Digital Culture and Education Review

ScienceIngress PUBLISHER

Vol.1, Issue.1, (2025)

Digital Culture and Education Review

Empowering the Future through Unleashing AI's Potential in Education to Transform Learning and Boost Digital Literacy

Sergey Barykin[1*], Sergey Sergeev[1], Olga Voronova[1], Ivan Golub[1]

[1]Peter the Great St. Petersburg Polytechnic University, St. Petersburg, 195251, Russia

Article Information

Article Type: Research Article

Dates:
Received: 21 March 2025
Revised: 19 April 2025
Accepted: 28 May 2025
Available online: 16 June 2025

Corresponding Author: Sergey Barykin
sbe@list.ru
ORCID: https://orcid.org/0000-0002-9048-009X

ABSTRACT

Recently, artificial intelligence (AI) has become a driving force in education, revolutionizing traditional learning models and opportunities to learn digital literacy. Studies that have examined the effect of AI on teaching and learning are scarce, as are those that investigate the relations between AI integration, teacher proficiency, student engagement, and digital literacy on educational platforms.

In this study, AI integration in educational platforms is explored as it plays a part in education digital literacy development and the transformation of learning spaces. The research employs the Technology Acceptance Model (T-A-M) to investigate how AI-based platforms, teacher AI ability, and student engagement affect learning satisfaction. Methodology: data collected from 219 Russian students were analyzed using a structural equation modeling (SEM) approach. The study found that AI integration in educational platforms magnifies student engagement, which, in turn, mediates the relationship between AI adoption and student learning satisfaction. The path coefficient of 0.215 and T-value of 5.429 also indicated the effect of engagement, although of positive and significant value on satisfaction, when contributing to AI-supported learning processes.H3 was conducted to examine the direct effect of teacher AI proficiency on learning satisfaction. This relationship had a path coefficient of 0.144; the T value was 3.531, indicating a significant positive effect. Whereas teacher's AI proficiency positively affects students' engagement with AI tools. This relationship was strongly supported by a path coefficient of 0.268 and a T value of 7.312, implying that teacher expertise in AI significantly improved students' willingness to interact with AI-driven technologies. The results suggest that perceived usefulness and ease of use, as conceived in T-A-M, are likely facilitating factors of digital literacy development through student engagement. Within the context of education, building upon T-A-M, this study extends the framework to incorporate teacher proficiency and engagement to extend our understanding of the adoption of AI in education. The implications of the research suggest the need for professionals to develop AI platforms and design user-friendly AI platforms.

Keywords: Educational revolution, Digital literacy, AI in education, Technology acceptance model (T-A-M), Student engagement

1. INTRODUCTION

Education stands out as an industry in which Artificial Intelligence (AI) is revolutionizing, and with AI, it is possible. Innovative teaching methodologies, personalized learning experiences, and academic achievements are experiencing resurrection through the integration of AI technologies in educational ecosystems (Yao & Wang, 2024). Such adaptive learning technology platforms can also use AI to assess the strengths and weaknesses of each learner and design content relevant to their needs (Hanum et al., 2024). Similarly, AI-powered tools like chat-bots and virtual assistants simplify administrative processes that leave educators to focus on pedagogy and stimulate student engagement. While these advancements show tremendous promise, there are big questions about what they mean for digital literacy and their implications for equitable access to learning environments powered by AI (Lijie et al., 2024).

As a robust theoretical foundation to explain the acceptance of emerging technologies, the Technology-Acceptance Model (T-A-M) was first underscored by (Davis, 1989). T-A-M perceives the usage of perceived usefulness (PU) and perceived ease of use (PEOU) to significantly impact users' attitudes and behavioral intentions to adopt technology. T-A-M has been widely used by scholars who have attempted to shed light on how students and educators perceive and embrace innovative tools (Venkatesh et al., 2003). While there has been previous work on cognitive determinants of technology adoption, such as usefulness and usability, the emotional and motivational aspects constituting digital literacy in the context of AI-enabled educational environments have not been well considered. This is especially true at a time of increasing reliance on AI to support education (Davis, 1992). Its ability to require critical thinking, algorithm literacy, and ethical engagement with AI in digital literacy (Yao & Wang, 2024).

This research contributes significantly to the existing theory of AI as a re-inventor of learning spaces and how it propels the need to understand digital literacy. In particular, it examines how students respond and relate to AI-enabled educational technology and how those interactions shape the development of students' digital literacy abilities. By leveraging the T-A-M framework, the study aims to address the following research questions:

RQ1: *How does adopting AI in education influence students' perceptions of digital literacy?*

RQ2: *What role do perceived usefulness and ease of use play in mediating the relationship between AI adoption and digital literacy development?*

This study introduces a novel perspective by integrating the Technology Acceptance Model (TAM) with the emerging concept of digital literacy within AI-enabled educational environments. While prior research has extensively focused on cognitive factors such as perceived usefulness and ease of use in technology adoption, this study uniquely emphasizes digital literacy's emotional, motivational, and ethical dimensions. It shifts the focus from mere adoption to the transformative impact of AI on students' digital literacy development. Doing so addresses a critical gap in the existing literature that how students' interactions with AI-powered tools shape their ability to think critically, understand algorithms, and engage ethically with technology. This approach broadens the application of TAM and provides new theoretical insights into the evolving relationship between AI and education.

2. LITERATURE REVIEW

2.1 Technology acceptance model (T-A-M)

It is assumed that the adoption and use of technology are determined by two factors: perceived usefulness (PU) and perceived ease of use (PEOU) (Davis, 1989). PU is the user's belief that using a particular technology will facilitate his or her performance, and PEOU is the level at which the user thinks the technology is easy to use. The T-A-M has been used widely by educational research to study how people accept different technologies like learning management systems, e-learning tools, and AI technology (Venkatesh et al., 2003). Taking the context of AI in education, PU and PEOU impact how much students and educators want to use AI tools like intelligent tutoring systems and personalized learning applications (Marangunić & Granić, 2015).

