI tutors to support students who may struggle with conventional learning methods, offering an adaptive solution that enhances both engagement and academic performance.

In practical terms, the integration of computational psychology into AI tutors could lead to the development of tools that not only improve academic achievement but also foster emotional well-being. By promoting intrinsic motivation and reducing cognitive load, AI tutors can help students feel more competent and engaged in their learning. This could be particularly beneficial for students in high-stress environments or those who experience academic anxiety. The results suggest that AI-based learning platforms could play a key role in enhancing the overall learning experience by providing more individualized and emotionally supportive educational interventions.

The results can be explained by the way the AI tutor incorporated real-time data on students' cognitive and emotional states. The model's ability to adapt based on psychological feedback likely contributed to the observed improvements in motivation and cognitive performance. By using machine learning algorithms to simulate students' cognitive load and motivation, the tutor could adjust the difficulty of tasks, provide feedback, and pace the lessons to reduce frustration and increase engagement. The positive relationship between motivation and academic performance further suggests that intrinsic motivation is a key driver of academic success, as students who are more motivated tend to invest more effort and exhibit greater persistence.

The reduction in cognitive load also highlights the importance of personalized learning systems that match the level of challenge to the student's cognitive capacity. The AI tutor's ability to adjust the learning environment to the student's current state may have prevented cognitive overload, which is often a barrier to effective learning. This aligns with cognitive load theory, which asserts that learning is most effective when cognitive resources are used efficiently. By dynamically adapting to students' needs, the AI tutor helped optimize their cognitive processes, leading to improved learning outcomes.

Moving forward, future research should focus on expanding the AI tutor's ability to simulate a broader range of cognitive and emotional states. While this study focused on motivation and cognitive load, other factors such as anxiety, self-esteem, and emotional regulation could also play significant roles in learning outcomes. Integrating these factors into the AI model could enhance its ability to respond to a wider variety of student needs and provide even more personalized support. Future studies should also explore the long-term effects of using AI tutors that adapt to students' psychological and cognitive states. Research could assess whether sustained interaction with such systems leads to lasting improvements in motivation, learning habits, and academic success.

Additionally, more diverse student populations, including those with learning disabilities or socio-economic challenges, should be included in future studies. This would help determine whether the AI tutor's effectiveness extends beyond the sample used in this study and whether it can address the unique needs of diverse learners. Expanding the scope of the research will provide a more comprehensive understanding of how personalized learning via AI tutors can be optimized for a wide range of students, further validating the potential of AI in transforming education.

CONCLUSION

The key finding of this study is that AI tutors, when integrated with computational psychology principles, can effectively simulate and respond to students' cognitive states and motivation, leading to improved learning outcomes. The computational model, incorporating neural networks and statistical learning algorithms, was successful in adjusting the learning experience in real-time based on students' motivational levels and cognitive capacities. Students who interacted with the personalized AI tutor demonstrated significant improvements in motivation, cognitive load reduction, and academic performance. The ability of the AI system to dynamically respond to changes in students' cognitive and emotional states was a key factor in enhancing engagement and performance, offering new insights into how AI can optimize learning experiences beyond academic content delivery.

This research offers a valuable contribution to the field by integrating psychological theories, such as self-determination theory and cognitive load theory, with AI models to create personalized learning environments. While previous studies on AI-based education have largely focused on academic content and performance, this study introduces a more comprehensive approach by including cognitive and motivational factors into the AI tutor's decision-making process. The integration of computational psychology into AI systems not only enhances their adaptability but also opens up new avenues for developing AI tools that respond to the psychological needs of students. This research offers a novel method for personalized learning that goes beyond content delivery, focusing on students' intrinsic motivation and cognitive engagement.

