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INVESTIGATING THE FACTORS INFLUENCING THE ADOPTION OF ARTIFICIAL INTELLIGENCE IN HIGHER EDUCATION USING PLS-SEM: THE CASE OF CHATGPT

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ABSTRACT

In recent years, the increasing use of artificial intelligence technologies in education has fundamentally transformed teaching methods and reshaped the ways in which students learn. One of the prominent tools in this transformation is ChatGPT, developed by OpenAI, which stands out for its support of individualized learning processes in higher education. However, there is limited knowledge and research regarding the factors influencing the adoption of ChatGPT in higher education. This study aims to analyze the individual and cognitive factors affecting the adoption of ChatGPT by employing Partial Least Squares Structural Equation Modeling (PLS-SEM). In the research model, relatedness, autonomy support, creative inspiration, and credibility are considered as independent variables; engagement in learning and perceived competence as mediating variables; and behavioral intention as the dependent variable. The research model and hypotheses were tested based on data collected from 141 participants currently enrolled in higher education. The findings revealed that perceived competence (PE.CO) had the strongest direct impact on behavioral intention (BE.IN), while engagement in learning (LE.EN) did not significantly influence behavioral intention. Moreover, creative inspiration (CR.IN) and credibility (TRUST) had significant indirect effects on behavioral intention through perceived competence, highlighting the importance of self-efficacy and trust in the adoption of AI-based educational technologies. However, relatedness (RELA) and autonomy support (AU.SU) did not demonstrate significant direct effects on behavioral intention. The findings aim to contribute to the theoretical framework surrounding the adoption of AI-based educational technologies and to offer practical insights for practitioners.

1. INTRODUCTION

In recent years, the use of artificial intelligence (AI) technologies in the field of education has rapidly increased and is regarded as a significant tool that transforms learning processes (Zhang, 2023). Especially language models and chatbots are widely used to support students' academic research, accelerate their access to information, and enhance their individual learning experiences (Foroughi et al., 2024). One such technology is ChatGPT, an AI-based language model developed by OpenAI, which provides instant feedback to users through natural language processing algorithms. Students actively use ChatGPT in the preparation of

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assignments, the creation of academic texts, conducting research, and solving problems (Shahzad, Xu, & Javed, 2024).

When examining the theoretical frameworks related to technology adoption, it is observed that models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) are frequently used to explain users' attitudes toward technology and their tendency to adopt it (Davis, 1989; Venkatesh et al., 2003). While the TAM model suggests that perceived ease of use and perceived usefulness determine individuals' attitudes toward technology, the UTAUT model includes additional factors such as social influence and performance expectancy in the technology adoption process (Venkatesh & Davis, 2000). However, it is stated that traditional acceptance models fall short in fully explaining individuals' motivational, cognitive, and emotional factors (Hair et al., 2017). For instance, the TAM model primarily focuses on the functional aspects of technology use, such as perceived ease of use (PEU) and perceived usefulness (PU), but may overlook important motivational factors such as self-efficacy, relatedness, and autonomy support, which are critical for understanding the deeper psychological drivers of technology acceptance (Ryan & Deci, 2000; Bandura, 1997). Therefore, there is a need to develop more comprehensive models to better understand and adopt the use of AI tools.

In this study, the factors affecting the adoption of ChatGPT in higher education were first identified through support from the literature. The proposed model integrates concepts from the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and Self-Determination Theory (SDT) to capture both the cognitive and motivational factors that influence technology adoption. Specifically, the model includes relatedness (RELA), autonomy support (AU.SU), creative inspiration (CR.IN), and credibility (TRUST) as independent variables; engagement in learning (LE.EN) and perceived competence (PE.CO) as mediating variables; and behavioral intention (BE.IN) as the dependent variable. This approach reflects a broader understanding of technology adoption by considering not only the functional aspects but also the psychological and emotional dimensions that shape user behavior.