2.2 Education and digital literacy

Digital literacy is undergoing a redefinition by AI: from being technically proficient to a more dynamically skillful approach involving critical thinking, reasoning about ethics, and collaborating in AI environments (Chisom et al., 2023). In the age of AI, digital literacy includes assessing critically AI-generated content, comprehending algorithmic biases, and behaving responsibly concerning AI (Memarian & Doleck, 2024). If this study have to integrate AI into education, then the people who need to develop digital literacy skills, both students and educators, would have to be adaptive. Recent studies mention that educational institutions cannot ignore digital literacy as a core competency for which the learners must receive equitable access to learning opportunities driven by AI (Memarian & Doleck, 2024).

2.3 Theoretical framework and hypotheses development

2.3.1 Research model

This study proposes an integrated T-A-M-based research model by integrating the existing literature. The research model aims to study the nexus among AI integration in education, its relevance to teacher proficiency in AI tools, and the extent of student engagement and learning satisfaction. Using this model, this study add to the Technology Acceptance Model (T-A-M) by adding factors that affect student and teacher interaction with AI-driven platforms. It hypothesizes direct and mediated relationships between these constructs to understand how AI integration changes an educational environment entirely. The research model is shown in Figure 1.

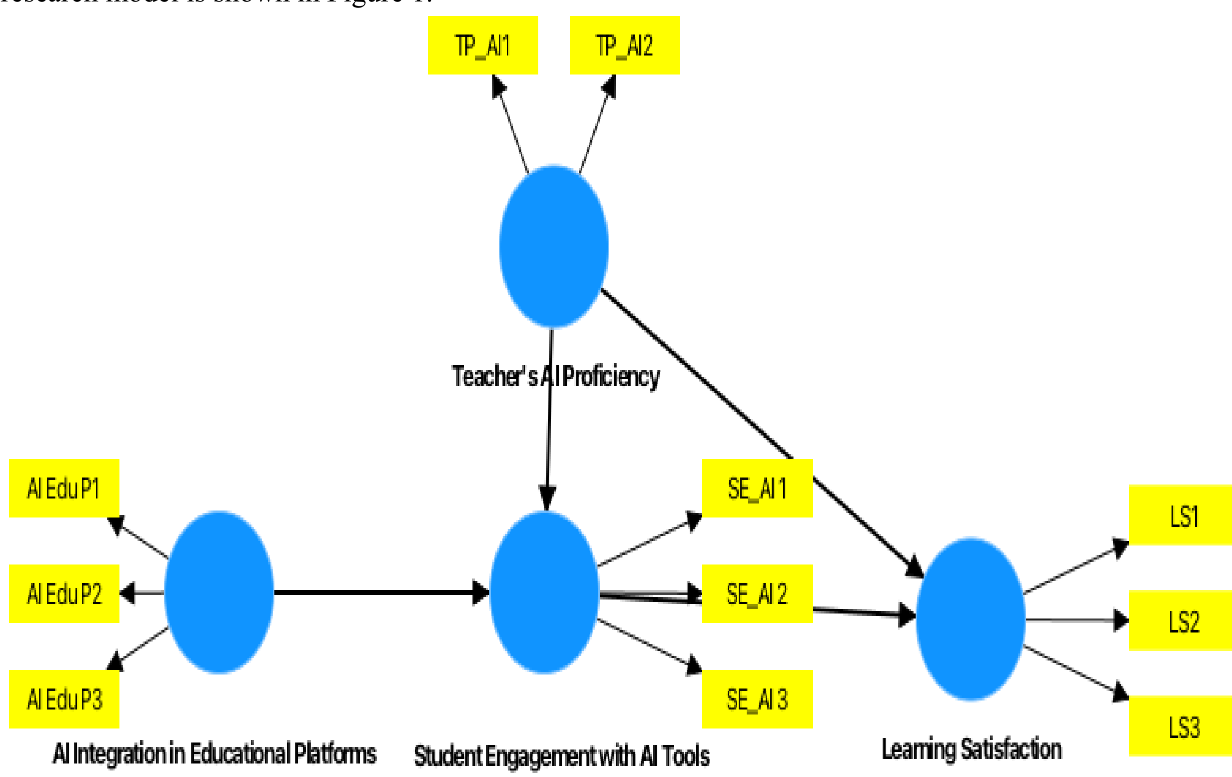

Figure 1: Research Framework

2.4 AI in educational platforms and student engagement with artificial intelligence tools

Educational platforms that use AI integration using AI media-powered technology, specifically adaptive learning systems, chat-bots, and virtual assistants, support learning and teaching. The interactivity and accessibility of learning materials rise to these platforms, so students will be driven to play with AI tools. Previously, AI-enhanced platforms have been shown to increase student motivation (Hu, 2022; Kim et al., 2022). Its provide students with a deeper level of engagement (Pedro et al., 2019). As well as personalize learning pathways (Kim et al., 2022). When students see these platforms as intuitive and helpful to their learning, they will be more likely to interact with the platform. Thus, it has been hypothesized:

H1: *Student engagement with AI tools in educational platforms is positively affected by AI integration.*

2.5 Learning satisfaction with AI tools and student engagement

Active interaction, exploration, and use of AI-driven educational technologies form the gamut of student engagement with AI tools. Academically engaged students will produce better measures of gains and experience higher learning satisfaction (Yao & Wang, 2024). AI tools encourage engagement that leads to a sense of personalization, and thus, learning is more efficient and delightful (Zhang & Aslan, 2021). Studies revealed that when students feel empowered to use AI tools effectively enough, their satisfaction with the learning process increases remarkably (Hu, 2022). Hence, its hypothesize:

H2: *Using AI tools, student engagement in learning is positively influenced by learning satisfaction.*

2.6 Teacher's AI proficiency and learning satisfaction

Teachers' AI proficiency is the degree to which they can use AI technologies to teach and support student learning (Xia et al., 2023). By doing so, proficient teachers can also create AI-strengthened activities, give away instructions, and resolve technical issues to enhance the total learning experience (Nguyen, 2024). Our research found that teacher competency in AI strongly predicts students' perception of the learning environment and satisfaction (Luckin & Holmes, 2016). Thus, it's hypothesized below:

H3: *Increasing teachers' AI proficiency is related to increasing learning satisfaction.*

2.7 Teacher's AI proficiency and student engagement with AI tools

Teachers act as facilitators in users' integration with AI tools. If teachers master AI technologies, they can master how to introduce the tools, demonstrate their usefulness, (Huang et al., 2024) and spark student engagement. This is to give students a feeling of confidence when using AI platforms, and they end up getting engaged (Xia et al., 2023). Previous work makes the important point that teachers can be a vital bridge between technology and students (Pokrivcakova, 2019). Therefore, it's hypothesize:

