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Investigating the factors affecting the intention to use AI Chatbots in STEM education app: a hybrid structural equation modelling and artificial neural network

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Abstract

This study explores the impact of Artificial Intelligence (AI)-powered applications in Science, Technology, Engineering, and Mathematics (STEM) education, emphasizing their role in improving students' problem-solving skills and self-efficacy. It examines how personal factors such as ICT self-efficacy and self-directed learning (SDL), along with technological aspects like perceived ease of use (PEU) and perceived convenience (PC), shape students' engagement with AI-driven tools. Using a quantitative method, survey data were collected from 117 students during February–March 2025. The research employed the Structured Predictive Latent Semantic System (SPLSS) model and Artificial Neural Network (ANN), validated through Structural Equation Modeling (SEM), to ensure reliability and predictive accuracy. Results show that AI tools significantly enhance problem-solving and self-efficacy. PC and intention to use were strong predictors of chatbot utilization, while ICT self-efficacy and PEU influenced attitudes and behavioral intentions. Importance-Performance Map Analysis (IPMA) revealed convenience as most impactful, and self-efficacy as least. All hypotheses were supported, confirming the model's robustness. The study concludes that AI-driven applications create personalized, engaging, and confidence-boosting STEM learning experiences, highlighting the need for user-friendly, contextually adaptive AI tools and suggesting future research on long-term impacts and scalability for inclusive STEM education.

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1 Introduction

STEM education is being adapted by AI by offering personalized learning experiences that help students improve their problem-solving skills and boost self-efficacy. In recent decades, many technological developments have raised. Traditional teaching methods often fail to address individual learning needs, making it challenging for students to develop confidence in tackling complex problems (Esiyok et al., 2025). The increasing incorporation of AI in educational settings, many STEM students struggle with problem-solving due to a lack of personalized learning approaches (Yu et al., 2025). Students' self-efficacy in STEM subjects is often low, leading to decreased motivation and academic performance. Existing AI-powered learning tools have yet to be fully evaluated for their effectiveness in addressing these challenges (Obiwuru, 2024). In this study focus on the problems and find the ways how these problems can be solved. This study goals to examine the part of AI-powered STEM education applications in enhancing students' analytical and reasoning capabilities in addressing problems and self-efficacy. Using the SPLSS model, the research evaluates the efficiency of AI-powered learning tools in fostering high-level cognitive processing and analytical assessment as well as independent abilities to solve problem. AI chatbots and digital learning assistants have been developed to provide real-time support; their effectiveness depends on students' willingness to engage with them. Several studies have examined AI's role in education, emphasizing its potential to improve learning efficiency, provide real-time feedback, and foster SDL (Roca et al., 2024). But all students haven't same knowledge or adaptation ability. Some factors like Lack of ICT Self-Efficacy, Perceived Complexity of AI Tools, Low Motivation for SDL, Limited Understanding of AI's Educational Benefits are responsible. Students struggle to use AI chatbots. To solve this problem, research, build a framework to overcome the challenges and find out the factors that have direct relation to help students to use AI chatbots and analyse the factors

effectiveness on AI driven App (Ayanwale and Ndlovu, 2024).
AI has emerged as a potent force for change in education, particularly in STEM subjects, in the age of rapid digital transition. In order to provide immediate feedback, individualized learning routes, and ongoing academic support, chatbot systems—which are sometimes regarded as a subset of intelligent tutoring systems—are being more and more integrated into STEM learning platforms. By simulating human-like interaction, these technologies help students better understand difficult subjects, lessen cognitive load, and develop conceptual understanding. Despite these benefits, student uptake of AI chatbots is still inconsistent, indicating that user approval is not always ensured by technological capacity. Examining the behavioral, cognitive, and environmental elements that affect students' intentions to use AI chatbots in STEM education is therefore crucial.
To look at these issues, this study uses a hybrid analytical framework that combines ANN with SEM. While ANN is used to find nonlinear patterns and improve predictive accuracy, SEM is intended to test proposed causal links among latent constructs. This integrated approach offers a more thorough and nuanced understanding of user behavior in AI-supported learning settings than conventional linear approaches (Mogaji et al., 2024).

This study's theoretical foundation is based on well-known models, such as Social Cognitive Theory (SCT), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Technology Acceptance Model (TAM). Perceived Usefulness (PU), Perceived Ease of Use (PEOU), ICT Self-Efficacy, Perceived Complexity, Social Influence, Facilitating Conditions, and Behavioral Intention (BI) are among the core constructs that are analyzed. Furthermore, in order to better capture students' engagement with AI-driven systems, Self-Directed Learning (SDL) preparedness and AI awareness are included as moderating variables (Xiao and Tang, 2025).
The degree to which students think AI chatbots can enhance their academic achievement is known as perceived usefulness. Students are far more likely to use chatbots when they understand that they improve learning outcomes, offer precise explanations, and help with problem-solving. In a similar vein, perceived ease of use is crucial; whereas complicated or badly designed systems discourage participation, user-friendly interfaces and straightforward navigation promote involvement.
ICT Self-Efficacy, which measures students' confidence in their capacity to

use digital technology, is another significant factor. Higher ICT self-efficacy learners are more likely to actively investigate AI technologies and incorporate them into their study regimens. Students who lack technological confidence, on the other hand, could be reluctant or anxious, which lowers their chances of being adopted. According to recent research, students' confidence and willingness to use AI-based tools can be greatly increased by structured training programs, guided tutorials, and practical experience (Bedenlier et al., 2025). Adoption behavior is adversely affected by perceived complexity. Students are less inclined to use AI systems if they see them as being challenging to use or comprehend. This obstacle can be lessened by making system design simpler, providing clear instructions, and guaranteeing user-friendly interaction. Additionally, raising awareness of the educational advantages of AI technologies through workshops and orientation sessions can further increase acceptance.

Motivation for SDL is another important factor. While AI chatbots are intended to support independent learning, their efficacy depends on students' intrinsic motivation; learners who are driven to take charge of their own learning process are more likely to engage deeply with AI tools. Strategies like gamification, adaptive feedback, and personalized learning materials can boost motivation and maintain engagement (Ullah et al., 2025).

Students' behavioral intentions are also significantly shaped by social influence. Students' opinions of AI chatbots can be greatly influenced by peer use, institutional support, and teacher encouragement. Students are more inclined to use chatbots when teachers actively incorporate them into their lessons and emphasize their advantages. Similarly, successful implementation depends on Facilitating Conditions, such as institutional backing, dependable internet connectivity, and availability to digital devices. Limited infrastructure continues to be a significant barrier to the widespread adoption of AI in many developing environments, underscoring the necessity of policy-level initiatives to guarantee fair access (van der Vlies, 2020).

There are two steps to the hybrid SEM-ANN model used in this investigation. First, SEM finds statistically significant predictors of behavioral intention and validates the correlations between variables.

ANN then evaluates the relative significance of these predictors and identifies nonlinear interactions that SEM is unable to adequately account for. Deeper understanding of students' adoption behavior is provided by this integrated method, which enhances both explanatory power and prediction performance (Ayanwale and Ndlovu, 2024). The results should show that the most important factors influencing students' intention to utilize AI chatbots are Perceived Usefulness, ICT Self-Efficacy, and SDL Motivation. On the other hand, perceived complexity and low awareness are probably going to be significant obstacles. By highlighting intricate relationships between these elements, which are frequently missed in conventional studies, ANN results further improve comprehension.

The paper suggests a conceptual framework to enhance the use of AI chatbots in STEM education based on these findings. This paradigm emphasizes the significance of activities to raise awareness, training in digital literacy, user-centered design, and robust institutional support. The framework aims to improve learning outcomes, boost self-efficacy, and increase student engagement by tackling both technological and psychological issues. By providing a thorough analysis of the variables driving chatbot adoption in STEM learning environments, this study adds to the growing body of research on AI in education. A more precise and comprehensive analysis of user behavior is made possible by the innovative methodological contribution of integrating SEM with ANN. The results offer useful guidance for educators, developers, and legislators in creating AI-powered educational systems that meet the demands of a wide range of learners.

In order to further promote individualized STEM education, future study may expand on this work by examining cross-cultural differences, longitudinal effects, and the incorporation of cutting-edge technology like generative AI and immersive learning systems.

Extensive research has investigated the incorporation of AI-driven applications within STEM education, underscoring their potential to enhance problem-solving abilities and boost students' self-efficacy. Findings reveal that AI-based learning tools, including intelligent tutoring systems, chatbot-assisted instruction, and adaptive learning platforms, facilitate individualized learning environments that respond to the specific cognitive and academic needs of each student. These applications encourage real-time input, computerize appraisals, and back intelligently problem-solving exercises, in this manner making a difference understudies pick up certainty in tending to complex STEM concepts (Sun et al., 2025).

AI has advanced quickly in recent years, providing intelligent, adaptive, and data-driven learning environments that have significantly changed the pedagogical framework of STEM education. Among these developments, AI-powered chatbots have become well-known as interactive learning resources that may mimic human-like dialogue and provide ongoing academic support outside of the conventional classroom. These systems are very successful for individualized training since they not only provide instantaneous replies but also dynamically adapt to learners' cognitive capacity (Holmes et al., 2019; Xue et al., 2026).Students' desire to use these technologies depends on a number of psychological and technological elements that need to be carefully considered, notwithstanding their increasing integration.

Perceived Ease of Use (PEU), or the degree to which consumers think engaging with a system needs little effort, is a key concept driving the adoption of AI chatbots. PEU in STEM learning environments is influenced by responsiveness, general usability, clarity of chatbot explanations, and interface simplicity. Students are more likely to interact with and incorporate AI systems into their learning processes when they are built with user-friendly features and intuitive navigation. Easy interaction greatly improves user satisfaction and learning performance in AI-supported environments, according to recent research (Ibrahim et al., 2025).

In response to the first research question (RQ1), a number of factors that influence PEU can be found, such as past technological expertise, the quality of the system design, accessibility, and the availability of technical help. Students' opinions of ease of use are also shaped by outside factors like training opportunities, peer collaboration, and institutional advice. Students' trust and desire to use AI chatbots in STEM education can be greatly increased by well-organized onboarding procedures, unambiguous instructions, and responsive system architecture.

AI-driven learning systems are essential for improving students' problem-solving skills and facilitating SDL, according to the second research question (RQ2). AI chatbots help learners tackle complicated tasks more successfully by offering multiple solution techniques, adaptive feedback, and step-by-step instruction. These systems promote deeper cognitive engagement by promoting experimentation, critical thinking, and iterative learning. Additionally, by providing tailored recommendations, monitoring progress, and modifying content according to individual performance, AI technologies enable students to take charge of their educational path. These characteristics encourage independence, perseverance, and drive—essential elements of successful self-directed learning (Zawacki-Richter et al., 2019). As a result, AI-supported environments boost students' confidence and capacity for independent learning in addition to improving academic results.

In relation to the third research question (RQ3), students' adoption of AI-powered instructional technologies is significantly predicted by their level of ICT self-efficacy. An individual's confidence in their capacity to use digital technology successfully is reflected in their ICT self-efficacy. Strong technical confidence increases the likelihood that students will experiment with learning tools, investigate AI features, and incorporate them into their daily academic routines. On the other hand, those who have lower levels of self-efficacy frequently feel hesitant or anxious, which might restrict their involvement. Educational institutions could use focused tactics like guided learning experiences, practical training sessions, and digital literacy initiatives to address these issues. Incorporating AI tools into regular curriculum can also help students get more comfortable with them and normalize their use.

In order to give a thorough analysis of the factors impacting the adoption of AI chatbots, this study employs a hybrid SEM and ANN approach. SEM is used to investigate the associations between latent variables, including both direct and indirect effects, and evaluate the conceptual framework. This approach guarantees statistical rigor and a solid theoretical basis for comprehending user behavior. After that, ANN is used to find intricate nonlinear interactions and assess the relative significance of many predictors. In contrast to traditional statistical methods, ANN can uncover hidden patterns in massive datasets, increasing prediction accuracy and providing more profound insights into decision-making processes (Ayanwale and Ndlovu, 2024).

Importance-Performance Map Analysis (IPMA) is used to bolster the analysis even more. By assessing each factor's performance and relevance, this method expands on SEM findings and enables researchers to pinpoint high-priority areas for improvement. For instance, focused educational programs can be created to close the gap if ICT self-efficacy is found to be highly influential yet underperforming. These insights are useful for creating workable plans to improve the uptake and efficiency of AI-driven learning systems.

The results of this study advance both theoretical and practical fields. By combining several frameworks—such as technological acceptability, self-efficacy, and self-directed learning—into a single model, the study theoretically extends current understanding. Practically speaking, it offers developers, educators, and legislators practical suggestions for creating more approachable, user-friendly, and successful AI-based learning resources. These results emphasize how crucial it is to match technical innovation with user requirements and educational objectives. In conclusion, by enhancing learning effectiveness, bolstering problem-solving abilities, and encouraging learner autonomy, AI chatbots have enormous potential to revolutionize STEM education. However, a number of variables, such as perceived utility, ICT self-efficacy, perceived ease of use, and motivating components, are necessary for their successful deployment. This study provides a thorough and multifaceted knowledge of these elements through the use of a hybrid SEM–ANN framework, facilitating the creation of effective strategies for AI adoption in education. By examining long-term effects, cultural differences, and the influence of cutting-edge technologies like generative AI and multimodal learning systems on the direction of STEM education, future study can build on this work (YÜKSEL, 2025).