Simultaneously, a model was proposed to describe behavioral intention toward the use of ChatGPT, based on the relationships among the considered factors, and hypotheses were designed. For example, H1 proposes that relatedness positively affects engagement in learning, while H3 suggests that creative inspiration positively influences perceived competence. These hypotheses reflect the importance of psychological factors such as self-efficacy and social connectedness in technology adoption (Bandura, 1997; Ryan & Deci, 2000). H4 hypothesizes that credibility positively affects perceived competence, emphasizing the critical role of trust in shaping user perceptions and intentions (Shahzad et al., 2024).

Subsequently, to measure the factors included in the proposed model, a data collection instrument was designed by utilizing the literature. Data were collected voluntarily from university students through the distribution of the developed instrument via social media. At the end of the study, the model fit and the relationships among the factors were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings of this research are expected to contribute to the theoretical framework explaining the adoption of AI-supported educational tools and to provide guidance for educational policies.

2. LITEREATURE REVIEW

Previous studies on the adoption of artificial intelligence (AI)-based educational technologies in higher education have focused on explaining the impact of these technologies on students' learning processes and user behaviors (Foroughi et al., 2024; Shahzad et al., 2024; Zhang, 2023). These studies generally highlight the role of individual, cognitive, and motivational factors in shaping students' attitudes toward AI tools like ChatGPT (Ryan & Deci, 2000; Bandura, 1997). In the literature, especially Technology Acceptance Models (TAM), the use of AI tools such as ChatGPT, and various theoretical and empirical approaches regarding the integration of these tools into educational environments stand out.

The Technology Acceptance Model (TAM), developed by Davis (1989), is presented as a basic framework explaining individuals' adoption process of a technology through the variables of perceived usefulness (PU) and perceived ease of use (PEU). This model was later expanded by Venkatesh and Davis (2000), allowing for a more comprehensive analysis of individuals' adoption of digital learning tools. Similarly, UTAUT developed by Venkatesh et al. (2003), provides a holistic structure including factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions, offering a broader understanding of the technology adoption process. However, these traditional models have been critiqued for not fully capturing the psychological and motivational dimensions of technology use, such as self-efficacy, autonomy, and relatedness, which are essential for understanding deeper user engagement and sustained adoption (Ryan & Deci, 2000; Bandura, 1997).

Recent studies explaining the adoption of AI-based educational technologies have become increasingly widespread. Foroughi et al. (2024) examined students’ motivations for using AI-based tools such as ChatGPT and found that performance expectancy and ease of use were the main elements that increased the intention to use ChatGPT. Similarly, in the study by Zhang (2023), the use of ChatGPT in higher education was analyzed, and it was revealed that this technology was a tool that accelerated the learning process and facilitated access to information for students. It was emphasized that students widely use ChatGPT for preparing assignments, conducting research, and improving academic writing processes. Moreover, these studies indicate that students perceive ChatGPT as a valuable tool for enhancing their academic performance and creativity, making it an essential component of their independent learning journeys (Alfaisal et al., 2024).

Another critical factor regarding technology use is trust. Shahzad et al. (2024) showed that students’ trust in the accuracy of the information provided by AI-based tools had a decisive effect on their long-term intention to use these technologies. Similarly, McKnight, Choudhury, and Kacmar (2002) stated that users’ trust in digital technologies directly affected their approach to technology and adoption behaviors. In the context of ChatGPT, trust is particularly significant, as the perceived reliability of the information generated by the system can strongly influence users' overall acceptance and continued use (Shahzad et al., 2024). This aligns with the broader findings in technology adoption research, which emphasize that trust acts as a critical enabler in reducing perceived risk and increasing users' confidence in technology (Nguyen et al., 2023). Therefore, trust (credibility) is hypothesized to positively affect perceived competence (H4).