H4: *High teacher proficiency in AI enhances student engagement with AI tools.*

2.8 Roles of student engagement in mediating the teacher's AI proficiency between the teachers and learning satisfaction

Teachers' AI skill level influences how students learn through its effect on student engagement. By providing access to the AI tools, proficient teachers enable students to explore and use the AI tools with enough depth to increase their engagement and satisfaction with the learning process (Wang et al., 2023). It points to the dynamic dynamism of the interplay between teacher proficiency, student engagement, and learning satisfaction (Huang et al., 2024; Ji et al., 2023). Its hypothesize:

H5: *Teachers' AI proficiency positively influences students' engagement with AI tools and learning satisfaction.*

2.9 Student engagement as a mediating role between AI integration and learning satisfaction

Information and communication technology (ICT) empowers educators and students to achieve metacognitive and metalinguistic knowledge in various complex societies. AI in educational platforms brings opportunities for better student engagement and, in turn, better learning satisfaction. AI platforms are developed to provide personalized, interactive, and participative learning experiences (Chiu et al., 2024; Yao & Wang, 2024). Higher satisfaction with the learning process was found for students who were engaged. Consequently, this mediating relationship emphasizes the need for engagement in remediating the benefits of integration with AI (Lijie et al., 2024). It's hypothesize:

H6: *AI integration in educational platforms affects student engagement with AI tools and increases learning satisfaction.*

3. METHODOLOGY

3.1 Measures

The research model was tested using a survey-based quantitative approach. Items adapted from validated scales from the literature were used to measure the constructs. The AI Integration in Educational Platforms and Student Engagement with AI Tools were measured as items from Mirdad (2024). This study adapted Teacher's AI Proficiency items from (Uerz et al., 2018). Which were focused on students' capacities to assess and appropriately use AI tools critically. Based on the work carried out by Chang and Chang (2012), Learning Satisfaction items were designed to assess the integration of AI in educational environments. A five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree) was used to measure all constructs. Table 1 presents the measurement items in detail.

Table 1. Measurement Items

Construct	Item Code	Measurement Item	Source
AI Integration in Educational Platforms	AI_EduP 1	The AI platform helps personalize my learning experience.	(Mirdad et al., 2024)
	AI_EduP 2	AI-driven tools make accessing educational resources easier and more efficient.	
	AI_EduP 3	Using AI in my educational platform improves the quality of my learning process.	
Student Engagement with AI Tools	SE_AI1	I actively interact with AI tools provided in my educational platform.	(Mirdad et al., 2024)
	SE_AI2	Using AI tools makes me more engaged in learning activities.	
	SE_AI3	I explore the features of AI tools to enhance my understanding of course material.	
Teacher's AI Proficiency	TP_AI1	My teacher effectively integrates AI tools into the learning process.	(Uerz et al., 2018)
	TP_AI2	My teacher is proficient in explaining how to use AI tools effectively.	
Learning Satisfaction	LS1	I am satisfied with the learning experience provided by the AI-driven platform.	(Chang & Chang, 2012)
	LS2	The AI-driven platform meets my expectations for effective learning.	

	LS3	Overall, I am content with the results achieved using the AI tools in my learning environment.

3.2 Sample and data collection

Data were collected from 219 university students in Russia who use AI-driven educational tools. Participants were distributed a structured online questionnaire through email and academic networks. A pilot study with 30 students was conducted to refine the questions. Results from the pilot study showed that the items were clear and relevant to the study objectives.

The dataset contained responses from students from diverse academic disciplines to ensure a representative sample. The 54% of respondents were female, 46% were male, and aged 18 to 25. Registered participants reported using AI tools, such as adaptive learning platforms, virtual assistants, and AI-supported assessment tools. Table 2 presents the demographics of the study.

Table 2: Demographic statistics

Demographic Variable	Categories	Percentage (%)
Gender	Male: 102, Female: 117	Male: 46.6%, Female: 53.4%
Age Group	18-24: 95, 25-34: 78, 35-44: 30, 45+: 16	18-24: 43.4%, 25-34: 35.6%, 35-44: 13.7%, 45+: 7.3%
Education Level	Undergraduate: 130, Postgraduate: 70, Other: 19	Undergraduate: 59.4%, Postgraduate: 32.0%, Other: 8.7%
AI Usage Experience	Beginner: 80, Intermediate: 95, Advanced: 44	Beginner: 36.5%, Intermediate: 43.4%, Advanced: 20.1%
Frequency of AI Tool Usage	Daily: 135, Weekly: 65, Occasionally: 19	Daily: 61.6%, Weekly: 29.7%, Occasionally: 8.7%

3.3 Data analysis

Both data were analyzed via Partial Least Squares Structural Equation Modeling (PLS-SEM), a great approach to analyzing complex models with multiple constructs and mediating relationships using the Smart-PLS program. Hair et al. (2019) two-step approach to analysis (evaluation of measurement model for reliability and validity followed by examination of the structural model to test proposed hypotheses) was followed (Hair et al., 2019) .

3.4 Ethical considerations

Data collection was done only after ethical approval. Participants were informed about this study, and their consent was obtained. The study was maintained anonymously and with confidentiality.

4. RESULTS AND ANALYSIS

4.1 Measurement model

In order to assess the degree of validity and reliability that the research has used the constructs, the measurement model was actually examined (Hair et al., 1998). Measurement properties were evaluated using confirmatory factor analysis (CFA), including internal consistency, convergent, and discriminant validity (Hair et al., 2019). Theoretical concepts under investigation were each analyzed carefully in order to confirm that, for each construct, they are effectively represented.

4.2 Reliability analysis

Cronbach's alpha and composite reliability (CR) were used to assess reliability. All constructs had Cronbach's alpha values greater than 0.7, as seen in Table 3, which means that all items used for measuring the constructs have a strong internal consistency. The composite reliability (CR) values also exceeded the minimum acceptable level (.85), verifying the constructs' reliability. All loadings for individual items were also examined, and all were over the minimum threshold of 0.7 (see Table 3).