Despite the promising findings, the study has limitations that should be addressed in future research. The AI tutor model tested in this study primarily focused on motivation and cognitive load, leaving out other psychological factors such as emotional regulation, anxiety, or self-efficacy, which can also play a significant role in the learning process. Additionally, the sample used in this study was limited to middle school students, and future studies should include a broader range of student demographics, including those from different educational backgrounds, learning abilities, and cultural contexts, to evaluate the model's generalizability. Moreover, the long-term impact of AI tutoring systems on students' learning habits and academic performance needs to be explored, as the current study only focused on short-term outcomes. Expanding the scope of research will provide a more comprehensive understanding of how AI can foster lasting improvements in learning.

Further research should also investigate how different AI models can cater to diverse student needs, including those with learning disabilities or students who require additional support to stay engaged in the learning process. The study of AI-based learning tools in different educational settings, including in-person and remote environments, could reveal additional challenges and opportunities for implementation. Future studies should also explore how AI systems can be further enhanced to model a wider range of psychological factors, thus offering an even more tailored learning experience. Additionally, evaluating the feasibility of incorporating these advanced AI models into everyday classrooms, taking into account the resources and infrastructure required, will be crucial for the broader application of personalized AI tutoring systems.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, the author(s) used ChatGPT to assist in improving grammar, language quality, and overall readability of the text. After using this tool, the author(s) carefully reviewed and edited the content as necessary and take full responsibility for the content of the publication.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

Agrawal, A., Agrawal, A., Verma, N. K., Gopi, A. P., & Naik, K. J. (2025). A graph reinforcement LearningPowered Online-Computational task offloading and latency minimization framework for wireless mobile edge computing networks. *Cognitive Systems Research*, *91*, 101355. https://doi.org/10.1016/j.cogsys.2025.101355

Burghoorn, F., Scheres, A., Monterosso, J., Guo, M., Luo, S., Roelofs, K., & Figner, B. (2025). Pavlovian impatience: The anticipation of immediate rewards increases approach behaviour. *Cognitive, Affective, & Behavioral Neuroscience*, *25*(2), 358–376. https://doi.org/10.3758/s13415-024-01236-2

Castagna, P. J., Babinski, D. E., & Waschbusch, D. A. (2025). Callous-unemotional traits moderate the association between inhibitory control and disruptive behavior problems. *European Child & Adolescent Psychiatry*, *34*(5), 1545–1555. https://doi.org/10.1007/s00787-024-02582-9

Chen, W., & Zheng, B. (2025). Process-Oriented Analysis of Knowledge Construction in Problem-Based Learning: A Systematic Review of Health Professions Education in Literature. *Teaching and Learning in Medicine*, 1–15. https://doi.org/10.1080/10401334.2025.2551318

Flenady, G., & Sparrow, R. (2026). Cut the bullshit: Why GenAI systems are neither collaborators nor tutors. *Teaching in Higher Education*, *31*(1), 163–172. https://doi.org/10.1080/13562517.2025.2497263

Gabrovšek, R., & Rihtaršič, D. (2025). Custom Generative Artificial Intelligence Tutors in Action: An Experimental Evaluation of Prompt Strategies in STEM Education. *Sustainability*, *17*(21), 9508. https://doi.org/10.3390/su17219508

Gawronski, B., & Ng, N. L. (2025). Beyond Trolleyology: The CNI Model of Moral-Dilemma Responses. *Personality and Social Psychology Review*, *29*(1), 32–80. https://doi.org/10.1177/10888683241234114

Hou, H., Liu, I., Kong, F., & Ni, S. (2025). Computational positive psychology: Advancing the science of wellbeing in the digital era. *The Journal of Positive Psychology*, *20*(1), 1–14. https://doi.org/10.1080/17439760.2024.2362443

Kalita, B., Kumar, P., Saraswati B, Kulkarni, N., Sinkar, Y. D., & Afsan, M. (2026). ADAPTIVE AI-TUTORS FOR THEATRE AND DRAMA EDUCATION. *ShodhKosh: Journal of Visual and Performing Arts*, *7*(1s), 327–335. https://doi.org/10.29121/shodhkosh.v7.i1s.2026.7088