One of the factors affecting students’ adoption of ChatGPT is engagement in learning. Özerbaş (2011) stated that learning environments designed with creative thinking methods increased students’ academic success and the retention of knowledge. Similarly, Zhang (2023) investigated the effect of AI-based tools on students’ independent learning processes and revealed a significant relationship between autonomy support and technology adoption. This is consistent with findings from Tiwari et al. (2023), who emphasized that while ChatGPT use can increase student motivation and engagement, excessive dependence on the technology may hinder critical thinking skills. This suggests that the balance between technology use and critical engagement is essential for effective learning outcomes. Based on these insights, relatedness and autonomy support are hypothesized to positively affect engagement in learning (H1, H2).

Additionally, engagement in learning is hypothesized to positively affect behavioral intention (H5).

The impact of AI-supported educational tools on creative thinking processes also stands out among the topics emphasized in the studies. Alfaisal et al. (2024) stated that ChatGPT made significant contributions in providing students with creative inspiration and improving their problem-solving skills. The study showed that the use of ChatGPT directly affected students' academic performance and supported their individual learning process. Polyportis and Pahos (2023), in the model they developed to determine how and to what extent students used ChatGPT in their educational processes, revealed that users' attitudes toward technology directly influenced the adoption of ChatGPT. These findings indicate that students perceive ChatGPT not only as a functional tool but also as a source of creative inspiration, which can positively impact their self-efficacy and learning outcomes (Bandura, 1997). Therefore, creative inspiration is hypothesized to positively affect perceived competence (H3), and perceived competence is hypothesized to positively affect behavioral intention (H6).

Moreover, previous research indicates that factors such as relatedness and autonomy support can also have direct influences on students' behavioral intentions to adopt new technologies, independent from their indirect effects through engagement (Polyportis & Pahos, 2023; Zhang, 2023). Thus, relatedness and autonomy support are also hypothesized to directly and positively affect behavioral intention (H7, H8).

Overall, the existing literature points to many factors that affect the adoption of ChatGPT. Variables such as relatedness, credibility, creative inspiration, and engagement in learning appear to stand out in this process. Analyses conducted using the PLS-SEM method reveal the validity of TAM in the context of higher education, and this study aims to evaluate the effect of individual and cognitive factors in a holistic manner by developing a model specific to ChatGPT, differentiating it from previous research. Therefore, this study aims to bridge the gap by incorporating motivational and psychological dimensions, providing a more comprehensive understanding of the factors influencing ChatGPT adoption among university students. Additionally, this study extends previous literature by clearly defining direct and indirect paths, enabling a deeper exploration of the cognitive and motivational dynamics involved in technology adoption.

3. MATERIAL AND METHOD

This research was structured within the framework of a relational survey model aiming to reveal the relationships between variables. Relational survey models are common research approaches used to identify the connections between two or more variables (Karasar, 2002). In this context, the relationships between independent and dependent variables were analyzed using the PLS-SEM method. PLS-SEM is a powerful analysis technique that is preferred due to its ability to provide high reliability even when the sample size is limited and its capacity to model multivariate relationships (Hair, Hult, Ringle & Sarstedt, 2017). The choice of PLS-SEM in this study is justified by its suitability for analyzing complex models with multiple relationships, its tolerance for smaller sample sizes, and its ability to assess both measurement and structural models simultaneously (Hair et al., 2017). Considering the exploratory nature of this study and the necessity to simultaneously evaluate multiple direct and indirect relationships, PLS-SEM was selected as the most appropriate analytical method (Hair et al., 2017).

3.1. Data Collection Tool and Sample

The research population consists of undergraduate and postgraduate students currently enrolled in universities in Turkey. The data collection process was conducted using an online survey method. The questionnaire was created via Google Forms and administered voluntarily to participants. The data were stored anonymously and processed in accordance with ethical principles.

A total of 160 participants were reached using the convenience sampling method. Convenience sampling was preferred due to ease of access to participants and practical constraints regarding data collection time and resources. However, this method limits the generalizability of the findings. Therefore, the limitation arising from the use of convenience sampling is clearly acknowledged and included in the research limitations section. Responses from participants who did not provide appropriate answers to the control question were excluded, and the analysis was based on data from 141 respondents. The adequacy of the sample size was determined through a power analysis using the GPower software. According to the GPower analysis, considering a power of 90%, a significance level of 5%, and a medium effect size ($f^2 = 0.15$), a minimum of 123 participants would be sufficient. In this context, the 141 participants included in the study were deemed appropriate in terms of sample adequacy.