Table 3: Reliability analysis

Variables	Item	Factor Loadings	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
AI Integration in Educational Platforms	AI Edu P1	0.890	0.824	0.895	0.74
	AI Edu P2	0.854			
	AI Edu P3	0.835			
Learning Satisfaction	LS1	0.855	0.803	0.883	0.715
	LS2	0.841			
	LS3	0.841			
Student Engagement with AI Tools	SE_AI 1	0.813	0.736	0.85	0.654
	SE_AI 2	0.810			
	SE_AI 3	0.803			
Teacher's AI Proficiency	TP_AI1	0.880	0.776	0.898	0.815
	TP_AI2	0.925			

These results confirm that the items align well with their constructs and provide a good foundation for the measurement model. The reliability analysis is depicted in Figure 2a, 2b, 2c below.

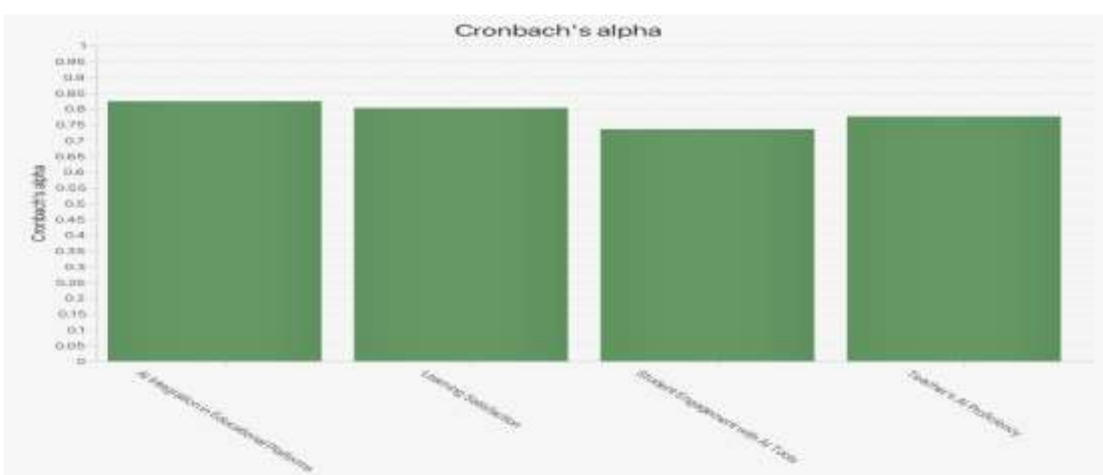

Figure 2a: Graphical Representation of Reliability Analysis

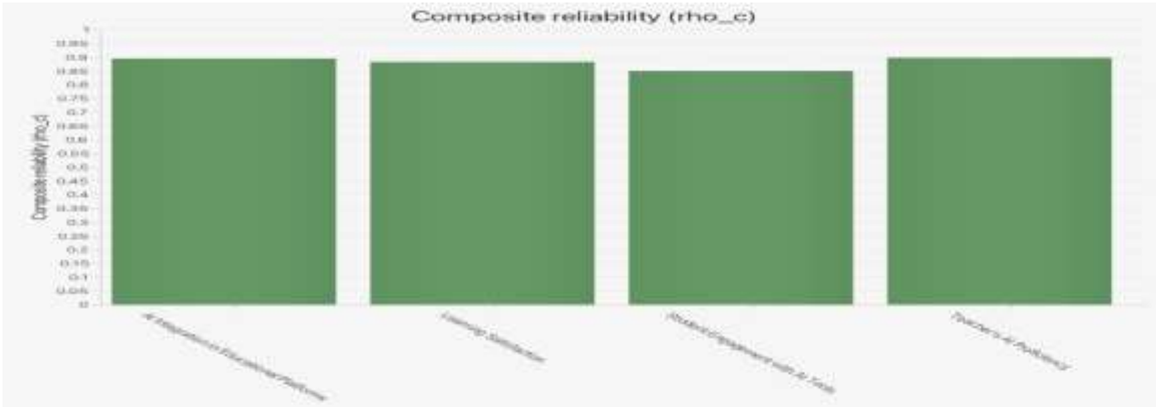

Figure 2b: Graphical Representation of Reliability Analysis

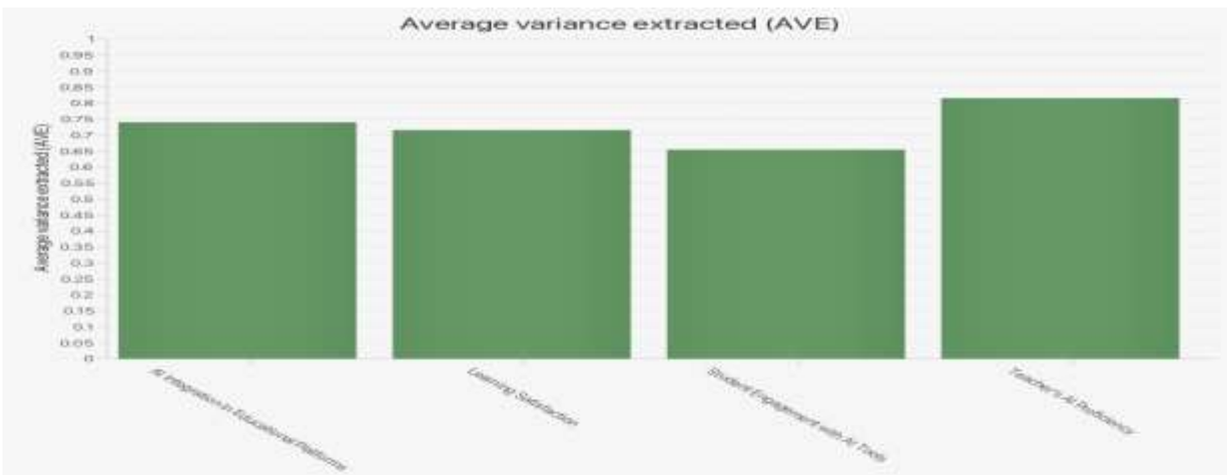

Figure 2c: Graphical Representation of Reliability Analysis

4.3 Convergent validity

AVE scores were calculated, and the data was assessed for convergent validity. As depicted in Table 3, all the construct's AVE were greater than the standard 0.5, meaning that the items measure their constructs well and share enough variance (Ab Hamid et al., 2017). These results demonstrate that each construct measures the theoretical variance it explains.