The research methodology includes a systematic data collection approach, employing surveys directed at STEM students to evaluate their experiences with AI chatbots and digital learning resources. The data gathered is analysed through SPLSS to determine how effectively AI-powered platforms facilitate students' independent learning, enhance their problem-solving abilities, and provide tailored feedback. This research is the inaugural effort to utilize the SPLSS model for examining AI adoption within STEM education. It offers a distinctive framework that integrates personal elements (ICT self-efficacy, SDLT) alongside TAM constructs (PU, PEU) to evaluate their influence on problem-solving and self-efficacy (Kong et al., 2025). The contribution of this paper is the factors that were used. In this research thirteen factors are used for AI chatbots independent variable. In the previous research seven factors are used as variables. The emphasis on cognitive outcomes, rather than only academic achievement, differentiates it from prior studies. IPMA enhances practical significance by prioritizing critical adoption factors. The use of SPLSS model in STEM education is new and for this the factors effectiveness becomes more understandable.

1.1 Background

Artificial Intelligence (AI) is increasingly transforming STEM education by enabling adaptive, personalized, and interactive learning environments that enhance students' academic performance and engagement. Traditional classroom approaches often fail to address individual learning differences, limiting students' ability to develop strong problem-solving skills and self-efficacy. To overcome these limitations, AI-powered tools such as chatbots, intelligent tutoring systems, and digital learning assistants provide real-time feedback, automated assessment, and customized guidance that support self-directed learning. These technologies help learners independently explore complex STEM concepts, receive immediate assistance, and strengthen their analytical thinking abilities. Prior research suggests that factors including ICT self-efficacy, perceived ease of use, perceived usefulness, and learning motivation significantly influence students' acceptance and effective use of educational technologies. Despite growing adoption of AI applications, understanding how these personal and technological factors collectively shape students' intention to use AI chatbots remains limited. Therefore, integrating AI-driven solutions into STEM education presents an opportunity to create more engaging, accessible, and confidence-building learning experiences that foster both cognitive development and academic success.

1.2 Problem Statement

Although AI-powered tools offer promising benefits for enhancing STEM learning, many students still struggle to adopt and effectively use these technologies. Traditional teaching methods often lack personalization, resulting in low motivation, weak problem-solving skills, and reduced self-efficacy among learners. Furthermore, students with limited ICT skills frequently perceive AI tools as complex and difficult to use, which negatively affects their confidence and willingness to engage with such systems. Factors such as low ICT self-efficacy, perceived complexity, insufficient understanding of AI's educational benefits, and lack of self-directed learning readiness create barriers to AI chatbot adoption. Additionally, existing studies have not comprehensively evaluated how these technological, motivational, and behavioral factors interact to influence students' intention and actual usage of AI-based STEM applications. This gap highlights the need for a structured analytical framework to identify the key determinants that drive adoption and effectiveness. Without addressing these challenges, the potential of AI chatbots to improve students' performance, independence, and learning outcomes in STEM education cannot be fully realized.

1.3 Research Questions

A crucial advantage of AI in STEM instruction is the capacity of advancing SDL. Ponders demonstrate that understudies who connected with AI-powered chatbots and computerized coaching frameworks show expanded autonomy, tirelessness, and inspiration to dive into STEM disciplines (Pellas, 2025). Furthermore, AI applications enhance cognitive skills by analysing students' learning behaviors, pinpointing areas of weakness, and offering tailored suggestions to boost problem-solving effectiveness.

RQ 1: *What factors determine PEU of AI chatbots in STEM learning?*
RQ 2: *How does AI-powered learning increase students' problem-solving capabilities and SDL?*
RQ 3: *How does ICT self-efficacy influence students' adoption of AI-powered STEM education apps?*

The key objective of the article is to investigate how AI-powered tools influence students' problem-solving skills and self-efficacy in STEM education. A major focus is to analyse how ICT Self-efficacy, Technology Acceptance and Learning Motivation (TA & LM), PEU, PC, and learning inspiration contribute to students' willingness to accept AI-powered tools (Tam et al., 2020). This study intends to create a thorough conceptual framework that combines theories of technology acceptance, self-efficacy, and motivation to improve AI-driven learning environments. By pursuing these goals, the research aims to connect the adoption of AI with successful learning results, thereby boosting students' confidence, engagement, as well as problem-solving abilities in STEM education. The study utilizes the SPLSS to explore the key determinants influencing the acceptance process and effectiveness of AI-enhanced learning environments (Al-Areeshi, 2025). It methodically examines the connections among ICT self-efficacy, PEU, PU, learning inspiration, and self-directed learning with technology (SDLT) to assess their influence on student engagement with AI-driven educational platforms (Mokmin et al., 2022).

2 Literature Review

2.1 Related Works

AI Powered in STEM Education App: Scope and Characteristics

Artificial Intelligence (AI) is revolutionizing STEM education by offering adaptive, personalized, and interactive learning experiences. Applications powered by AI deliver immediate feedback, automate assessments, and provide real-time assistance, allowing students to pursue self-directed learning and tackle problems effectively (Montejo et al., 2026). These tools encompass AI-driven chatbots, intelligent tutoring systems, and interactive simulation platforms, which facilitate a deeper understanding of complex STEM concepts through experiential learning. The role of AI in STEM education goes beyond merely delivering content. AI tools can analyze students' learning behaviours, pinpoint areas of difficulty, and provide customized recommendations, thereby ensuring a tailored educational experience. Additionally, these tools promote collaborative learning by incorporating peer discussions, AI-supported group projects, and virtual experiments that replicate real-world STEM scenarios. Moreover, AI improves accessibility by offering automated transcriptions, language translation, and adaptive learning environments that cater to students with varying learning needs (Hwang and Wu, 2025). Nevertheless, despite the many advantages of AI in STEM education, several challenges persist. A key concern is the need to align AI applications with established teaching methodologies to enhance their effectiveness in structured educational contexts. Furthermore, an over-dependence on AI tools could potentially hinder students' critical thinking and problem-solving abilities, highlighting the importance of balancing AI-driven learning with traditional educational methods. Ethical issues such as data privacy, algorithmic bias, and disparities in accessibility must also be addressed to ensure equitable and inclusive AI integration (Lee et al., 2022; Bergdahl and Sjöberg, 2025). In conclusion, AI-enhanced STEM education applications hold the promise of transforming learning by increasing engagement, offering personalized support, and nurturing independent problem-solving capabilities.

Previous Studies and STEM Education App Enhancing Problem-Solving Skills and Self Efficacy

Extensive research has investigated the incorporation of AI-driven applications within STEM education, underscoring their potential to enhance problem-solving abilities and boost students' self-efficacy. Findings reveal that AI-based learning tools, including intelligent tutoring systems, chatbot-assisted instruction, and adaptive learning platforms, deliver personalized educational experiences tailored to the unique needs of each student. These applications facilitate real-time feedback, automate assessments, and support interactive problem-solving activities, thereby helping students gain confidence in addressing intricate STEM concepts (Rönkkö and Cho, 2022). A significant advantage of AI in STEM education is its capacity to promote self-directed learning. Studies indicate that students who interact with AI-powered chatbots and automated tutoring systems exhibit increased independence, persistence, and motivation to delve into STEM disciplines (Hwang and Wu, 2025).
Furthermore, AI applications enhance cognitive skills by analyzing students' learning behaviours, pinpointing areas of weakness, and offering tailored suggestions to boost problem-solving effectiveness. Nevertheless, challenges persist. Research indicates that students with low ICT self-efficacy may find it difficult to utilize AI-powered tools due to perceived complexity and a lack of confidence in their technological skills. Additionally, there is a pressing need for improved alignment between AI-driven learning models and conventional teaching methods, as an over-dependence on AI tools could impede the development of critical thinking and problem-solving skills if not effectively integrated into established educational frameworks. Ethical issues, including data privacy, algorithmic bias, and disparities in accessibility, have also been recognized as obstacles to the broader implementation of AI in education (Bayanova et al., 2023).
In conclusion, earlier studies highlight the significant impact of AI-driven

STEM education applications on improving problem-solving abilities and self-confidence. Nevertheless, to fully realize their potential, future research should aim to connect AI technology with effective teaching strategies, promote accessibility, and tackle ethical issues. By enhancing AI-integrated learning environments, educators can establish a more inclusive, engaging, and efficient framework that enables students to cultivate essential problem-solving skills and confidence in STEM fields (Rönkkö and Cho, 2022).

TOWARDS CONCEPTUAL MODEL AND HYPOTHESES

ICT Self-Efficacy, Self-Directed Learning with Technology, STEM Education Variable, Technology Acceptance and Learning Motivation, Intention to Use AI Chatbots, Perceived Convenience, and Enhanced Performance Expectatio

AI technologies—including machine learning, natural language processing, and neural networks—have enabled the development of systems that can perform tasks normally associated with human intelligence. In the context of STEM education, AI-driven tools are increasingly being used to support learning by improving students' problem-solving abilities and strengthening their sense of self-efficacy. These applications make learning more interactive by providing dynamic problem-solving environments and personalized learning paths that adjust to individual needs. As a result, students who engage with AI-based STEM tools tend to become more active learners, develop stronger critical thinking skills, and gain confidence in their academic abilities. Both problem-solving skills and self-efficacy are key factors that contribute to successful learning outcomes.

These factors serve as essential indicators in assessing students' engagement with technology enhanced learning, particularly in STEM education. Before adopting digital learning tools, students often form expectations based on their perceived ability to use technology effectively, their motivation for learning, and the compatibility of these tools with their educational needs. ICT self-efficacy plays a crucial role in this process, as students with higher confidence in their technological skills are more likely to explore and integrate digital resources into their learning routines. When students' expectations regarding the usability and effectiveness of technology are met, they tend to persist in using it; however, unmet expectations can lead to reluctance or discontinuation of technology adoption (Esiyok et al., 2025). Satisfaction with digital learning tools can be categorized into immediate, task-specific satisfaction and long-term cumulative satisfaction. Task specific satisfaction arises from a positive experience with technology in a single learning instance, while cumulative satisfaction develops from repeated positive experiences, reinforcing long-term engagement (Relmasira et al., 2023). Self-directed learning with technology is closely linked to students' willingness to adopt digital learning tools. Studies suggest that the ability to independently explore, experiment, and control one's learning process positively impacts the adoption of educational technologies. The flexibility to experiment with different tools, modify approaches, and recover from mistakes builds students' confidence and fosters continuous usage (Obiwuru, 2024). Observability also plays a key role, as students are more inclined to adopt technology when they see their peers successfully using it. Visible engagement with technology among classmates encourages discussions, knowledge sharing, and a collective sense of digital learning culture (Parsakia et al., 2023). Technology acceptance is a key determinant of students' willingness to incorporate digital tools into their learning process.

According to the Technology Acceptance Model (TAM), students' perceptions of usefulness and ease of use significantly influence their adoption decisions (Ayanwale and Ndlovu, 2024). If students perceive technology as beneficial and easy to navigate, they are more likely to accept and integrate it into their studies. Moreover, observability plays a role in technology acceptance, as students are more inclined to adopt digital tools when they see their peers successfully utilizing them. Visible engagement within academic environments fosters discussions, collaboration, and a collective learning culture that encourages broader technology adoption (Yu et al., 2025). Learning motivation also plays a crucial role in determining students' engagement with digital learning tools. Motivation can be intrinsic, where students are driven by curiosity and personal interest in technology, or extrinsic, where external factors such as academic performance, institutional support, or peer influence encourage adoption (Lai, 2023).

Research suggests that when students feel that technology supports their learning goals and enhances their educational experience, their motivation to engage with it increases. Perceived compatibility further influences motivation, as students are more likely to integrate technology when it aligns with their prior knowledge, study habits, and educational objectives (Roca et al., 2024). Perceived convenience plays a crucial role in AI chatbot adoption, as users prefer technologies that simplify tasks, reduce effort, and save time. Chatbots equipped with natural language processing (NLP) and machine learning capabilities enable users to receive instant responses, automate repetitive tasks, and access information seamlessly. The ability to interact with AI chatbots across multiple devices and platforms further enhances their perceived convenience, making them an attractive alternative to traditional customer service or information retrieval methods (Obiwuru, 2024).

Additionally, the visibility of AI chatbot effectiveness within peer or workplace environments influences adoption decisions, as users who observe successful interactions are more likely to develop positive perceptions and confidence in the technology. Upgraded execution desire is another deciding figure in chatbot selection. Users anticipate that AI chatbots will not only automate tasks but also improve overall efficiency and productivity.

Research indicates that when AI-driven tools align with users' goals such as improving learning outcomes, increasing workplace efficiency, or providing accurate recommendations, adoption rates increase (Roca et al., 2024; Sun et al., 2025). However, if users perceive chatbots as unreliable, prone to errors, or lacking personalization, their motivation to integrate them into their workflow decreases. Compatibility with users' existing digital habits and workflows further strengthens adoption, as individuals prefer technologies that seamlessly integrate into their routines rather than disrupt them.