3.2. Research Model and Hypothesis Design

Artificial intelligence-based technologies have been playing an increasingly significant role, especially in the field of education. However, the adoption process of these technologies depends not only on technological features but also on users' cognitive, motivational, and psychological characteristics. The literature points to the existence of many factors that influence students' behavioral intentions toward AI tools. In this context, the TAM is a widely used model to explain individuals' attitudes and behaviors toward technology use (Davis, 1989). TPB posits that individuals' intentions are shaped by attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991). Self-Efficacy Theory, on the other hand, states that individuals' perceptions of their capacity to perform a specific task significantly affect their technology adoption behavior (Bandura, 1997). Building upon these foundational theories, this study proposes an integrated theoretical model, combining elements from TAM, TPB, and Self-Efficacy Theory to comprehensively analyze students' adoption behaviors towards ChatGPT.

The questionnaire used in the study was prepared based on scales available in the literature, whose validity and reliability have been previously tested. The questionnaire consists of 22 items, all of which were measured using a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The scales were structured based on the works of Ryan and Deci (2000), Bandura (1997), McKnight et al. (2002), Polyportis and Pahos (2023), and Zhang (2023). The items were translated into Turkish and evaluated through expert opinion.

A structural model was developed to analyze the factors affecting the adoption of ChatGPT in higher education. The model evaluates the effects of relatedness (RELA), autonomy support (AU.SU), creative inspiration (CR.IN), and credibility (TRUST) on engagement in learning (LE.EN), perceived competence (PE.CO), and behavioral intention (BE.IN). The research model was constructed based on the TAM, TPB, and Self-Efficacy Theory, and it particularly focuses on understanding the role of cognitive and motivational factors in students' adoption behaviors toward ChatGPT. As shown in Figure 1, the structure of the proposed model suggests that independent variables may affect behavioral intention (BE.IN) through engagement in learning (LE.EN) and perceived competence (PE.CO).

Studies on the factors influencing the adoption of ChatGPT have shown that variables such as relatedness, autonomy support, creative inspiration, and credibility shape students' attitudes toward technology (Polyportis & Pahos, 2023). Specifically, relatedness refers to the extent to which students perceive ChatGPT aligns with their educational needs, positively influencing their engagement (Zhang, 2023). Autonomy support represents how ChatGPT facilitates independent learning, enhancing students' intrinsic motivation and engagement (Ryan & Deci, 2000; Zhang, 2023). Creative inspiration involves how ChatGPT encourages innovative thinking, thus increasing students' perceived competence and motivation toward technology use (Alfaisal et al., 2024). Credibility or trust addresses the reliability of the information provided by ChatGPT, significantly affecting users’ confidence and perceived competence (Shahzad et al., 2024). Based on these theoretical foundations and prior empirical findings, the following hypotheses are formulated:

H1: Relatedness positively affects engagement in learning.

H2: Autonomy support positively affects engagement in learning.

H3: Creative inspiration positively affects perceived competence.

H4: Credibility positively affects perceived competence.

Students’ perceptions of how well ChatGPT aligns with their academic needs (relatedness) and the extent to which it allows for independent action in the learning process (autonomy support) play a critical role in the adoption of this technology (Zhang, 2023). Furthermore, the trust students place in the accuracy and reliability of the information provided by ChatGPT is also seen as a direct factor affecting usage intention (Shahzad et al., 2024). Additionally, engagement in learning and perceived competence are identified as critical mediators facilitating the transition from cognitive and motivational perceptions toward concrete behavioral intentions (Bandura, 1997; Ryan & Deci, 2000). Therefore:

H5: Engagement in learning positively affects behavioral intention.