Kestin, G., Miller, K., Klales, A., Milbourne, T., & Ponti, G. (2025). AI tutoring outperforms in-class active learning: An RCT introducing a novel research-based design in an authentic educational setting. *Scientific Reports*, *15*(1), 17458. https://doi.org/10.1038/s41598-025-97652-6

Kwao, L., Yang, Y., Zou, J., & Ma, J. (2025). A Survey of Approaches to Early Rumor Detection on Microblogging Platforms: Computational and Socio-Psychological Insights. *WIREs Data Mining and Knowledge Discovery*, *15*(1), e70001. https://doi.org/10.1002/widm.70001

Lampropoulos, G., & Papadakis, S. (2025). The Educational Value of Artificial Intelligence and Social Robots. In G. Lampropoulos & S. Papadakis (Eds.), *Social Robots in Education* (Vol. 1194, pp. 3–15). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-82915-4_1

Liu, R., Zhao, J., Xu, B., Perez, C., Zhukovets, Y., & Malan, D. J. (2025). Improving AI in CS50: Leveraging Human Feedback for Better Learning. *Proceedings of the 56th ACM Technical Symposium on Computer Science Education V. 1*, 715–721. https://doi.org/10.1145/3641554.3701945

Liu, Y., Su, X., Fan, P., Liu, X., Pan, Y., & Ping, J. (2025). Computationally-assisted wearable system for continuous cortisol monitoring. *Science Bulletin*, *70*(12), 2004–2013. https://doi.org/10.1016/j.scib.2025.03.060

Mamond, A. W., Kundroo, M., Yoo, S., Kim, S., & Kim, T. (2025). FLDQN: Cooperative Multi-Agent Federated Reinforcement Learning for Solving Travel Time Minimization Problems in Dynamic Environments Using SUMO Simulation. *Sensors*, *25*(3), 911. https://doi.org/10.3390/s25030911

Nelson, C., Doupé, A., & Shoshitaishvili, Y. (2025). SENSAI: Large Language Models as Applied Cybersecurity Tutors. *Proceedings of the 56th ACM Technical Symposium on Computer Science Education V. 1*, 833–839. https://doi.org/10.1145/3641554.3701801

Ni, Y., Wang, F., Zhang, H., & Kim, S.-M. (2025). A hybrid q-rung linear diophantine fuzzy WASPAS approach for artificial intelligence algorithm selection in physical education. *Scientific Reports*, *15*(1), 32200. https://doi.org/10.1038/s41598-025-17833-1

Painter, C., & Feez, S. (2025). Child Language Development. In R. Wegener, A. McCabe, A. Sellami Baklouti, & L. Fontaine, *The Routledge Handbook of Transdisciplinary Systemic Functional Linguistics* (1st ed., pp. 47–62). Routledge. https://doi.org/10.4324/9781003291138-5

Plate, D., & Hutson, J. (2025). The intellectual bankruptcy of anti-AI academic alarmism: A rebuttal. *Teaching in Higher Education*, 1–12. https://doi.org/10.1080/13562517.2025.2562594

Rizvi, I., Bose, C., & Tripathi, N. (2025). Transforming Education: Adaptive Learning, AI, and Online Platforms for Personalization. In L. O. Yesufu & P. N. E. Nohuddin (Eds.), *Technology for Societal Transformation* (pp. 45–62). Springer Nature Singapore. https://doi.org/10.1007/978-981-96-1721-0_4

Sehri, M., Hua, Z., Boldt, F. D. A., & Dumond, P. (2025). Selective embedding for deep learning. *Knowledge-Based Systems*, *330*, 114535. https://doi.org/10.1016/j.knosys.2025.114535