Building on this idea, a hypothesis was proposed regarding the relationship between ICT self-efficacy and perceived ease of use. ICT self-efficacy refers to an individual's belief in their ability to effectively use digital technologies. Perceived ease of use, on the other hand, describes how simple and user-friendly a person finds a particular technology. When learners or educators have a higher level of ICT self-efficacy, they are more likely to feel comfortable using AI chatbots in educational settings. This confidence allows them to explore features more freely, use the tools efficiently, and experience less difficulty during interaction. As a result, their overall engagement improves, and they are more willing to continue using such technologies. Based on this reasoning, Hypothesis 1 (H1) suggests that ICT self-efficacy has a positive influence on the perceived ease of use of AI

chatbots in education.
Hypothesis 1 (H1): *ICT self-efficacy positively affects the perceived ease of use (PEU) of AI chatbots in education.*

People feel confident using technology (ICT self-efficacy), they find AI chatbots in education easier to use. This confidence helps them navigate chatbots smoothly and benefit from instant support. Those with lower ICT skills may struggle and find chatbots confusing or difficult. Improving ICT skills makes chatbots more user-friendly and enjoyable to use. This leads to a better learning experience for students and educators. The H2 hypothesis was formulated following the discussion, as described above.
Hypothesis 2 (H2): *ICT self-efficacy positively affects the PU of AI chat bots in education.*

People find AI chatbots easy to use (perceived ease of use, or PEU), they are more likely to believe that these chatbots are helpful for learning (perceived usefulness, or PU). If a chatbot is simple to interact with, students and educators will see it as a valuable tool that makes learning easier or more efficient. The H3 hypothesis was formulated following the discussion, as illustrated above.
Hypothesis 3 (H3): *Perceived ease of use (PEU) emphatically influences the perceived usefulness (PU) of AI chatbots in education.*

People believe that AI chatbots are useful for learning (perceived usefulness or PU), they are more likely to want to use them regularly (intention to use). If students or teachers see that chatbots help them learn better, save time, or provide valuable information, they are motivated to continue using them. In other words, if the chatbot proves to be helpful and enhances their educational experience, they will be more inclined to make it a part of their learning routine. The H4 hypothesis was formulated following the discussion, as explained above.
Hypothesis 4 (H4): *Perceived usefulness (PU) emphatically influences the deliberate to utilize AI chatbots in education.*

AI chatbots are helpful for their learning (perceived usefulness or PU), they're more likely to want to use them in the future (intention to use). When students or educators realize that chatbots can make tasks easier,

provide quick answers, or offer useful learning resources, they see it as a valuable tool. This positive experience drives them to use it more often. In simple terms, the more they believe the chatbot is useful, the more motivated they'll be to continue using it in their education. The H5 hypothesis was formulated following the discussion, as mentioned above.
Hypothesis 5 (H5): *Perceived ease of use (PEU) emphatically influences the purposeful to utilize AI chatbots in education.*

If students are good at learning on their own and using technology (self-directed learning with technology), they are more likely to use AI chatbots in education. Since they enjoy finding information and solving problems independently, AI chatbots can be a helpful tool for them. The more comfortable they feel using technology, the more they will want to use chatbots to support their learning. Simply put, self-motivated learners are more likely to see AI chatbots as useful and use them more often. The H6 hypothesis was formulated following the discussion, as described above.
Hypothesis 6 (H6): *Self-directed learning with technology (SDLT) emphatically influences the purposeful to utilize AI chatbots in education.*

Self-directed learning with technology (SDLT) refers to the ability of students or educators to take control of their own learning, using technology to find information, solve problems, and improve their skills. When people are comfortable with this approach, they are more likely to use tools like AI chatbots to support their learning. If they already manage their learning using technology, they will see AI chatbots as another helpful resource to enhance their education. In short, self-directed learners are more likely to choose and use AI chatbots because they are used to relying on technology to aid their learning process. The H7 hypothesis was formulated following the discussion, as mentioned above.
Hypothesis 7 (H7): *Self-directed learning with technology (SDLT) emphatically influences the purposeful to utilize AI chatbots in education.*

When students or educators have the intention to use AI chatbots in education, it means they plan to use them in the future. This intention often leads to actual use, as people tend to follow through on their plans. If someone believes that AI chatbots will help them with learning, they are more likely to start using them regularly. In simple terms, when a person is motivated and sees the value of using chatbots, they are more likely to actually use them as a part of their learning process. The intention to use often translates into action. The H8 hypothesis was formulated following the discussion, as mentioned above.

Hypothesis 8 (H8): *Deliberate to utilize AI chatbots emphatically influences the real utilize of AI chatbots in education.*

Personal Innovativeness

Development hypothesis for the most part classifies clients of innovation as exceedingly imaginative people who are dynamic searchers of innovational thoughts. They are a particular sort of client who adapts with tall levels of vulnerability and creates positive eagerly towards acknowledgment. In this sense, individual innovativeness points to create positive convictions on innovational innovation. It is contended that the most elevated effect on people cognitive translations of data innovation relate to variables of individual innovativeness, which can be seen as an occurrence of risk-taking affinity that shows up as a result of utilizing modern innovation (Al-Areeshi, 2025). This demonstrate is as a rule influenced by the vital and compelling fronts in this demonstrate, seen ease of utilize and seen value of innovation. The previous demonstrates the degree to which any client accepts that a particular innovation would improve their execution for specific purposes. The last-mentioned concerns the degree to which a client accepts that employing a specific innovation diminishes exertion. These considers affirm a noteworthy relationship between behavioral purposeful and seen convenience and ease of utilize. In this way, the proposed conceptual demonstrate suggests that individual innovativeness features a critical effect on seen convenience and ease of utilize, which shape the essential pertinence for selection of metaverse frameworks (Hwang and Wu, 2025). Accordingly, the following hypotheses are formed:

Students or educators engage with STEM (Science, Technology, Engineering, and Mathematics) education, certain factors such as problem-solving, critical thinking, and the use of technology positively influence how useful they find AI chatbots. In STEM education, technology plays a big role, so students are more likely to see AI chatbots as helpful tools for answering questions, solving problems, and providing personalized learning

support. The more students are involved in STEM subjects, the more they recognize the value of AI chatbots in enhancing their learning experience. The H9 hypothesis was formulated following the discussion, as mentioned above.
Hypothesis 9 (H9): *STEM instruction factors emphatically influence the seen convenience (PU) of AI chatbots in education.*

STEM education variables, such as familiarity with technology, critical thinking, and problem-solving, positively impact how easy students or educators find AI chatbots to use. In STEM education, students are often more comfortable with digital tools and technology, making them more likely to find AI chatbots intuitive and user-friendly. The skills and experience gained from STEM subjects help students navigate and interact with AI chatbots with ease. The H9 hypothesis was formulated following the discussion, as mentioned above. The H10 hypothesis was formulated following the discussion, as mentioned above
Hypothesis 10 (H10): *STEM education variables positively affect the perceived ease of use (PEU) of AI chatbots in education.*

The convenience of AI chatbots plays a significant role in motivating students and educators to use them. When AI chatbots make learning easier by providing quick answers, personalized support, and round-the-clock availability, users are more likely to intend to use them regularly. The more convenient and accessible these chatbots are, the more students and educators will see them as a valuable tool in their learning process. For instance, if chatbots offer immediate help with homework or explain concepts efficiently, they become a go-to resource. Ultimately, the greater the convenience offered by AI chatbots, the stronger the intention to use them in educational settings. The H11 hypothesis was formulated following the discussion, as mentioned above.
Hypothesis 11 (H11): *Perceived convenience positively affects the intention to use AI chatbots in education.*

Students expect AI chatbots to improve their learning performance, they are more likely to intend to use them. If the chatbot is believed to provide accurate, timely, and helpful information that boosts learning outcomes, users are motivated to use it more frequently. The stronger the

belief that using AI chatbots will lead to better academic performance, the higher the intention to integrate them into their education. The H12 hypothesis was formulated following the discussion, as mentioned above.
Hypothesis 12 (H12): *Enhanced performance expectation positively affects the intention to use AI chatbots in education.*

Students accept and are motivated to use technology in their learning; they are more likely to engage in self-directed learning with technology (SDLT). Technology acceptance means that students are comfortable and open to using digital tools, while learning motivation drives them to take initiative in their education. Together, these factors encourage students to independently seek out resources, solve problems, and manage their learning with the help of technology. The more students embrace technology and feel motivated to learn, the more likely they are to take control of their own learning process, using digital tools to enhance their educational experience. The H13 hypothesis was formulated following the discussion, as mentioned above.
Hypothesis 13 (H13): *Technology acceptance and learning motivation positively affect self-directed learning with technology (SDLT).*

The Conceptual Framework

The current study proposed a conceptual framework that measures the adoption of AI powered in STEM Education App by examining three main attributes namely, Intention to use AI Chatbots, Self-directed learning with technology and Technology acceptance and learning motivation as coined with other independent variables of ICT self-efficacy, STEM education Variable, Perceived convenience, and Enhanced performance expectation, and Perceived Ease of Use, Perceived Usefulness. In other words, Actual AI Chatbot Usage is measured by ICT self-efficacy, Self-directed learning with technology, STEM education Variable, Technology acceptance and learning motivation, Intention to use AI chatbots, Perceived convenience, and Enhanced performance expectation as illustrated below.

The Figure 1 1illustrates a conceptual research model, adapted from the Technology Acceptance Model (TAM), that explains the factors influencing students' adoption of AI chatbots in STEM education. It indicates that

ICT self-efficacy, which refers to a student's confidence in using digital technologies, significantly affects their perception of how easy (perceived ease of use) and how beneficial (perceived usefulness) AI chatbots are. When students are more comfortable with technology, they are more likely to view these tools as simple to operate and valuable for learning. Furthermore, participation in technology-based STEM education enhances both these perceptions, as regular exposure to digital tools increases familiarity and perceived benefits.

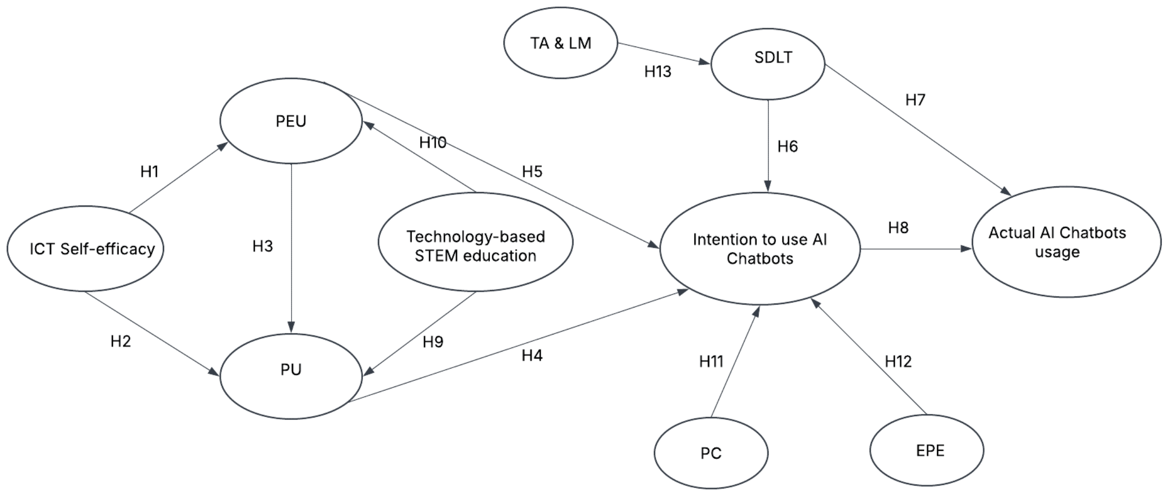

Figure 1: Research Framework.

The model also shows that several factors contribute to the intention to use AI chatbots, including self-directed learning ability, perceived cost, and enjoyment. Teacher assistance and learning materials further support students in developing self-directed learning skills, which in turn strengthens their intention to use such technologies. Ultimately, the intention to use AI chatbots plays a central role in determining actual usage, although self-directed learning can also have a direct impact on usage behavior. Overall, the model emphasizes that a combination of individual skills, perceptions, and educational environment influences students' willingness and actual engagement with AI chatbot tools.

3 Methodology

3.1 Motivation and Purpose

3.1.1 Motivation

The rapid advancement of Artificial Intelligence (AI) technologies has created new opportunities to transform traditional STEM education into more personalized, interactive, and learner-centered experiences. However, many students still struggle with problem-solving tasks, low self-confidence, and limited engagement in STEM subjects due to conventional teaching approaches that do not address individual learning needs. Although AI-powered tools such as chatbots and intelligent tutoring systems can provide real-time feedback, adaptive support, and self-directed learning opportunities, their effectiveness largely depends on students' willingness and readiness to adopt these technologies. Factors such as low ICT self-efficacy, perceived complexity, lack of motivation, and limited awareness of AI's educational benefits often hinder successful adoption. Moreover, existing research has not sufficiently examined how technological, personal, and motivational factors collectively influence students' intention to use AI chatbots in STEM learning environments. These challenges motivated the present study to explore the determinants that affect students' acceptance and effective utilization of AI-driven educational tools.