H6: Perceived competence positively affects behavioral intention.

In this context, the aim is to reveal how individual, cognitive, and motivational variables interact with each other. The research model includes relatedness, autonomy support, creative inspiration, and credibility as independent variables; engagement in learning and perceived competence as mediating variables; and behavioral intention as the dependent variable. Moreover, existing literature suggests direct effects of relatedness and autonomy support on behavioral intentions, independent of mediation (Zhang, 2023; Polyportis & Pahos, 2023). Therefore, the following direct-effect hypotheses are also formulated:

H7: Relatedness directly and positively affects behavioral intention.

H8: Autonomy support directly and positively affects behavioral intention.

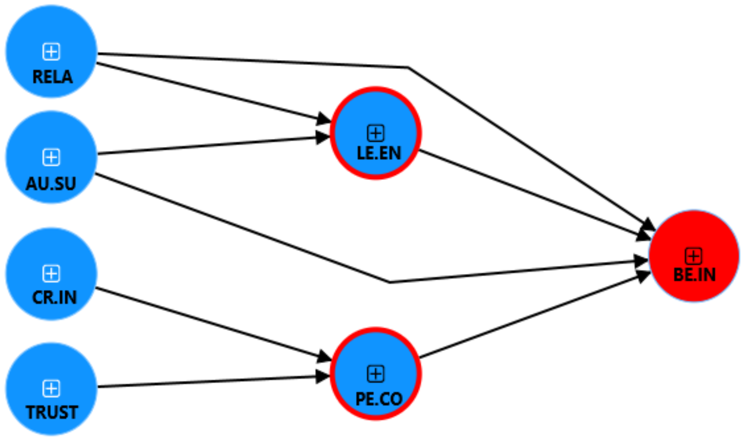

Figure 1. Research Model

RELA: Relatedness, AU.SU: Autonomy Support, CR.IN: Creative Inspiration, TRUST: Credibility, LE.EN: Learning Engagement, PE.CO: Perceived Competence, BE.IN: Behavioral Intention

These hypotheses aim to reveal how cognitive, motivational, and trust-based factors interact in the use of ChatGPT in educational settings.

4. FINDINGS

4.1. Descriptive Statistics

Among the total of 166 students who participated in the study, 47.6% (n=79) were female and 52.4% (n=87) were male. The majority of the participants were undergraduate students (71.1%), followed by graduate (25.9%) and doctoral students (3%). To ensure data accuracy, the questionnaire included a control question ("Please mark this item as 'Strongly agree'"), and responses from 25 participants who answered this question incorrectly were excluded from the analysis. The final analyses were conducted based on the remaining 141 valid responses.

4.2. Validity and Reliability of the Measurement Model

Within the scope of the PLS-SEM method, the validity and reliability of the measurement model were evaluated using the criteria of convergent validity and discriminant validity. Three criteria are used to ensure convergent validity (Topçuoğlu, Yılmaz, & Arı, 2022, p. 87). First, the standardized factor loading of the observed variables associated with the latent variables must be statistically significant and greater than 0.50 (Fornell & Larcker, 1981). Second, the composite reliability (CR) and Cronbach's Alpha (CA) values of the latent variables should exceed 0.70 (Hair, Anderson, Tatham, & Black, 1998). Third, the average variance extracted (AVE) for each latent variable must be greater than 0.50 (Fornell & Larcker, 1981).

Table 1.
Construct Reliability and Validity of The Measurement Model

Factors	CA	CR	AVE
AU.SU	0.859	0.914	0.781
BE.IN	0.874	0.923	0.799
CR.IN	0.871	0.921	0.795
LE.EN	0.863	0.916	0.784
PE.CO	0.828	0.897	0.744
RELA	0.793	0.878	0.707
TRUST	0.849	0.909	0.770

Table 1 shows CA, CR and AVE values of the factors. It is observed that all factor loadings range between 0.793 and 0.874, and AVE values range from 0.707 to 0.799. The CA and CR values are above 0.70, indicating that the model meets internal consistency reliability and construct validity.