4.4 Discriminant validity

In the table: 4 discriminant validity was evaluated using the Heterotrait Monotrait Ratio of Correlation (HTMT) and the Fornell–Larcker criterion. As shown in Table 4, all of the HTMT values for construct pairs fell below the suggested threshold of 0.85, indicating that the constructs are distinct and do not share high correlations.

Table 4: Heterotrait-monotrait ratio (HTMT) – Matrix

	AI Integration in Educational Platforms	Learning Satisfaction	Student Engagement with AI Tools	Teacher's AI Proficiency
AI Integration in Educational Platforms				
Learning Satisfaction	0.238			
Student Engagement with AI Tools	0.370	0.333		
Teacher's AI Proficiency	0.205	0.258	0.403	

Furthermore, the results in Table 5 were obtained by applying the Fornell-Larcker criterion, which compared the square root of AVE for each construct with its correlations with other constructs. Diagonal correlations had higher values than off-diagonal ones in all these cases, further supporting the constructs' discriminant validity.

Table 5: Fornell-Larcker criterion

	AI Integration in Educational Platforms	Learning Satisfaction	Student Engagement with AI Tools	Teacher's AI Proficiency
AI Integration in Educational Platforms	0.860			
Learning Satisfaction	0.197	0.846		
Student Engagement with AI Tools	0.290	0.259	0.809	
Teacher's AI Proficiency	0.168	0.210	0.309	0.903

Overall, measurement model analysis results indicate that the constructs used in the study are reliable and valid. As one can see from Cronbach's alpha and CR in Table 3, the constructs are measured consistently across different items, supporting the high internal consistency of the items. The convergent validity of the constructs is supported by the AVE scores that indicate the constructs can capture the variance of their respective indicators. Moreover, the discriminant validity of the constructs is validated via the HTMT analysis (Table 4) and the Fornell-Larcker criterion (Table 5). Figure 3 represents the overall measurement model. The measurement model is the foundation for structural model analysis and testing by providing guaranteed robust reliability and validity. The results presented are essential in demonstrating that these constructs capture the theoretical underpinning of the study and offer valuable insights into the synergistic relationships between AI integration, student engagement, teacher proficiencies, and learning satisfaction within AI-empowered educational platforms.

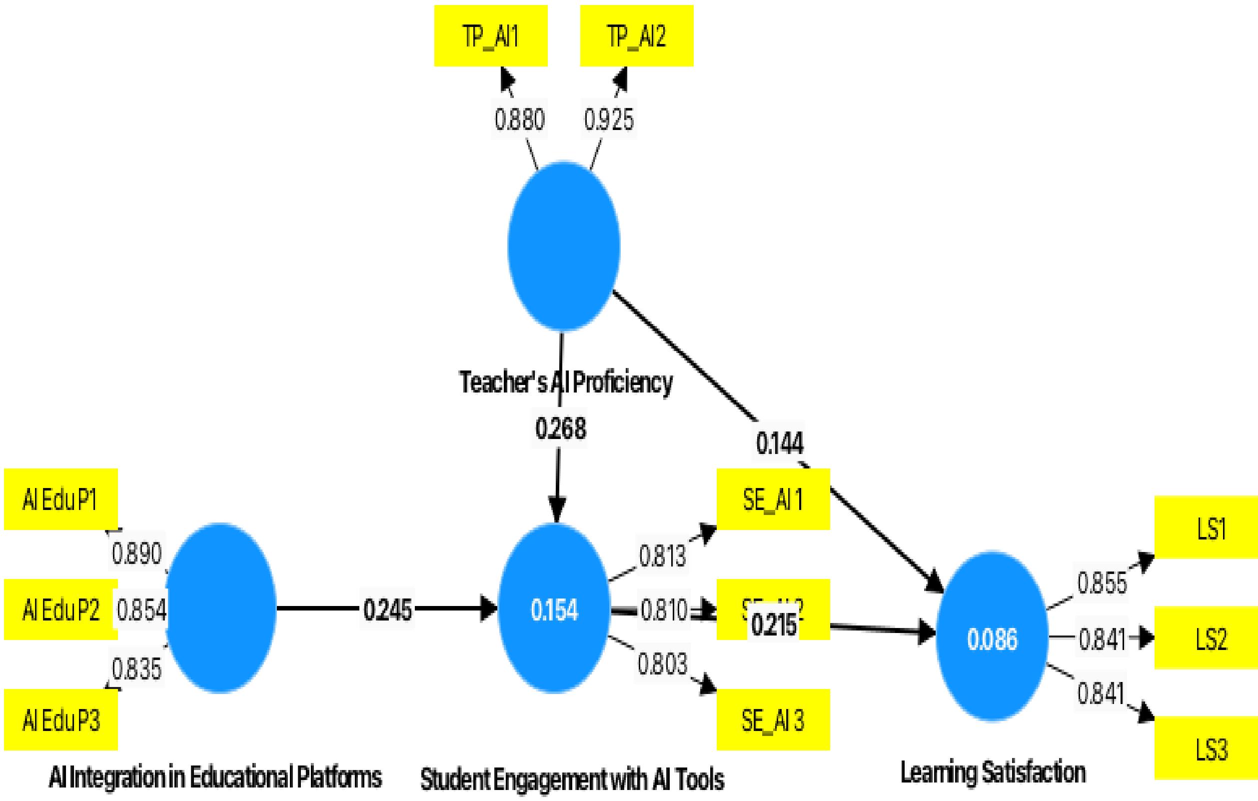

Figure 3: Measurement Model

4.5 Structural model

This study's structural model was analyzed to investigate the hypothesized relationship between AI integration in educational platforms, student engagement with AI tools, teacher AI proficiency, and learning satisfaction. Smart-PLS was used to conduct the analysis, and the results show strength and significance in all of the proposed relationships.

4.6 Hypotheses testing along with path coefficients

Table 6 presents the path coefficients, T statistics, and the p values of the hypotheses. Results indicate that all hypothesized relationships were statistically significant at p 0:05, indicating the structural model's robustness. Figure 4 represents the structural model visually.