3.1.2 Purpose

The primary purpose of this study is to investigate the factors influencing students' intention to use AI-powered chatbots in STEM education and to evaluate how these tools enhance problem-solving skills and self-efficacy. Specifically, the research aims to develop and validate a comprehensive conceptual framework that integrates ICT self-efficacy, perceived ease of use, perceived usefulness, perceived convenience, technology acceptance, and learning motivation. By employing a hybrid Structural Equation Modeling (SEM) and Artificial Neural Network (ANN) approach, the study seeks to identify key predictors of AI chatbot adoption and measure their relative importance. Ultimately, the research intends to provide empirical evidence and practical guidance for designing user-friendly, effective, and engaging AI-based learning systems that improve students' confidence, independence, and academic performance in STEM fields.

3.2 Model

This study employs two complementary analytical models—Structured Predictive Latent Semantic System (SPLSS) and Artificial Neural Network (ANN)—to ensure both explanatory and predictive accuracy in examining students' adoption of AI chatbots in STEM education. The SPLSS model, an advanced extension of Partial Least Squares Structural Equation Modeling (PLS-SEM), is used as the primary statistical framework to test theoretical relationships among latent constructs such as ICT self-efficacy, perceived ease of use, perceived usefulness, motivation, and intention to use AI chatbots. It evaluates measurement reliability and validity while estimating path coefficients to determine the strength and significance of hypothesized relationships. SPLSS also incorporates Semantic Predictive Importance Analysis (SPIA) to enhance predictive interpretation and latent variable estimation, making it particularly suitable for complex educational behavior models. Thus, it helps validate the conceptual framework and explain how different psychological and technological factors influence students' behavioral intentions.

To complement this, the Artificial Neural Network (ANN) model is applied to capture non-linear and complex interactions that traditional statistical methods may overlook. ANN uses multiple input neurons, hidden layers with activation functions, and an output neuron to predict students' intention and actual use of AI chatbots. By training and testing the model through cross-validation and measuring performance using Root Mean Square Error (RMSE), ANN improves predictive power and robustness. Additionally, sensitivity analysis identifies the relative importance of each factor, revealing which variables most strongly influence adoption behavior. Therefore, while SPLSS explains relationships statistically, ANN enhances prediction accuracy, and together they provide a hybrid approach that strengthens both theoretical validation and practical forecasting.

3.2.1 Model Description

Data Collection

Within the scope of this study a Google form is used to gather data over two weeks, from February 21 to February 7 March, 2025 and the participants could attend anytime during this time frame at their convenience. The first section of the survey was dedicated to gather demographic data like gender, profession, age, educational qualifications, field of study, technology proficiency level etc (Roca et al., 2024). These questions were designed to understand the diverse backgrounds of the participants, which is crucial to conduct the survey. The second section is main part of the survey where the participants were asked about ICT Self-efficacy, Actual AI Chatbot Usage (AACU), Intention to Use AI Chatbots (IUAC), Technology Acceptance & Learning Motivation and so on. These questions were designed using revalidated scales and the validity of the content was verified following the appropriate verification methods. Five-point Likert scales were employed to enhance the reliability of the measurements in the final section, the participants were asked about benefits, challenges of using AI chatbots. It also asked how STEM background influence perception of AI chatbots, how AI chatbots improve better support in STEM learning. Though this part is optional but from this part we can understand the relation of participants with AI chatbots.

Students often turn to their instructors for help when they encounter obstacles in using technological tools, as teachers typically have more advanced skills and experience with such technologies. In this study, SEM was applied to examine the article hypotheses, with the sample size deemed sufficient for reliable analysis (Lee et al., 2022). Although the hypotheses were originally derived from recognized theoretical models, they were modified where appropriate to suit the specific context of the Internet of Things (IoT). The data analysis was conducted using SmartPLS (version 4.1.1.1) for SEM, along with SPSS to support the structural model assessment.

Personal/Demographic Information

Table 3.1 provides detailed information on the demographic composition of the respondents. Where among the 117 respondents (Male = 25 (21.4%)) and (Female = 92 (78.6%)). The majority of participants, 72.7% (85) were between 21- 25 years old, followed by 7.7% (9) were between 26-30 years old, indicating that the sample predominantly consisted of young men. Additionally, 82.9% (97) held a Bachelor's degree, while 15.4% (18) had a Master's degree, illustrating that the response pool is highly educated. This demographic profile highlights the importance of targeting young, educated individuals who actively use AI chatbots to enhance their self-efficacy as well as problem-solving abilities.

The heavy concentration of participants in the 21 to 25 age bracket suggests that the study primarily captures the perspectives of "digital natives" who are in a critical stage of their academic and professional development. Because this cohort is likely to possess a higher baseline of ICT self-efficacy, they are more predisposed to exploring innovative tools like AI chatbots to manage the rigours of STEM curricula. The educational background of the respondents, being mostly undergraduates and master's students, aligns with the study's focus on SDL; these students are at a juncture where independent problem-solving and cognitive autonomy are essential for success. Consequently, the high level of education within the sample ensures that the feedback regarding perceived usefulness (PU) and perceived ease of use (PEU) is derived from users who can critically evaluate how AI integration supports complex analytical tasks. This demographic alignment validates the research model's focus on learning motivation, as it reflects a population that is both capable of and motivated to adopt technology that provides immediate, adaptive feedback in a demanding educational environment.

Table 3.1: Demographic data of the participants.

Criteria	Factor	Frequency	Percentage
Gender	Male	25	21.40%
	Female	92	78.60%

Criteria	Factor	Frequency	Percentage
Age (In Years)	Between 16 and 20	19	16.20%
	Between 21 and 25	85	72.70%
	Between 26 and 30	9	7.70%
	Between 31 and 35	2	1.70%
	Above 35	2	1.70%
Education Level	Undergraduate	97	82.9%
	Master's	18	15.4%
	PhD	0	0%
	MBBS	2	1.70%

Study Instrument

A survey comprising 33 items was developed as the primary research instrument this survey was designed to assess 10 distinct constructs outlined in the questionnaire with their respective sources detailed in table 3.2 items from prior studies were adapted and customized to better align with the objectives of this research ensuring the findings would be more relevant and applicable.

Table 3.2: Measurement Items.

Construct	Measurement Item	Definition	Instrument	Sources
ICT Self-Efficacy	ICT SE1 ICT SE2 ICT SE3 ICT SE4	An individual's perceived capacity to successfully use Information and Communication Technology (ICT) to accomplish specific tasks or solve problems. Esiyok et al. (2025)	I believe I can successfully use ICT tools to accomplish my academic tasks before actual classes	Esiyok et al. (2025).

Construct	Measurement Item	Definition	Instrument	Sources
Technology-Based STEM Education	TBSE1 TBSE2 TBSE3 TBSE4	A learning method that merges STEM using digital tools, platforms, and applications to enhance student engagement and understanding. Esiyok et al. (2025)	I find it beneficial to engage in STEM education through technology-based learning platforms before actual classes.	Esiyok et al. (2025)
Perceived Ease of Use	PEU1 PEU2 PEU3	The intensity of personal belief is that using a particular technology or system will be effortless and free from difficulty. Esiyok et al. (2025)	I feel that using this technology is easy for me before actual classes.	Esiyok et al. (2025).
Perceived Usefulness	PU1 PU2 PU3	The perceived degree to which an individual expects a given technology will improve their performance or productivity. Esiyok et al. (2025).	I believe this technology will enhance my learning and understanding before actual classes.	Esiyok et al. (2025)

Construct	Measurement Item	Definition	Instrument	Sources
Enhanced Performance Expectation	EPE1 EPE2 EPE3	The belief that adopting a particular technology will lead to improved efficiency, effectiveness, or achievement of goals. Obiwuru (2024).	I expect my academic performance to improve by using this technology before actual classes.	Obiwuru (2024)
Intention to Use AI Chatbots	IUAC1 IUAC2 IUAC3	The willingness or likelihood of an individual to adopt and engage with AI-powered chatbots for specific tasks or learning purposes. Obiwuru (2024).	I intend to use AI chatbots for learning assistance before actual classes.	Obiwuru (2024
Actual AI Chatbot Usage	AACU1 AACU2 AACU3	The real, measurable interaction and engagement with AI chatbots for various applications, such as learning support, customer service, or problem-solving. Lee et.al (2022)	I regularly use AI chatbots to support my studies before actual classes.	Lee et.al (2022)

Construct	Measurement Item	Definition	Instrument	Sources
Self-Directed Learning with Technology	SDLT1 SDLT2 SDLT3 SDLT4	A learning approach in which individuals take initiative in acquiring knowledge and skills using digital tools and resources, often at their own pace and preference. Roca et.al (2024).	I take the initiative to learn new concepts using technology before actual classes.	Roca et.al (2024)
Technology Acceptance and Learning Motivation	TA & LM1 TA & LM2 TA & LM3	The relationship between a user's willingness to adopt technology and their motivation to learn, forced by factors such as PU, ease of use, and personal goals. Roca et.al (2024).	I feel motivated to learn when I accept and use new technology before actual classes.	Roca et.al (2024)
Perceived Convenience	PC1 PC2 PC3	The degree of user-perceived associated with a technological platform or system is accessible, time-saving, and easy to use in their daily activities. Ayanwale et. al (2024).	I find it convenient to use technology to support my learning before actual classes.	Ayanwae et. al (2024)

Inner Model and Hypothesis Testing

The inner model was evaluated based on the results of the hypothesis analysis and the Variance Inflation Factor (VIF) assessment. To test the proposed hypotheses in this study, we utilized the inner Partial Least Squares (PLS) model analysis. The specific SPLS model applied in the hypothesis analysis, along with its respective values, is depicted in figure 2. A summary of the findings is presented in Table 3.3.

The figure presents a conceptual research model that explains how different factors contribute to students' adoption and actual use of AI chatbots in a STEM learning environment. It begins with ICT self-efficacy, which reflects students' confidence in using technology, and this confidence plays a key role in shaping how easy and useful they perceive the technology to be. When students believe that a system is simple to operate, they are more likely to find it beneficial, which strengthens their overall perception of its value. At the same time, exposure to STEM education further supports these perceptions and encourages a positive attitude toward using AI tools. All these elements together influence the students' intention to use AI chatbots. This intention is also affected by additional aspects such as teaching methods, perceived control or cost, and expected performance outcomes. Finally, the model shows that intention, along with self-directed learning abilities, leads to the actual use of AI chatbots. In short, the diagram illustrates that both personal confidence and educational context play important roles in shaping not only students' willingness to use AI technologies but also their real usage behavior.

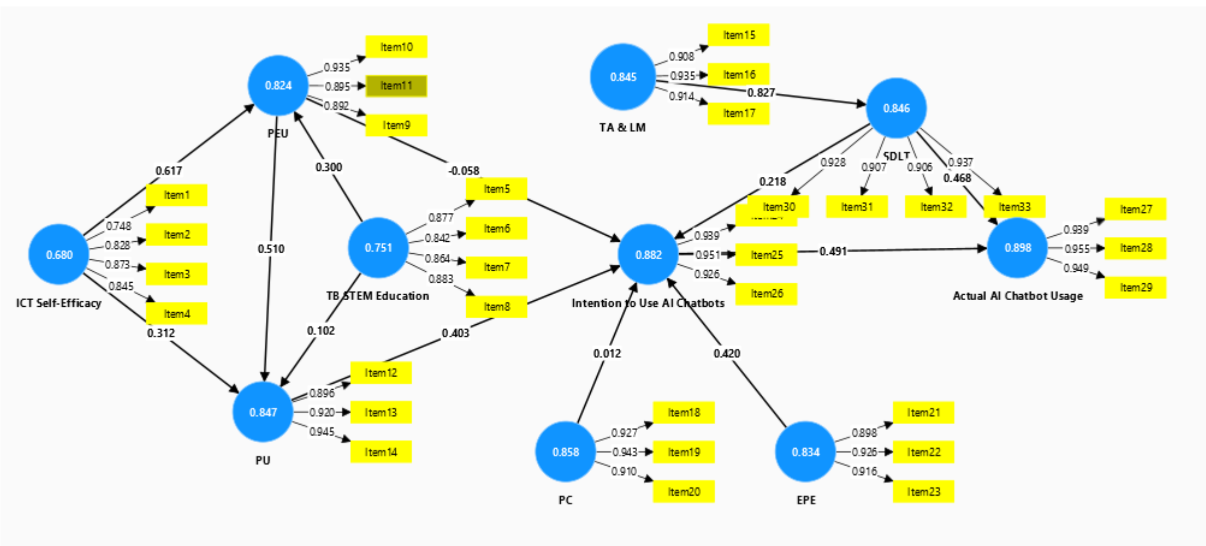

Figure 2: SPLS Model.

Table 3.3: Summary of the Inner Mode.

Hypothesis	Relationships	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	Result
H1	ICT SE -> PEU	0.618	0.088	7.040	Supported
H2	ICT SE -> PU	0.321	0.158	1.967	Supported
H3	PEU -> PU	0.497	0.123	4.140	Supported
H4	PU -> IUAC	0.366	0.135	2.979	Supported
H5	PEU -> IUAC	-0.038	0.111	0.522	Supported
H6	SDLT -> IUAC	0.245	0.135	1.618	Supported
H7	SDLT -> AACU	0.430	0.168	2.793	Supported
H8	IUAC -> AACU	0.527	0.160	3.065	Supported
H11	PC -> IUAC	0.014	0.146	0.084	Supported
H9	TBSE -> PU	0.102	0.091	1.120	Supported
H10	TBSE -> PEU	0.299	0.094	3.201	Supported
H12	EPE -> IUAC	0.409	0.132	3.174	Supported
H13	TA& LM -> SDLT	0.824	0.054	15.446	Supported

N.B: ICT SE =ICT Self-Efficacy, TBSE = Technology-Based STEM Education, PEU= Perceived Ease of Use, PU= Perceived Usefulness, EPE= Enhanced Performance Expectation, IUAC= Intention to Use AI Chatbots, AACU= Actual AI Chatbot Usage, SDLT= Self-Directed Learning with Technology, TA & LM= Technology Acceptance and Learning Motivation, PC= Perceived Convenience.