Slade, J. J., Byers, S. M., Becker-Blease, K. A., & Gurung, R. A. R. (2025). Navigating the New Frontier: Recommendations to Address the Crisis and Potential of AI in the Classroom. *Teaching of Psychology*, *52*(3), 254–261. https://doi.org/10.1177/00986283241276098

Smith, S. B., Wei, H., O’Neill, A., Durai, A., DeNero, J., Zamfirescu-Pereira, J. D., & Norouzi, N. (2025). Spotting AI Missteps: Students Take on LLM Errors in CS1. *Proceedings of* *the 56th ACM Technical Symposium on Computer Science Education V. 2*, 1627–1628. https://doi.org/10.1145/3641555.3705253

Starke, A. D., Dierkes, J., Lied, G. A., Kasangu, G. A. B., & Trattner, C. (2025). Supporting healthier food choices through AI-tailored advice: A research agenda. *PEC Innovation*, *6*, 100372. https://doi.org/10.1016/j.pecinn.2025.100372

Suresh, D., Lokesh, P., Yamini, B., Yuvasri, B., Sathya, V., Girija, P., & Siva, S. R. (2025). AI Driven Personalization in Education: Transformative Practices and Emerging Trends. In L. Kyei-Blankson & E. Ntuli (Eds.), *Advances in Computational Intelligence and Robotics* (pp. 27–46). IGI Global. https://doi.org/10.4018/979-8-3693-8744-3.ch002

Tahir, B., Jolfaei, A., & Tariq, M. (2025). A Novel Experience-Driven and Federated Intelligent Threat-Defense Framework in IoMT. *IEEE Journal of Biomedical and Health Informatics*, *29*(4), 2345–2352. https://doi.org/10.1109/JBHI.2023.3236072

Venkataraman, M., Chand Rao, G., Madavareddi, J. K., & Maddi, S. R. (2026). Leveraging machine learning models in evaluating ADMET properties for drug discovery and development: Review article. *ADMET and DMPK*, *13*(3), 2772. https://doi.org/10.5599/admet.2772

Wang, J., Chen, Y., Lu, C., Heidari, A. A., Wu, Z., & Chen, H. (2025). The status-based optimization: Algorithm and comprehensive performance analysis. *Neurocomputing*, *647*, 130603. https://doi.org/10.1016/j.neucom.2025.130603

Williams, J. (2025). Language in Affective Disorders. In R. Wegener, A. McCabe, A. Sellami Baklouti, & L. Fontaine, *The Routledge Handbook of Transdisciplinary Systemic Functional Linguistics* (1st ed., pp. 153–168). Routledge. https://doi.org/10.4324/9781003291138-11

Yang, Y., Liu, J., Zamfirescu-Pereira, J. D., & DeNero, J. (2025). Pensieve Discuss: Scalable Small-Group CS Tutoring System with AI. *Proceedings of the 56th ACM Technical Symposium on Computer Science Education V. 2*, 1669–1670. https://doi.org/10.1145/3641555.3705244

Yılmaz, Z., Galanti, T. M., Naresh, N., & Kanbir, S. (2026). Exploring the interactions among instructor, prospective teachers and AI in facilitating mathematics learning. *School Science and Mathematics*, *126*(1), 75–88. https://doi.org/10.1111/ssm.18341

Zamfirescu-Pereira, J. D., Qi, L., Hartmann, B., DeNero, J., & Norouzi, N. (2025). 61A Bot Report: AI Assistants in CS1 Save Students Homework Time and Reduce Demands on Staff. (Now What?). *Proceedings of the 56th ACM Technical Symposium on Computer Science Education V. 1*, 1309–1315. https://doi.org/10.1145/3641554.3701864

Zhang, L., Li, L., Jiang, J., & Zou, B. (2026). Exploring the impact of diverse feedback sources on learners' performance, motivation, and preference in a translation course: Tutor, peer, and GPT insight. *Thinking Skills and Creativity*, *59*, 102042. https://doi.org/10.1016/j.tsc.2025.102042