Table 6: Path coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI Integration in Educational Platforms -> Student Engagement with AI Tools	0.245	0.247	0.035	6.955	0.000
H2:Student Engagement with AI Tools -> Learning Satisfaction	0.215	0.217	0.040	5.429	0.000
H3:Teacher's AI Proficiency -> Learning Satisfaction	0.144	0.145	0.041	3.531	0.000

H4:Teacher's AI Proficiency -> Student Engagement with AI Tools	0.268	0.269	0.037	7.312	0.000
H5:Teacher's AI Proficiency -> Student Engagement with AI Tools -> Learning Satisfaction	0.058	0.058	0.013	4.312	0.000
H6:AI Integration in Educational Platforms -> Student Engagement with AI Tools -> Learning Satisfaction	0.053	0.054	0.013	3.940	0.000

In figure 4 the results supported the first hypothesis (H1) of the positive impact of AI integration on student engagement with AI tools through a path coefficient of 0.245 and a T value of 6.955. One of these findings also shows that AI integration is integral to engaging students with AI-powered educational tools.

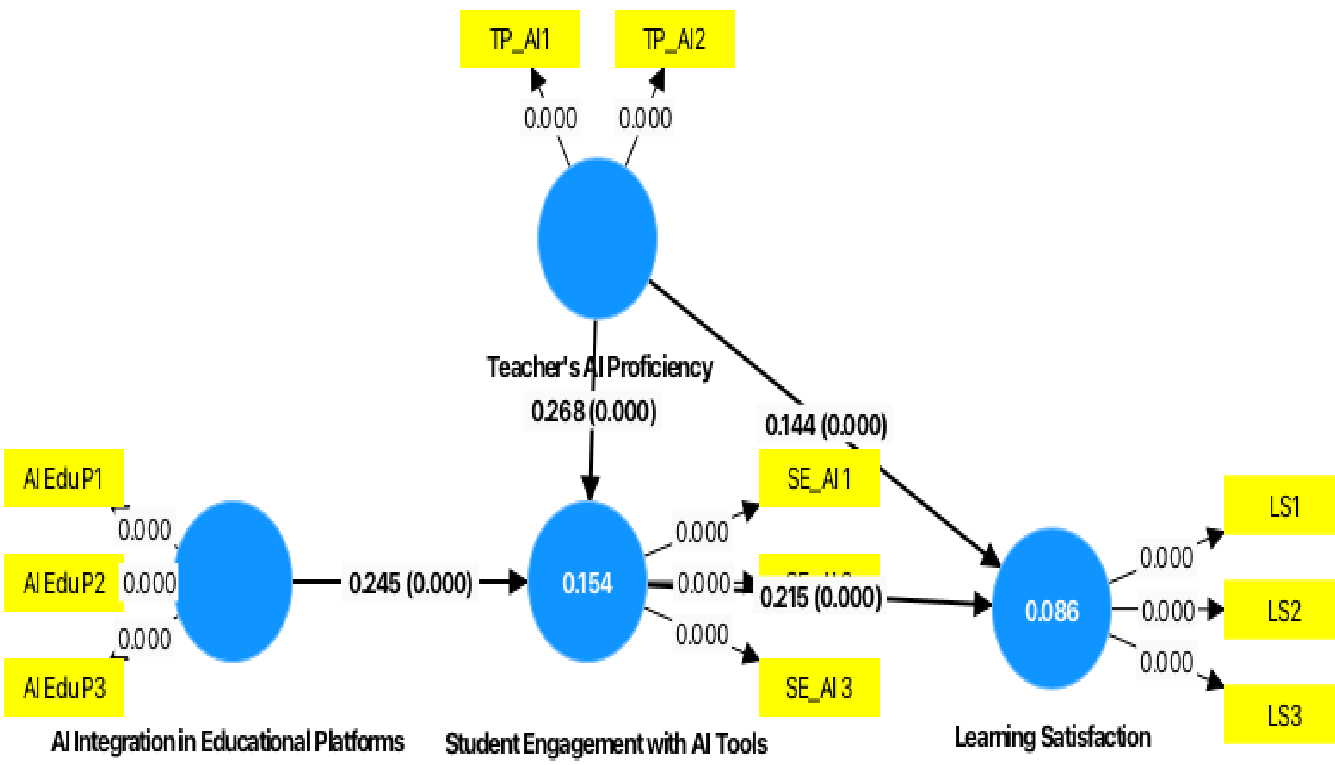

Figure 4: Structural model

5. DISCUSSION

This study aimed to explore the role of AI integration in educational platforms in transforming learning spaces and its implications for digital literacy, guided by two key research questions (RQs): RQ1: What does adopting AI in education mean for students' views of digital literacy? The paper shows that integrating AI into educational platforms significantly affects students' interest in using tools with AI (H1). This engagement mediates AI adoption and learning satisfaction (H6). These results imply that in AI-driven platforms, AI technologies create an environment actively geared toward students to interact and harness

AI technologies. As a result, students gain a greater understanding of digital tools and are better prepared for their digital literacy. That is consistent with earlier research, such as that done by Hanum et al. (2024) & Hartati et al. (2024), on AI's transformative role in driving personalized and adaptive learning environments. RQ2: How do perceived usefulness and ease of use mediate the relationship between AI adoption and digital literacy development?

The results suggest that, as anticipated in H4 and H3, teacher AI proficiency is heavily implicated in student engagement and learning satisfaction. Additionally, the indirect relationships (H5 and H6) indicate that student engagement is promoted by students' ability to perceive usefulness and ease of use associated with teacher proficiency and AI platform integration. This is consistent with previous research under Davis et al.'s Technology Acceptance Model (T-A-M) Davis et al. (1989), which found that perceived ease of use and usefulness are major drivers of technology adoption and skill development. These results corroborate the findings of Lijie et al. (2024) and Marlina et al. (2024) on how the role of teacher expertise is key to explaining technology use in education.

The H2 studied the relationship between students' engagement with AI tools and learning satisfaction. The path coefficient of 0.215 and T-value of 5.429 also indicated the effect of engagement, although of positive and significant value on satisfaction, when contributing to AI-supported learning processes.H3 was conducted to examine the direct effect of teacher AI proficiency on learning satisfaction. This relationship had a path coefficient of 0.144; the T value was 3.531, indicating a significant positive effect. It underscores the need for improved teacher training by teaching them about AI to improve student satisfaction.