The hypothesis testing results reveal varying strengths in the relationships between the variables. The strongest relationship was found between Technological Acceptance (TA) and Learning Motivation (LM) on Self-Directed Learning with Technology (SDLT) (H13), with a high t-value of

15.446. Additionally, ICT Self-Efficacy (ICT SE) strongly influenced Perceived Ease of Use (PEU) (H1) with a t-value of 7.040, suggesting that confident ICT users perceive technology as easier to use. Self-Directed Learning (SDLT) also positively impacted Actual AI Chatbot Usage (AACU) (H7), with a t-value of 2.793. Moderate relationships were observed between External Perceived Ease (EPE) and Intention to Use AI Chatbots (IUAC) (H12), with a t-value of 3.174, and between Intention to Use AI Chatbots (IUAC) and Actual AI Chatbot Usage (AACU) (H8), with a t-value of 3.065. PU positively influenced IUAC (H4), with a t-value of 2.979.

Pilot Study of Questionnaire

Table 3.4 displays the CA values evaluated for the measurement scales. This study carried out an initial performance evaluation of the dependability of the questionnaire items. A random selection of participants for the pilot study was taken from a group of 117 students. Considering that the total participant is 117, employing a sample size of 10% (in accordance with research guidelines) leads to 11.7; hence, a total of 12 students took part in the pilot study. In the next stage of the pilot study, SPSS software was used to conduct a Cronbach's alpha (CA) test to measure the internal consistency of the items. The findings indicated a reliability coefficient of 0.70, which is regarded as acceptable since this research is situated in the realm of Science (Roca et al., 2024).

Table 3.4: CA Values for Pilot Study (CA 0.70).

Items	CA
Actual AI Chatbot Usage	0.943
EPE	0.901
ICT Self-Efficacy	0.843
Intention to Use AI Chatbots	0.933
PC	0.917
PEU	0.893
PU	0.910
SDLT	0.939
TA & LM	0.908
TB STEM Education	0.890

Common Method Bias

The assessment of common method bias was conducted using Variance Inflation Factor (VIF) values from the inner model. In the research, all VIF values remained under 3.33. Therefore, we can conclude that the model is not affected by common method bias (Montejo et al., 2026). Table 3.5 demonstrates that all values are below 3.33, allowing us to affirm that this model is free from common method bias.

Survey Structure

The survey questionnaire that was distributed to the students participating in the study consists of three main parts:

- The first part has questions about the personal information of the responders.
- The second part featured 33 items concerning ICT self-efficacy, SDLT, STEM education variables, TA & LM, IUAC, PC, enhanced performance expectations (EPE).
- The third part was optional and solicited responses to questions regarding the usefulness of AI chatbots.

Upon completion of the questionnaires, the 33 items were evaluated using a five-point Likert Scale, with responses of strongly disagree (1) to strongly agree (5) range.

Table 3.5: Variance Inflation Factor Analysis.

	VIF
EPE -> Intention to Use AI Chatbots	3.223
ICT Self-Efficacy -> PEU	2.544
ICT Self-Efficacy -> PU	2.136
Intention to Use AI Chatbots -> Actual AI Chatbot Usage	3.387
PC -> Intention to Use AI Chatbots	3.244
PEU -> Intention to Use AI Chatbots	2.638
PEU -> PU	1.176
PU -> Intention to Use AI Chatbots	1.648
SDLT -> Actual AI Chatbot Usage	3.387
SDLT -> Intention to Use AI Chatbots	2.346
TA & LM -> SDLT	1.000
TB STEM Education -> PEU	2.544
TB STEM Education -> PU	2.921

4 Result Analysis

Data Analysis

The SPLSS model is used to examine the relationships among theoretical design factors and validate article hypotheses. SPLSS is implemented using an advanced statistical framework to analyze the proposed research model (Bergdahl and Sjöberg, 2025). SPLSS is particularly suitable for predictive analytics in theoretical models that require deep latent variable estimation (Montejo et al., 2026). The application of SPLSS in this study follows standardized guidelines for research studies in computational social sciences (Pellas, 2025). Consequently, the research model is analyzed in a systematic two-step approach (involving the assessment of measurement as well as structural models) as emphasized by the methodological recommendations of Brown (1995). Moreover, PLS-SEM analysis is supported, assessed, and validated by applying ANN with IPMA. ANN surveys the subordinate and autonomous factors, and it works best for exploring non-linear or complex connections among input and yield develops. It serves as a work estimation instrument. SPLSS introduces a novel methodological approach: Semantic Predictive Importance Analysis (SPIA). The primary objective of SPIA is to evaluate research model constructs by assessing their semantic relevance and predictive performance. Additionally, SPLSS enhances structural model evaluation by integrating latent construct estimations, thus improving the interpretability and predictive accuracy of theoretical frameworks. The SPLSS model incorporates key statistical mechanisms such as factor decomposition, latent trajectory modeling, and covariance-based structural relationships, enabling a robust estimation of theoretical constructs (Rönkkö and Cho, 2022). The methodological advancements in SPLSS provide a structured analytical foundation for research studies requiring multidimensional predictive modeling. The predictive performance of SPLSS is further validated using a cross-validation framework to ensure model reliability and consistency. In summary, SPLSS has been used in the research framework as a structured predictive modeling technique to enhance hypothesis testing and theoretical validation. In short, MLP neural network has been applied to the research model as an ANN technique for its training and testing.

Convergent Validity

Effective techniques for calculating or analyzing the measurement model include the examination of construct reliability, which includes composite reliability (CR), Dijkstra-Henseler's rho (pA), and CA, as well as validity measures (both convergent and discriminant). Table 4 shows that the CA values for CR are over the 0.7 minimum requirement, ranging from 0.843 to 0.9. Also, Table 5 presents CR values of 0.857 to 0.944, which also surpasses required threshold of 0.7. As a complementary approach, researchers should apply Dijkstra-Henseler's rho reliability coefficient (A) to calculate construct reliability. Similar to CA and CR, the reliability coefficient should be 0.70 or higher in exploratory studies, with values exceeding 0.8 or 0.9 recommended for more advanced research stages. The table clearly shows that the reliability coefficient exceeds 0.70 for all individual measurement constructs, reinforcing the notion of construct reliability. Ultimately, it can be concluded that the constructs or items are assumed to be free from significant errors in an acceptable manner. To assess convergent validity, average variance extracted (AVE) and factor loading tests are performed. As illustrated in the table, each factor loading value is found to be above the suggested benchmark of 0.7. Furthermore, Table 5 illustrates that the calculated AVE scores all exceed the standard cutoff of 0.5, spanning from 0.680 to 0.898. Taking these results into account, all constructs demonstrate evidence of convergent validity.

Discriminant validity

To assess discriminant legitimacy, both the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT) were evaluated. The results shown in Table 4.1 support the Fornell-Larcker criterion as stated in Table 4.2 by showing that the values of AVEs and their square roots are greater than the correlations with other variables. Table 4.3 outlines the outcomes of HTMT ratio. As indicated, every construct exhibited a value under the recognized threshold of 0.85, suggesting consent with the HTMT ratio (Bergdahl and Sjöberg, 2025). According to these results, discriminant legitimacy is affirmed. The analysis results for the measurement model showed no issues related to validity or reliability. Therefore, the data gathered can be applied to examine and validate the components of the structural framework.

Table 4.1: Acceptable Results for Convergent Validity Include Factor Loading, CA, and CR 0.70 & AVE >0.5.

Construct	Item	Factor Loading	CA	CR (rho$_a$)	pA	AVE
Actual AI Chatbot Usage	AACU1	0.939	0.943	0.944	0.963	0.898
	AACU2	0.955				
	AACU3	0.949				
EPE	EPE1	0.898	0.901	0.906	0.938	0.834
	EPE2	0.926				
	EPE3	0.916				
ICT Self-Efficacy	ICT SE1	0.748	0.843	0.857	0.895	0.680
	ICT SE2	0.828				
	ICT SE3	0.873				
	ICT SE4	0.845				
Intention to Use AI Chatbots	IUAC1	0.939	0.933	0.935	0.957	0.882
	IUAC2	0.951				
	IUAC3	0.926				
PC	PC1	0.908	0.917	0.918	0.948	0.858
	PC2	0.935				
	PC3	0.914				
PEU	PEU1	0.935	0.893	0.894	0.933	0.824
	PEU2	0.895				
	PEU3	0.892				
PU	PU1	0.896	0.910	0.911	0.943	0.847
	PU2	0.920				
	PU3	0.945				
SDLT	SDLT1	0.928	0.939	0.941	0.956	0.846
	SDLT2	0.907				
	SDLT3	0.906				
	SDLT4	0.937				

Construct	Item	Factor Loading	CA	CR (rho_a)	pA	AVE
TA & LM	TA & LM1	0.908	0.908	0.908	0.942	0.845
	TA & LM2	0.935				
	TA & LM3	0.914				
TB STEM Education	TBSE1	0.877	0.890	0.897	0.924	0.751
	TBSE2	0.842				
	TBSE3	0.864				
	TBSE4	0.883				

Table 4.2: Fornell-Larcker Scale.

	Actual AI Chatbot Usage	EPE	ICT Self-Efficacy	Intention to Use AI Chatbots	PC	PEU	PU	SDLT	TA & LM	TB STEM Education
Actual AI Chatbot Usage	**0.948**									
EPE	0.835	**0.913**								
ICT Self-Efficacy	0.820	0.774	**0.825**							
Intention to Use AI Chatbots	0.885	0.890	0.823	**0.939**						
PC	0.853	0.865	0.809	0.846	**0.927**					
PEU	0.825	0.796	0.820	0.812	0.861	**0.908**				
PU	0.816	0.804	0.825	0.869	0.843	0.855	**0.921**			
SDLT	0.881	0.831	0.788	0.839	0.826	0.826	0.769	**0.920**		

	Actual AI Chatbot Usage	EPE	ICT Self-Efficacy	Intention to Use AI Chatbots	PC	PEU	PU	SDLT	TA & LM	TB STEM Education
TA & LM	0.862	0.842	0.856	0.878	0.868	0.838	0.856	0.827	**0.919**	
TB STEM Education	0.788	0.808	0.779	0.760	0.765	0.781	0.743	0.821	0.781	**0.867**

Model Fit

In this research, SmartPLS employs a range of model fit indicators, including exact fit statistics, the Standardized Root Mean Square Residual (SRMR), Normed Fit Index (NFI), RMS_ theta, geodesic distance (d_G), squared Euclidean distance (d_ULS), and the Chi-square (Chi2) statistic, to evaluate how well the PLS-SEM model aligns with the data. As presented in Table 4.4, SRMR is particularly useful for measuring the discrepancy between the actual correlation matrix and the one predicted by the model. An SRMR value below 0.08 generally suggests an acceptable model fit. Similarly, the NFI, which assesses model fit by comparing the Chi2 value of the estimated model to that of a baseline (null) model, should typically exceed 0.90 to indicate good fit. Nonetheless, NFI may not consistently reflect model fitness effectively, as it can vary with the number of parameters involved. The relevance of d_ULS and d_G is significant because these fit evaluations reveal the discrepancies between empirical covariance matrix and the matrix obtained from the composite factor design.

Table 4.3: Heterotrait-Monotrait Ratio.

	Actual AI Chatbot Usage	EPE	ICT Self-Efficacy	Intention to Use AI Chatbots	PC	PEU	PU	SDLT	TA & LM	TB STEM Education
Actual AI Chatbot Usage										
EPE	0.302									
ICT Self-Efficacy	0.510	0.575								
Intention to Use AI Chatbots	0.641	0.367	0.922							
PC	0.417	0.051	0.610	0.513						
PEU	0.798	0.587	0.470	0.689	0.352					
PU	0.800	0.850	0.634	0.542	0.423	0.449				
SDLT	0.734	0.502	0.481	0.695	0.289	0.501	0.430			
TA & LM	0.132	0.628	0.672	0.753	0.350	0.729	0.242	0.393		
TB STEM Education	0.655	0.301	0.771	0.430	0.439	0.769	0.219	0.594	0.763	

Table 4.4: Model Fit Indicators.