The discriminant validity of the measurement model is critically important to determine whether each variable is statistically distinct from others (Gürbüz & Yılmaz, 2023, p. 1390). Discriminant validity is a criterion used to verify that latent variables are independent of one another and that the measurements only reflect the relevant constructs (Hair, Hult, Ringle & Sarstedt, 2022). In this context, discriminant validity was tested using the Fornell and Larcker (1981) Criterion and the HTMT (Heterotrait-Monotrait Ratio) Criterion proposed by Henseler, Ringle, and Sarstedt (2015).

According to the Fornell and Larcker (1981) Criterion, the square root of the AVE of a construct should be greater than the correlation values with other latent constructs. This criterion is widely used to assess whether constructs are distinct from each other. According to the Fornell-Larcker criterion results presented in Table 2, the square root of the AVE values of each factor is greater than the correlation coefficients with other factors. This finding indicates that the constructs in the model are distinguishable, and that discriminant validity has been achieved.

Table 2.
Fornell-Larcker Criter

	AU.SU	BE.IN	CR.IN	LE.EN	PE.CO	RELA	TRUST
AU.SU	0.884						
BE.IN	0.521	0.894					
CR.IN	0.516	0.605	0.892				
LE.EN	0.465	0.614	0.695	0.886			
PE.CO	0.496	0.800	0.683	0.756	0.863		
RELA	0.643	0.596	0.583	0.569	0.611	0.841	
TRUST	0.552	0.598	0.547	0.596	0.688	0.641	0.878

NOTE: Diagonal elements represent the square roots of the AVE values.

The HTMT Criterion, proposed by Henseler et al. (2015), evaluates discriminant validity by calculating the ratio between the average correlations of indicators across different constructs and the geometric mean of the average correlations within the same construct. An HTMT value exceeding 0.85 indicates a high overlap between constructs and a lack of discriminant validity (Henseler et al., 2015; Yılmaz & Kinaş, 2021, p. 143). According to the HTMT analysis presented in Table 3, all HTMT values in the model are below 0.85, confirming that the model meets the criteria for discriminant validity.

Table 3.
Heterotrait-monotrait ratio (HTMT) – Matrix

	AU.SU	BE.IN	CR.IN	LE.EN	PE.CO	RELA	TRUST
AU.SU							
BE.IN	0.596						
CR.IN	0.593	0.690					
LE.EN	0.531	0.698	0.797				
PE.CO	0.584	0.938	0.797	0.891			
RELA	0.769	0.714	0.705	0.679	0.757		
TRUST	0.649	0.692	0.637	0.700	0.821	0.783	

As a result, based on both the Fornell-Larcker Criterion and the HTMT Criterion, it has been determined that the measurement model used in the study possesses discriminant validity and that the latent variables were measured independently of each other. The findings demonstrate that the model is reliable in terms of both internal consistency and discriminant validity. These results confirm that the variables addressed in the study were measured independently and support the theoretical foundation of the model.

4.3. Structural Model

Following the confirmation of the validity and reliability of the measurement model, the structural model was analyzed using the SmartPLS software. For the evaluation of the structural model, hypothesis testing, effect size (f^2), multicollinearity test (VIF), and model fit indices (SRMR, d_ULS, d_G, NFI) were considered.

Effect size (f^2) values were calculated to measure the influence of independent variables on dependent variables. According to Cohen's (1988) f^2 criteria as presented in Table 4 (Yılmaz & Kinaş, 2020, p. 446), $0.02 < f^2 < 0.15$ is considered a weak effect, $0.15 < f^2 < 0.35$ a moderate effect, and $f^2 > 0.35$ a strong effect. The obtained f^2 values indicate which variables in the model have weak ($0.02 < f^2 < 0.14$), moderate ($0.15 < f^2 < 0.34$), or strong ($f^2 > 0.34$) effects on the dependent variables. As shown in Table 4, the paths CR.IN → PE.CO (0.341) and TRUST → PE.CO (0.360) have a moderate effect, while PE.CO → BE.IN (0.550) has a strong effect.