Next, this study hypothesizes that a teacher's AI proficiency positively affects students' engagement with AI tools. This relationship was strongly supported by a path coefficient of 0.268 and a T value of 7.312, implying that teacher expertise in AI significantly improved students' willingness to interact with AI-driven technologies. To mediate the relationship between teachers' AI proficiency and learning satisfaction, H5 investigated the mediating effect of student engagement with AI tools. Thus, the significant contribution of engagement in the role of mediator bridged teachers' proficiency to student satisfaction was confirmed by a significant indirect effect with a path coefficient of 0.058 and a T-value of 4.312. H6 also investigated whether student engagement mediated the link between AI integration into educational platforms and learning satisfaction. It indicates a significant indirect effect, with a path coefficient of 0.053 and a T value of 3.940; student engagement is a key factor for translating AI integration to higher levels of learning satisfaction.

6. CONCLUSION

This study illuminates the transformative role of AI integration in educational platforms, fundamentally reshaping learning environments and advancing digital literacy among students. By extending the Technology Acceptance Model (T-A-M), the research highlights the pivotal influence of teacher AI proficiency and student engagement in bridging AI adoption with enhanced learning satisfaction. The findings demonstrate that AI-driven platforms foster active student interaction with technology, cultivating a deeper understanding of digital tools and preparing students for a technology-driven future. These insights align with prior research, reinforcing the significance of cognitive and behavioral factors in successful technology adoption within educational settings.

The practical implications are significant for educators, policymakers, and technology developers. Institutions must invest in robust teacher training programs to build AI proficiency, empowering educators to guide students effectively in navigating AI tools. Policymakers should prioritize equitable access to AI technologies to ensure inclusive learning environments, addressing the digital divide and fostering universal opportunities for skill development. Technology developers are urged to create intuitive, user-centric AI platforms tailored to the diverse needs of students and educators, enhancing usability and engagement.

While the study offers valuable contributions, its limitations, such as a sample limited to a specific demographic, suggest caution in generalizing findings. Future research should explore diverse populations and incorporate additional factors, such as motivation or institutional support, to provide a more comprehensive understanding of AI's role in education. Longitudinal studies are also essential to assess the long-term impact of AI adoption on learning outcomes and digital literacy. Ultimately, this research underscores AI's potential to revolutionize education by creating dynamic, inclusive learning spaces and equipping students with critical digital literacy skills. Strategic investments in teacher training, equitable access, and innovative platform design are crucial to realizing the full promise of AI in transforming education for future generations.

6.1 Theoretical implications

This study makes several theoretical contributions. First, we extend the T-A-M framework, combining the roles of teacher proficiency and student engagement into the space of AI-driven education. Contribution of the study: Confirmation of a mediating role of student engagement in the connection between AI integration and learning satisfaction, thus expanding knowledge on cognitive and behavioral technologies. The research also contributes to the literature on digital literacy by showing how AI technologies can catalyze skill learning. Third, it offers empirical evidence to add to the growing body of evidence establishing teacher AI proficiency as a prerequisite for the successful adoption of technologies in the classroom, which has been overlooked in prior T-A-M studies.

6.2 practical implications

The results from the study can help educators, policymakers and technology developers. It also highlights that teachers must be trained in AI to get the most from AI tools. Since guidance in an institution needs professional skills, the institution should focus on developing teachers with training courses. It is important for policymakers to make sure that all students can use AI in school so that the digital divide is reduced and all can learn equally. The findings matter a lot to those who design AI platforms, who are urged to create tools that both teachers and students appreciate as being both straightforward to use and appealing.

6.3 Future research directions

There are a number of limitations to this research. Resulting data might have only applied to students from a certain group, limiting how broadly the data could be applied. Studies on similar topics should be done with other populations to check the findings in different circumstances. The research mainly considered only a few variables such as AI integration, how well teachers could use it and how engaged students were. Other factors, includes motivation, socio-emotional aspects and institutional efforts may be looked into in future studies about AI in education. Also, the fact that the study is cross-sectional does not allow us to draw conclusions about causality. Analyses could follow AI use over the years to find out if there are changes in the way people and organizations perceive and achieve desired outcomes.

Acknowledgements: The authors express their gratitude to Peter the Great St. Petersburg Polytechnic University for providing the necessary resources and support to conduct this research. We also thank the participants for their valuable time and contributions to the study.
Author contributions: Sergey Barykin: Conceptualization, methodology, **Olga Voronova:** data collection, analysis, **Ivan Golub:** writing original draft preparation, **Sergey Sergeev:** writing review and editing.
Ethical Statement: This study was conducted in accordance with ethical guidelines. Informed consent was obtained from all participants prior to their involvement. The research involved human participants, and ethical approval was granted by the Ethics Committee of Peter the Great St. Petersburg Polytechnic University. Participants were informed about the study's objectives, their right to withdraw at any time, and the confidentiality of their data.
Consent to Participate: Before conducting this research study, permission was obtained from the host department at Peter the Great St. Petersburg Polytechnic University. The researcher explained the objectives of the study to the respondents before conducting interviews. Respondents were assured that their information would be used solely for research purposes. They were also informed that they could withdraw from the interview at any stage if they felt uneasy or did not wish to continue.
Competing Interests: The author declares that this work has no competing interests.
Grant/Funding information: The author declared that no grants supported this work.
Data Availability Statement: The associated data is available upon request from the corresponding author.
Declaration Statement of Generative AI: The authors declare that no generative AI tools or services were used during the preparation of this study.