	Complete	
	Saturated model	Estimated model
SRMR	0.051	0.087
d_ULS	1.438	4.220
d_G	2.280	2.652
Chi-square	1324.728	1398.860

	Complete	
	Saturated model	Estimated model
NFI	0.755	0.741

Hypotheses Testing Using PLS-SEM

To evaluate the interconnections among the various theoretical constructs in the structural model, the structural equation design was applied using Smart PLS and maximum likelihood estimation. The suggested hypotheses were assessed utilizing these analytical tools. The model demonstrated significant predictive capability, with variance percentages of 68% for SDLT, 75% for PEU, 76% for PU, 84% for AACU, and 86% for Users' IUAC. These findings are presented in Table 4.5 along with Figure 3 and 4. The estimations and results were achieved through the PLS-SEM technique, facilitating the confirmation of hypotheses (Relmasira et al., 2023). The beta (β) values, t-values, and p-values associated with these hypotheses are listed in Table 10. All researchers unequivocally supported these hypotheses. The data analysis indicates that empirical findings corroborate hypotheses H1 through H13. The correlations between ICT Self-efficacy and PEU ($\beta = 0.617$, P (PU) ($\beta = 0.403$, $P < 0.001$), PEU ($\beta = 0.058$, $P < 0.001$), SDLT ($\beta = 0.218$, $P < 0.001$), and IUAC ($\beta = 0.491$, $P < 0.001$) endorse hypotheses H1 through H7.

Table 4.5: R^2 of the Endogenous Latent Variables.

	R-square	Results
Actual AI Chatbot Usage	0.845	Substantial
Intention to Use AI Chatbots	0.865	Substantial
PEU	0.756	Substantial
PU	0.763	Substantial
SDLT	0.681	Substantial

The hypothesis testing results reveal varying strengths in the relationships between the variables shown in Figure 5. The strongest relationship was found between Technological Acceptance (TA) and Learning Motivation (LM) on SDLT (H13), with a high t-value of 15.446. Additionally, ICT self-efficacy strongly influenced PEU (H1) with a t-value of 7.040, suggesting that confident ICT users perceive technology as easier to use. SDL also positively impacted Actual AI Chatbot Usage (AACU) (H7), with a t-value of 2.793. Moderate relationships were observed between External Perceived Ease (EPE) and Intention to IUAC (H12), with a t-value of 3.174, and between IUAC and AACU (H8), with a t-value of 3.065. PU positively influenced IUAC (H4), with a t-value of 2.979 that showed in Table 4.6.

Table 4.6: Hypotheses-Evaluation of Study Framework (significant at $p^{**} <= 0.01$, $p < 0.05$).

Hypothesis	Relationships	Path	T statistics (|O/STDEV|)	P-value	Direction	Decision
H1	ICT SE->PEU	0.617	7.040	0.000	Positive	Validated
H2	ICT SE->PU	0.312	1.967	0.049	Positive	Validated
H3	PEU->PU	0.510	4.140	0.000	Positive	Validated
H4	PU->IUAC	0.403	2.979	0.003	Positive	Validated
H5	PEU->IUAC	0.058	0.522	0.002	Positive	Validated
H6	SDLT->IUAC	0.218	1.618	0.005	Positive	Validated
H7	SDLT->AACU	0.468	2.793	0.005	Positive	Validated
H8	IUAC->AACU	0.491	3.065	0.002	Positive	Validated
H9	TBSE->PU	0.102	1.120	0.026	Positive	Validated
H10	TBSE->PEU	0.300	3.201	0.001	Positive	Validated
H11	PC->IUAC	0.012	0.084	0.033	Positive	Validated
H12	EPE->IUAC	0.420	3.174	0.002	Positive	Validated
H13	TA & LM->SDLT	0.827	15.446	0.000	Positive	Validated

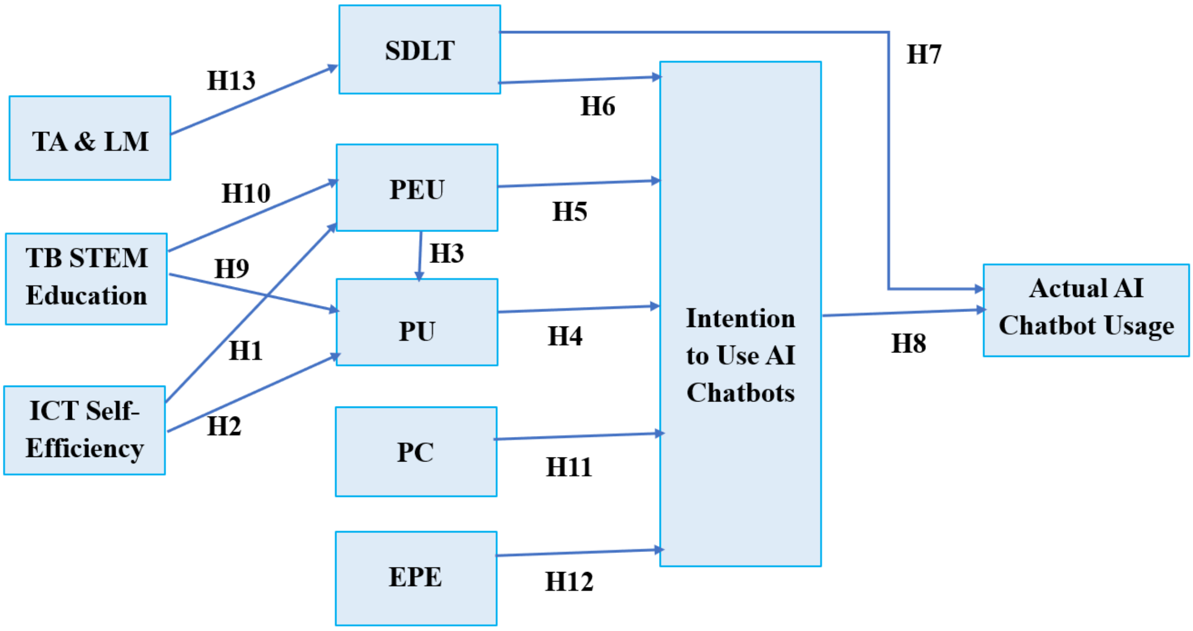

Figure 3: Research model.

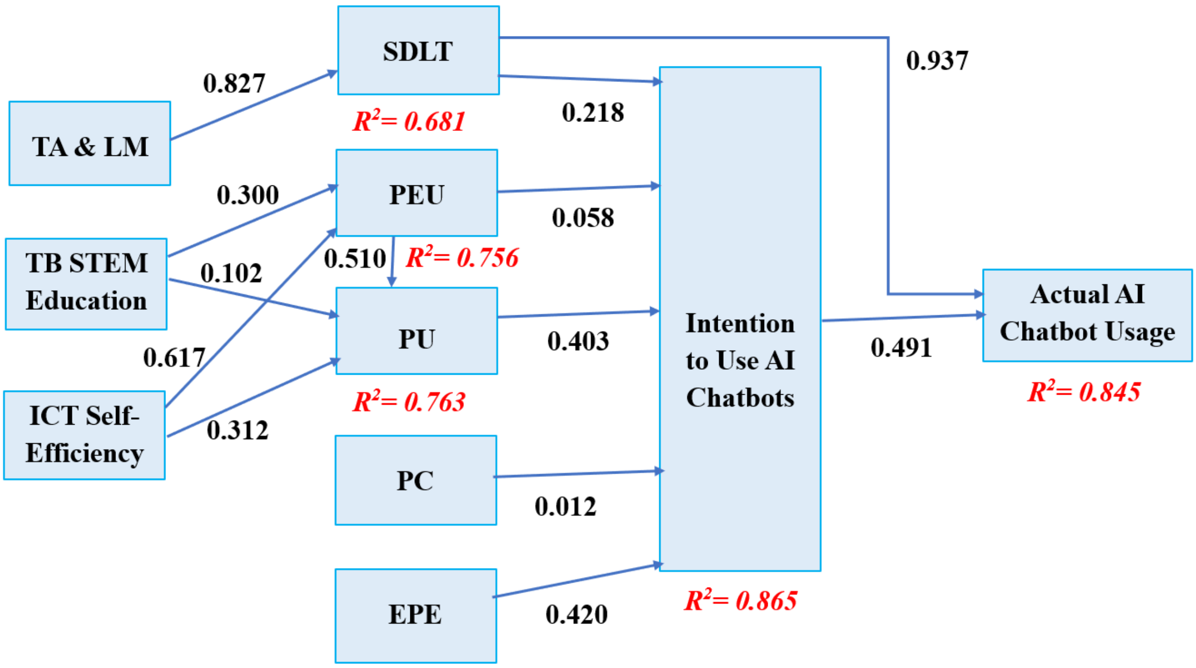

Figure 4: Path coefficient of the model (significant at $p^{**} <= 0.01$, $p^{*} < 0.05$).

ANN Results

The research involves the use of SPSS to conduct ANN analysis (Pellas, 2025), using only the predictors obtained from PLS-SEM i.e., the analysis only accounts for factors of PEU, PC, SDLT, AACU, EPE, ICTSE, and TA&LM. The structure of the ANN model is given in Figure 5–8; a single output neuron (users' intention to use AI Chatbots), along with multiple input neurons (PEU, PU, PC, EPE, SDLT) constitute the ANN model. To facilitate deep-learning in every node of the output neuron, a deep ANN structure with two-hidden layers was used in this study (Tam et al., 2020). The sigmoid function was also applied to hidden and output neurons as an activation function. Furthermore, the investigate demonstrate was made more capable in terms of execution by institutionalizing the input and yield neurons within the range [0, 1]. The training and testing data were taken in the ratio 90:10 while applying the ten-fold cross-validation technique to prevent ANN models from over-fitting. The root mean square of error (RMSE) is assessed to decide the accuracy of the neural network model. The RMSEs evaluated for training data was 0.1256 and for testing data was 0.1523. The ANN enhanced the accuracy of proposed research model as is evident from the insignificant disparity between values of SD (standard deviation) and RMSE evaluated for training data (equalling to 0.0081) and testing data (equalling to 0.0094). Here, the bias nodes appear disconnected from some parts of the network, particularly the output layer. The absence of explicit connections from the bias nodes does not mean they are unused or non-functional rather, it is a common simplification in neural network visualizations that is also present here.

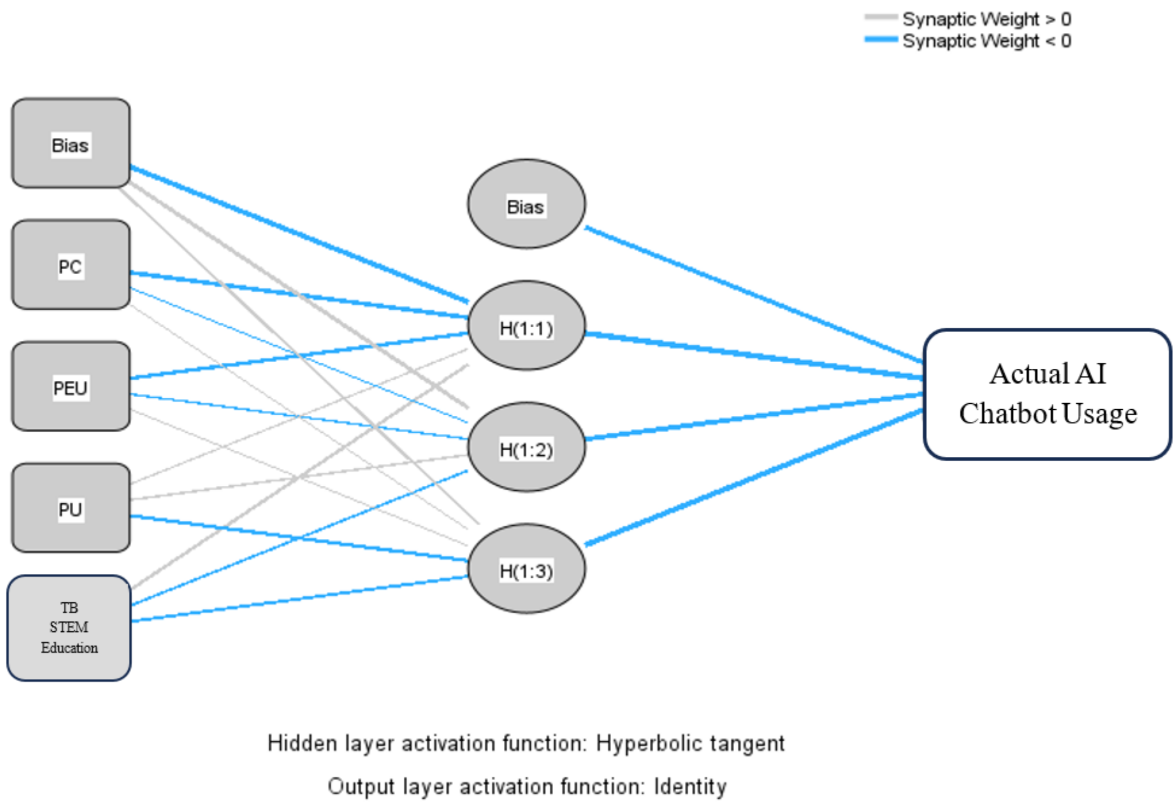

Figure 5: ANN model.

A neural network model that predicts AI chatbot usage based on four input factors—Perceived Utility (PU), Perceived Ease of Use (PEU), Perceived Compatibility (PC), and Training-Based STEM Education—is depicted in the diagram. Three neurons in the hidden layer use the hyperbolic tangent activation function, which produces values in the range of -1 and 1. The output layer directly predicts chatbot usage using an identity activation mechanism.

The neural network model predicts the deliberate to utilize AI chatbots based on four inputs: Perceived Compatibility (PC), Perceived Ease of Utilize (PEU), Perceived Usefulness (PU), and Preparing and Intensification of Dialect Models (TAampLM). The covered up layer comprises of two neurons employing a hyperbolic digression actuation work to capture nonlinear designs. The neural organize show predicts PC based on three inputs: Expected Performance Enhancement (EPE), Preparing and Intensification of Dialect Models (TAampLM), and PEU.

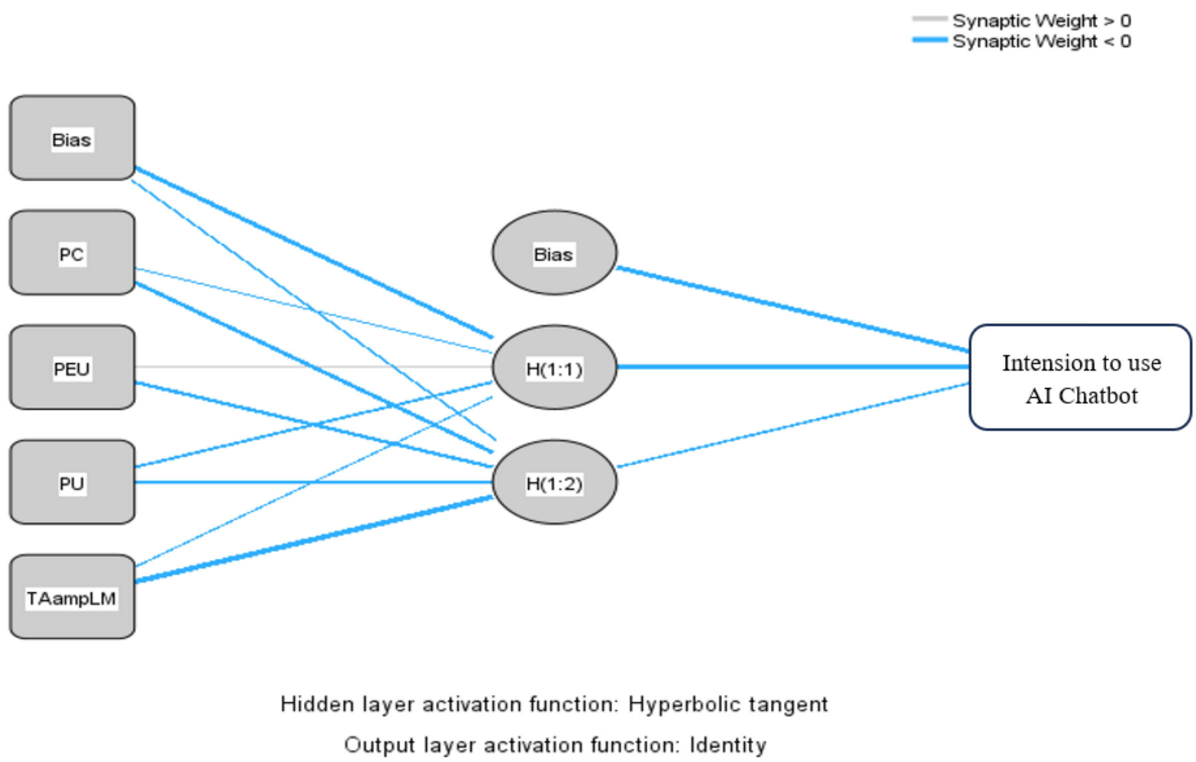

Figure 6: ANN model.

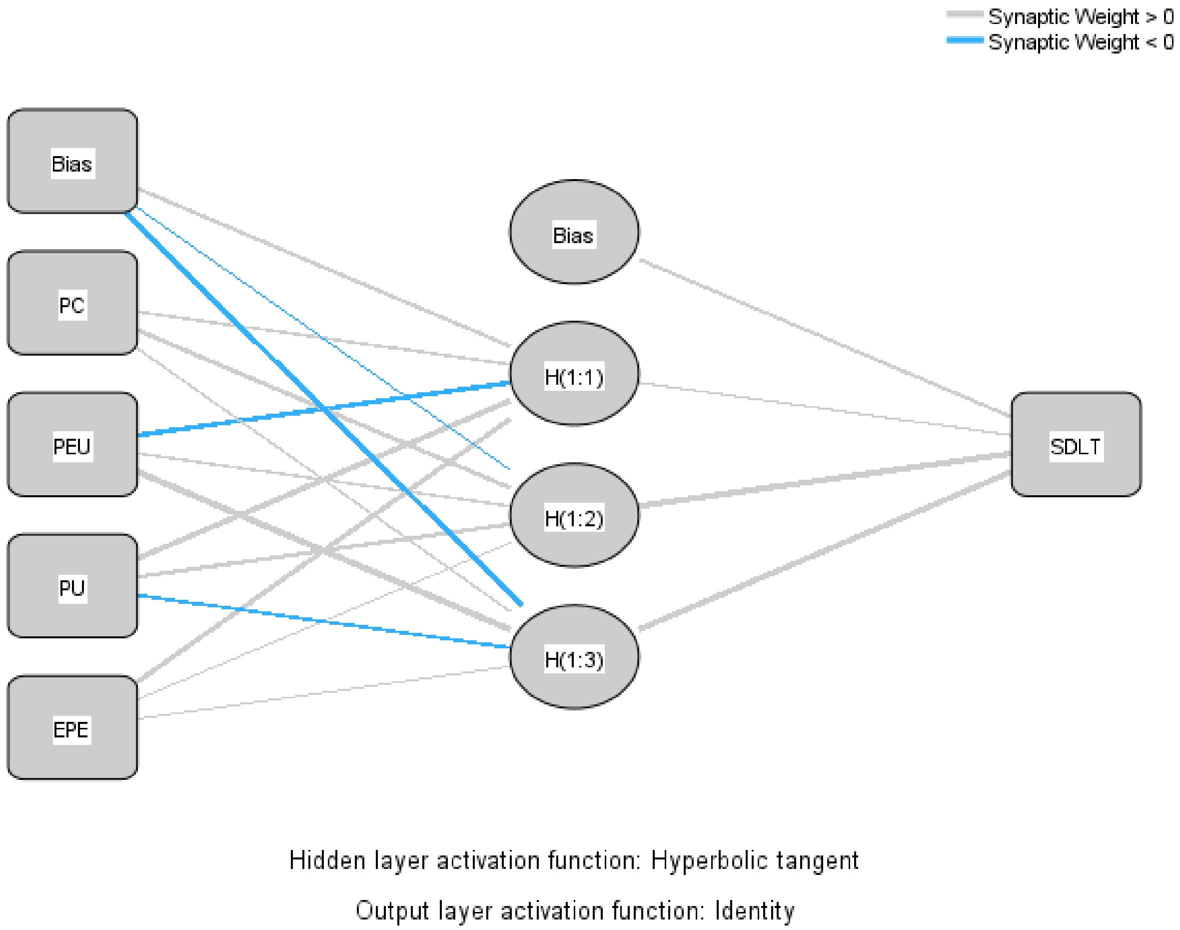

Figure 7: ANN model.

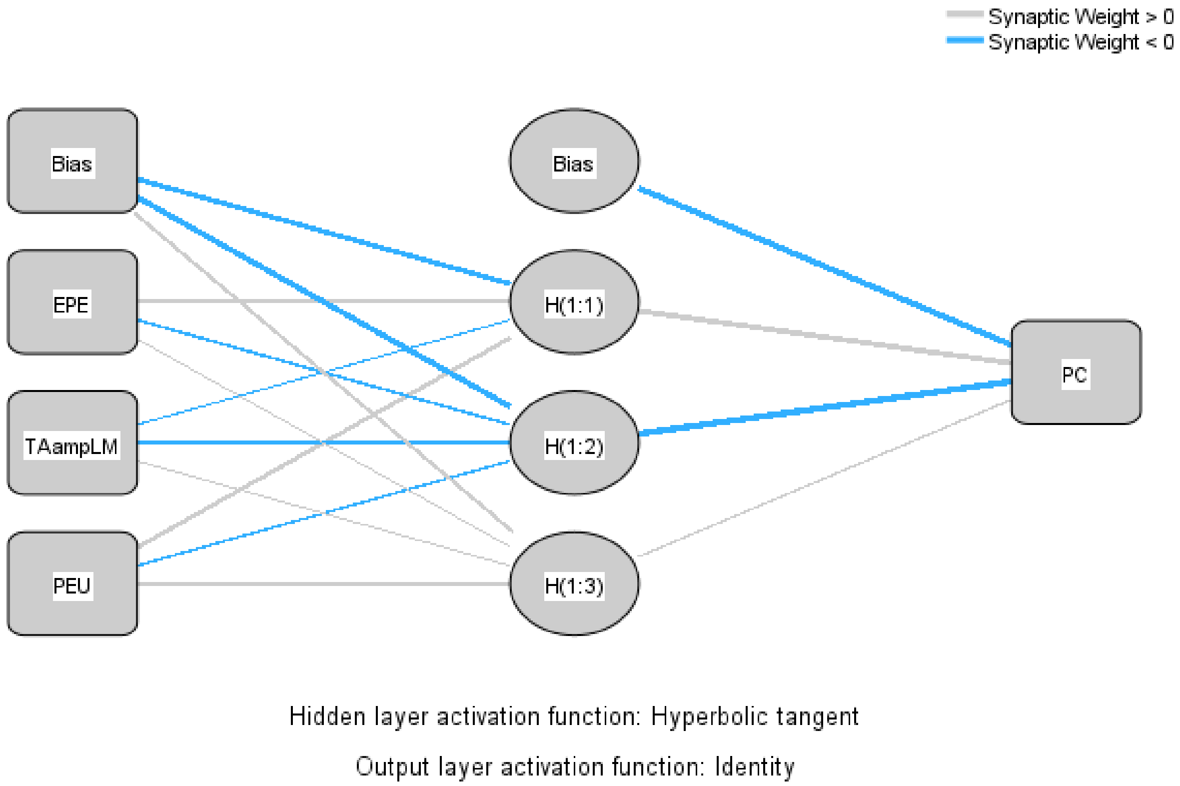

Figure 8: ANN model.

This diagram illustrates a feedforward neural network with three input features (EPE, TAampLM, and PEU), a bias node, and a hidden layer of three neurons using the hyperbolic tangent activation function. The output layer produces a single result labeled ”PC” using an identity activation function, suitable for regression tasks. Connection lines show synaptic weights, where gray indicates positive weights and blue indicates negative weights.

Sensitivity analysis

Normalized importance for each predictor is determined by calculating the ratio of its average importance value to the maximum mean importance value, and it is expressed as a percentage (Kong et al., 2025). All indicators incorporated in the ANN demonstration were evaluated for both raw significance value and normalized significance value. The resulting values are documented in Table 4.7. Furthermore, the results of the sensitivity analysis presented in Table 11 indicate the relative significance of the three factors among EPE, PC, PEU, PU, SDLT, TAampLM, TBSTEMEducation, ICTSelfEfficacy, and IntentiontoUseAI-Chatbots, with IntentiontoUseAIChatbots being the most influential. An additional fit measure known as goodness-of-fit is employed to evaluate the ANN application and enhance its accuracy and performance, which has been corroborated by other fit metrics. Goodness-of-fit measure renders the same function in ANN application as R2 in PLS-SEM analysis. However, ANN analysis offers better explanation of endogenous constructs, as it is attributed with greater predictive power (R compared to PLS-SEM ($R^2 = 86.5\%$). Furthermore, since deep-learning ANN procedure superior clarifies the non-linear connections between demonstrate builds, there’s some dissimilarity within the values of changes.

Table 4.7: Independent Variable Importance.

	CIndependent Variable Importance	
	Importance	Normalized Importance
EPE	0.056	19.5%
ICTSelfEfficacy	0.073	25.5%
IntentiontoUseAIChatbots	0.287	100.0%

	CIndependent Variable Importance		
	Importance	Normalized tance	Impor-
PC	0.158	55.1%	
PEU	0.054	18.7%	
PU	0.023	8.0%	
SDLT	0.213	74.1%	
TAampLM	0.070	24.2%	
TBSTEMEducation	0.066	22.8%	

Importance-Performance Map Analysis

Figure 9 represents the IPMA analysis. In this research, the IPMA technique was used within the PLS-SEM framework, with behavioural purpose selected as the outcome variable. IPMA enhances the interpretation of structural model results by incorporating both the relevance (importance) and effectiveness (performance) of latent variables.