REFERENCES

Ab Hamid, M., Sami, W., & Sidek, M. M. (2017). Discriminant validity assessment: Use of Fornell & Larcker criterion versus HTMT criterion. Journal of Physics: Conference Series, http://dx.doi.org/10.1088/1742-6596/890/1/012163

Chang, I.-Y., & Chang, W.-Y. (2012). The effect of student learning motivation on learning satisfaction. *International Journal of Organizational Innovation*, *4*(3). http://dx.doi.org/10.4236/ce.2016.717253

Chisom, O. N., Unachukwu, C. C., & Osawaru, B. (2023). Review of AI in education: transforming learning environments in Africa. *International Journal of Applied Research in Social Sciences*, *5*(10), 637-654. http://dx.doi.org/10.51594/ijarss.v5i10.725

Chiu, T. K., Moorhouse, B. L., Chai, C. S., & Ismailov, M. (2024). Teacher support and student motivation to learn with Artificial Intelligence (AI) based chatbot. *Interactive Learning Environments*, *32*(7), 3240-3256. http://dx.doi.org/10.1080/10494820.2023.2172044

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340. http://dx.doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management science*, *35*(8), 982-1003. http://dx.doi.org/10.1287/mnsc.35.8.982

Davis, J. H. (1992). Some compelling intuitions about group consensus decisions, theoretical and empirical research, and interpersonal aggregation phenomena: Selected examples 1950–1990. *Organizational behavior and human decision processes*, *52*(1), 3-38. https://doi.org/10.1016/0749-5978(92)90044-8

Hair, J. F., Anderson, R., Tatham, R., & Black, W. (1998). Factor analysis. Multivariate data analysis. *NJ Prentice-Hall*, *3*, 98-99.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European business review*, *31*(1), 2-24. http://dx.doi.org/10.1108/EBR-11-2018-0203

Hanum, G. K., Syahputra, M., Suryono, W., Rukiyanto, B. A., & Hariyadi, S. (2024). The Role of AI in Scaling Global Access to Quality Education in Low-Resource Regions. *Journal Emerging Technologies in Education*, *2*(5). http://dx.doi.org/10.70177/jete.v2i5.1366

Hartati, T. A. W., Lestari, P. B., Istiawan, N., & Darmawan, E. (2024). Digital literacy level of prospective teacher students in the 4.0 industrial revolution era. *Journal of Research in Instructional*, *4*(2), 601-609.

Hu, Y.-H. (2022). Effects and acceptance of precision education in an AI-supported smart learning environment. *Education and Information Technologies*, *27*(2), 2013-2037. https://link.springer.com/article/10.1007%2Fs10639-021-10664-3

Huang, F., Wang, Y., & Zhang, H. (2024). Modelling Generative AI Acceptance, Perceived Teachers' Enthusiasm and Self-Efficacy to English as a Foreign Language Learners' Well-Being in the Digital Era. *European Journal of Education*, *59*(4), e12770. http://dx.doi.org/10.1111/ejed.12770

Ji, H., Han, I., & Ko, Y. (2023). A systematic review of conversational AI in language education: Focusing on the collaboration with human teachers. *Journal of Research on Technology in Education*, *55*(1), 48-63. http://dx.doi.org/10.1080/15391523.2022.2142873

Kim, J., Lee, H., & Cho, Y. H. (2022). Learning design to support student-AI collaboration: Perspectives of leading teachers for AI in education. *Education and Information Technologies*, *27*(5), 6069-6104. http://dx.doi.org/10.1007/s10639-021-10831-6

Lijie, H., Mat Yusoff, S., & Mohamad Marzaini, A. F. (2024). Influence of AI-driven educational tools on critical thinking dispositions among university students in Malaysia: a study of key factors and correlations. *Education and Information Technologies*, 1-25. http://dx.doi.org/10.1007/s10639-024-13150-8

Luckin, R., & Holmes, W. (2016). Intelligence unleashed: An argument for AI in education.

Marangunić, N., & Granić, A. (2015). Technology acceptance model: a literature review from 1986 to 2013. *Universal access in the information society*, *14*, 81-95. https://doi.org/10.1007/S10209-014-0348-1

Marlina, R., Suwono, H., Yuenyong, C., Ibrohim, I., Pamungkas, R., & Hamdani, H. (2024). Micro Teaching as Efficient Technique to Increase Self-Efficacy of Prospective Biology Teacher: Evidence from Fi-rst Year Teacher. *Jurnal Pendidikan Sains Indonesia*, *12*(4), 769-785. http://dx.doi.org/10.24815/jpsi.v12i4.38720

Memarian, B., & Doleck, T. (2024). Embodied AI in education: A review on the body, environment, and mind. *Education and Information Technologies*, *29*(1), 895-916. http://dx.doi.org/10.1007/s10639-023-12346-8

Mirdad, K., Daeli, O. P. M., Septiani, N., Ekawati, A., & Rusilowati, U. (2024). Optimizing student engagement and performance usingai-enabled educational tools. *CORISINTA*, *1*(1), 53-60. http://dx.doi.org/10.34306

Nguyen, T. H. C. (2024). Exploring the Role of Artificial Intelligence-Powered Facilitator in Enhancing Digital Competencies of Primary School Teachers. *European Journal of Educational Research*, *13*(1).

Pedro, F., Subosa, M., Rivas, A., & Valverde, P. (2019). Artificial intelligence in education: Challenges and opportunities for sustainable development. https://doi.org/10.12973/eu-jer.13.1.219

Pokrivcakova, S. (2019). Preparing teachers for the application of AI-powered technologies in foreign language education. *Journal of Language and Cultural Education*, *7*(3), 135-153. http://dx.doi.org/10.2478/jolace-2019-0025

Uerz, D., Volman, M., & Kral, M. (2018). Teacher educators' competences in fostering student teachers' proficiency in teaching and learning with technology: An overview of relevant research literature. *Teaching and Teacher Education*, *70*, 12-23. http://dx.doi.org/10.1016/j.tate.2017.11.005

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478. http://dx.doi.org/10.2307/30036540

Wang, X., Li, L., Tan, S. C., Yang, L., & Lei, J. (2023). Preparing for AI-enhanced education: Conceptualizing and empirically examining teachers' AI readiness. *Computers in Human Behavior*, *146*, 107798. http://dx.doi.org/10.1016/j.chb.2023.107798

Xia, Q., Chiu, T. K., Chai, C. S., & Xie, K. (2023). The mediating effects of needs satisfaction on the relatio-nships between prior knowledge and self-regulated learning through artificial intelligence chatbot. *British Journal of Educational Technology*, *54*(4), 967-986. http://dx.doi.org/10.1111/bjet.13305

Yao, N., & Wang, Q. (2024). Factors influencing pre-service special education teachers' intention toward AI in education: Digital literacy, teacher self-efficacy, perceived ease of use, and perceived usefulness. *Heliyon*, *10*(14). http://dx.doi.org/10.1016/j.heliyon.2024.e34894

Zhang, K., & Aslan, A. B. (2021). AI technologies for education: Recent research & future directions. *Com-puters and Education: Artificial Intelligence*, *2*, 100025. http://dx.doi.org/10.1016/j.caeai.2021.100025