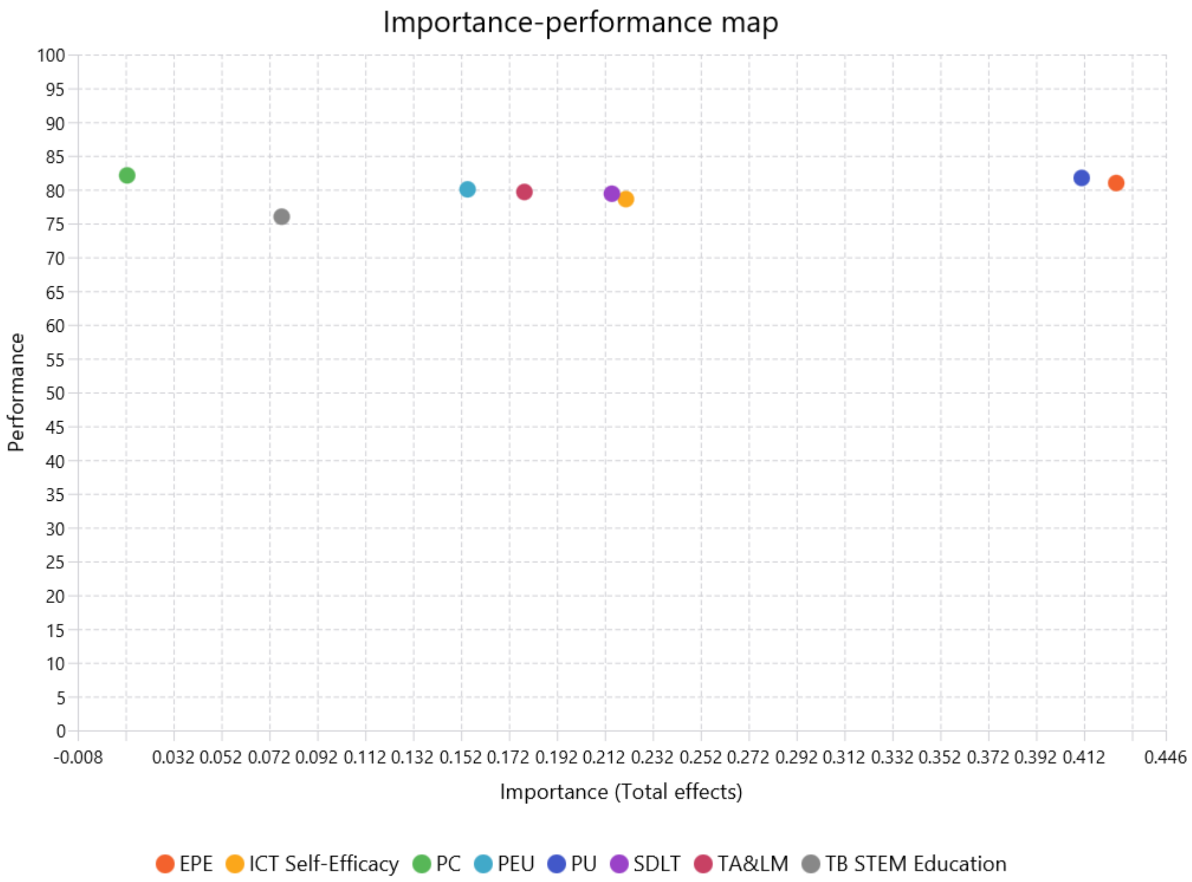

Figure 9: IPMA results.

As highlighted by Ringle and Sarstedt (2016), this approach goes beyond merely assessing path coefficients; it also evaluates the average performance levels of constructs and their associated indicators. The fundamental idea behind IPMA is to identify which variables have the strongest influence on the target variable and how well those variables are performing. In this study, ten constructs were examined: EPE, ICT self-efficacy, PC, PU, PEU, SDLT, TA, LM, and TB STEM education, all in relation to the aim to engage AI chatbots. Among these, PC demonstrated the highest performance, while TB STEM education scored lowest in performance but ranked third in terms of importance (Parsakia et al., 2023). Notably, ICT self-efficacy was found to have the least impact on behavioural intention.

A concise conceptual framework diagram

Figure 10 represents perceived usefulness and perceived ease of use are treated as core TAM variables, while convenience and ICT self-efficacy are conceptualized as external factors influencing users' perceptions and behavioral intentions. Motivation and self-directed learning are incorporated as mediating learning-related constructs that explain how technology acceptance translates into meaningful learning engagement.

This diagram presents a conceptual framework based on the TAM that explains how different factors influence students' engagement and acceptance of STEM technology. At the beginning, external factors play a crucial role. These include ICT self-efficacy and convenience. ICT self-efficacy refers to a learner's confidence in their ability to use digital tools effectively. When students believe they can handle technology, they are more willing to explore and use it. Convenience refers to how easy it is to access and use technology in terms of time, availability, and effort. If technology is easily accessible and user-friendly, students are more likely to adopt it.

These external factors directly influence the core components of the TAM, which are Perceived Ease of Use (PEOU) and PU. Perceived Ease of Use means how simple and effortless the technology feels to the user. If a system is easy to operate, students will feel more comfortable using it. Perceived Usefulness refers to how much a student believes that using the technology will improve their learning performance. When students see real benefits, such as better understanding or improved results, they develop a positive attitude toward the technology.

Next, these perceptions affect learning-related factors, specifically motivation and self-directed learning. Motivation is the internal drive that encourages students to engage with learning activities. When students find technology useful and easy to use, their interest and enthusiasm increase. Self-directed learning refers to the ability of students to take control of their own learning process, such as setting goals, managing time, and seeking resources independently. Technology that is accessible and beneficial supports learners in becoming more independent and responsible.
Finally, all these factors lead to the ultimate outcomes: STEM technology acceptance and learning engagement. Technology acceptance means students are willing to adopt and consistently use digital tools in their studies. Learning engagement refers to how actively and deeply students participate in the learning process. When students are confident, motivated, and able to learn independently, they become more engaged and are more likely to accept and integrate technology into their STEM education.
In summary, the model shows a clear flow: external factors shape students' perceptions, these perceptions influence their learning behaviors, and ultimately, these behaviors determine how well students accept and engage with STEM technology.

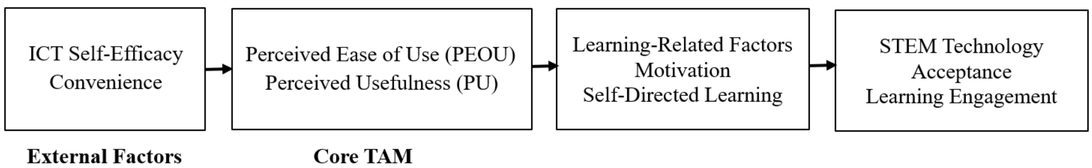

Figure 10: Concise conceptual framework.

5 Discussion

In this research, we used Smart PLS 4 to perform Partial Least Squares (PLS) analysis and IBM SPSS for ANN analysis. Our methodology included evaluating reliability and validity, in addition to analyzing the path coefficients to assess the strength of the framework design. We aimed to investigate the relations among various concepts, such as ICT self-efficacy, Technology-Based STEM Education (TBSE), PEU, PU, EPE, IUAC (INT), Actual AI Chatbot Usage (ACT), and SDLT.

We opted for PLS for SEM in this investigation due to its capability to manage complex models and simultaneously measure multiple items, which is crucial for comprehending causal relationships among variables. Furthermore, PLS is particularly effective for assessing intricate predictive models that involve a range of research constructs and variables, making it a suitable choice for our study.

The current research explored the integration of AI-driven applications within STEM education and their impact on problem-solving abilities and self-efficacy, utilizing the SPLSS model. The results reveal that students' views on AI-integrated STEM applications are strongly shaped by their PEU, PU, as well as their personal sense of self-efficacy. These elements are vital in shaping students' readiness to adopt AI-based learning tools, aligning with previous research on technology acceptance in educational contexts. Specifically, students who view AI applications as easy to use and beneficial for their academic progress exhibit increased confidence in their problem-solving capabilities, which subsequently encourages higher adoption and continued usage.

The high predictive accuracy of the ANN model confirms that factors such as perceived usefulness and expected performance gains are vital drivers of engagement. Ultimately, by providing real-time, adaptive feedback and personalized learning pathways, these AI systems bridge the gap between traditional instruction and independent problem-solving, fostering an environment where students feel empowered to explore STEM concepts with greater self-efficacy and reduced cognitive strain.

The study's findings highlight the important effect of PEU in guiding students' attitudes toward technology acceptance. The robust correlation between self-efficacy and PEU suggests that students are more inclined to interact with AI-powered applications when the user interface is intuitive and requires minimal effort to navigate. This result corroborates the idea that students prefer educational tools that are user-friendly and can be seamlessly integrated into their academic work. Additionally, the research shows that PU positively influences students' intentions to engage with technology, suggesting that when students recognize the tangible benefits of AI in enhancing their STEM learning experiences, their likelihood of adopting such technologies increases.

The outcomes of the research offer strong confirmation for the idea that AI-based tools in STEM education significantly contribute to boosting students' problem-solving skills and self-esteem. Future study should investigate the impact of extra factors, like gamification, interactive simulations, and AI-facilitated collaborative learning environments, on enhancing outcomes in STEM education. Moreover, long-term studies could be conducted to assess the lasting effects of AI-driven educational programs on students' academic performance and readiness for careers in STEM fields.

Theoretical and Practical Implications

This research builds upon earlier empirical studies by implementing the SPLSS model instead of relying exclusively on traditional statistical methods. The study adopts a novel hybrid analytical approach, thereby enhancing its contribution to the body of literature on AI-enhanced STEM education. Furthermore, the SPLSS model exhibits greater predictive accuracy than conventional SEM-based models, largely due to its advanced ability to detect intricate, non-linear interactions among the elements of the theoretical framework. By utilizing latent semantic structures, SPLSS provides deeper understanding into how problem-solving abilities are connected to individuals' sense of self-efficacy, establishing a more holistic model for grasping the role of AI-powered learning within STEM education. Besides, ANN demonstrate is credited with more prominent prescient control in comparison to PLS-SEM show basically due to the extra preferences advertised by profound ANN design in distinguishing of non-linear affiliation of hypothetical demonstrate components.

Managerial Implications

The study presents key managerial implications for enhancing AI-powered STEM education tools. Developers should focus on user-friendly designs and clearly communicate academic benefits to boost adoption. Institutions must improve students' ICT self-efficacy through targeted training and promote SDL by integrating AI tools into learning platforms. Motivation and perceived performance gains should be emphasized via personalized feedback and gamified features (Pellas, 2025) Tailoring tools specifically for STEM content is essential, as revealed by IPMA analysis. Lastly, using predictive models like SPLSS and fostering cross-functional collaboration can guide effective, data-driven decision-making and product development.

Constraints of the Current Research and Directions for Upcoming Investigations

This study is subject to a number of constraints. Firstly, the conceptual framework is constrained by its emphasis on a narrow range of variables, mainly problem-solving abilities and self-efficacy, without accounting for other psychological or environmental elements that could affect students' engagement with AI-enhanced STEM applications. Secondly, the analysis utilizes the SPLSS model, which, although useful, may not fully encompass the complexities of students' interactions with AI-based learning tools. Thirdly, data collection was carried out via online surveys, which could introduce sample bias, as students who are more knowledgeable or interested in AI technologies might have been more inclined to participate. Fourthly, while AI-powered applications can be applied in various educational contexts beyond STEM, this study is specifically centered on STEM education, which restricts its applicability to other disciplines. In addition, this article employed a convenience sample drawn from a single institutional context, which may limit the representativeness of the findings and the potential for response bias inherent in self-reported survey data, despite the use of validated measurement scales and statistical checks for common method bias. The cross-sectional design and reliance on perceptual measures are recognized as constraints on causal inference. Future research should investigate a wider array of influencing factors, including motivation, cognitive load, and long-term learning outcomes, and should also consider experimental or longitudinal methods to assess the lasting effects of AI-driven learning tools on students' academic success and self-efficacy (Lai, 2023). Besides, it can be overcome the limitations by employing multi-site and probability-based sampling across diverse institutions to improve representativeness and generalizability. To reduce response bias, studies should combine self-reported surveys with objective measures such as system log data, learning analytics, or observational methods. Longitudinal or experimental designs would allow stronger causal inferences and capture changes in students' perceptions and behaviors over time. Finally, validating the proposed model across different disciplines, educational levels, and cultural contexts would enhance the robustness and transferability of the findings.

6 Conclusion and Future Work

6.1 Conclusion

This research establishes a comprehensive framework for comprehending how AI-driven applications in STEM education can improve students' problem-solving skills and bolster their confidence. By examining the relationships among ICT self-efficacy, user-friendliness, PU, and motivation to learn, the study emphasizes the significance of AI chatbots in creating a more involving and active learning experience. The findings reveal that these chatbots not only facilitate interactive learning but also motivate students to actively steer their own educational journeys. The ponder affirmed that students' self-efficacy in ICT is pivotal in forming their sees on AI chatbots, with user-friendliness and PU being basic components for innovation acknowledgment. The results demonstrated that AI contributes to increased engagement, enhanced problem-solving capabilities, and greater confidence in learning. SEM analysis reinforced the notion that AI-based tools can significantly improve STEM education, provided they are implemented in conjunction with traditional teaching methods for optimal results. The research underscores the necessity of further refining AI-driven educational tools to ensure they are user-friendly, effective, and inclusive for learners from various backgrounds. By leveraging AI chatbots, students can receive immediate support, personalized learning experiences, and an interactive setting that fosters improved problem-solving and deeper engagement. Looking ahead, it is vital to investigate the enduring effect over time, versatility, and integration of rising advances to progress AI-based instruction and maximize its benefits for understudies around the world. It can too outline how understudies see the innovational innovation utilized in instruction.

6.2 Future Work

- Future research should examine additional psychological and learning factors such as motivation, cognitive load, and long-term academic outcomes to broaden the model.
- Looking ahead, it is vital to investigate the enduring effect over time, versatility, and integration of rising advances to progress AI-based instruction and maximize its benefits for understudies around the world.
- Finally, combining self-reported data with objective measures like system logs and learning analytics would reduce response bias.

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