To detect multicollinearity, the Variance Inflation Factor (VIF) values were examined. VIF values below 5 indicate that there is no multicollinearity problem among the variables (Hair et al., 2017). In this study, the analysis was conducted considering that the VIF values should be below 3 to ensure the structural validity of the model. All VIF values were calculated to range between 1.428 and 2.656. This result indicates that there is no multicollinearity among the dependent variables in the model.

The SRMR value of the model was calculated as 0.062, and an SRMR value less than 0.08 indicates that the model exhibits an acceptable fit (Hu & Bentler, 1999). The NFI value was found to be 0.766, which also indicates an overall acceptable level of model fit (Tenenhaus, Amato, & Esposito Vinzi, 2004). The other model fit indices were calculated as d_ULS = 0.896, d_G = 0.650, and Chi-Square = 547.263.

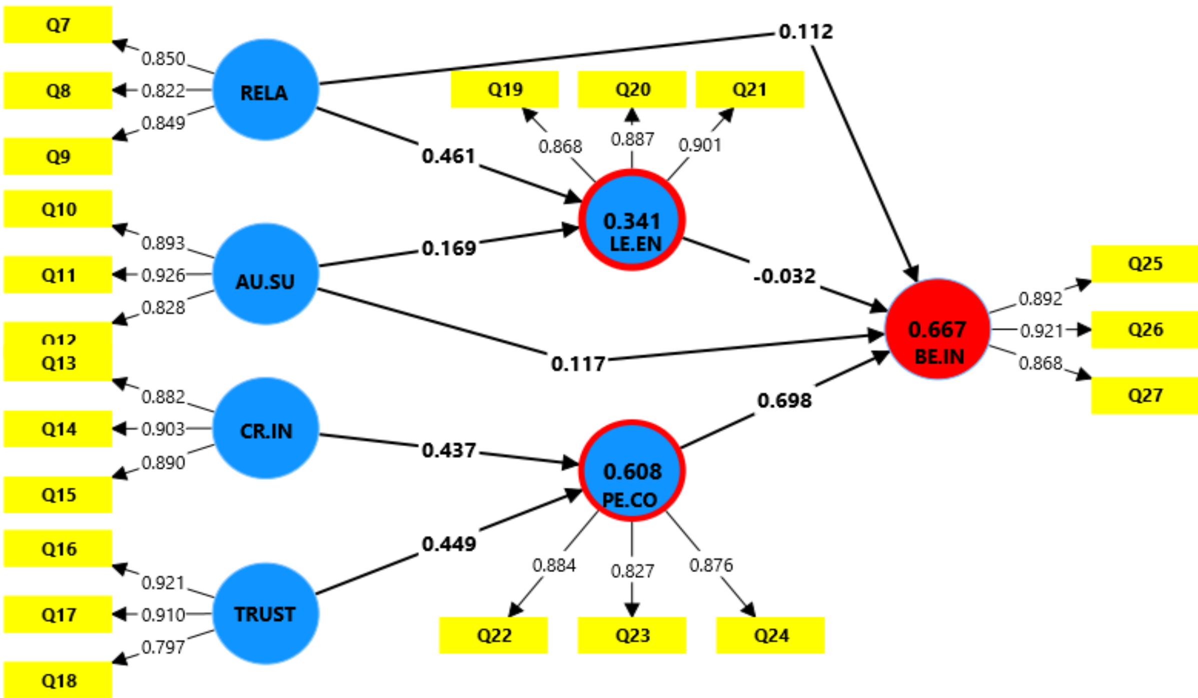

Figure 2. Measurement Model

According to the results presented in Figure 2, it was found that relatedness (RELA) has a positive and significant effect on learning engagement (LE.EN) (RELA → LE.EN: 0.461; $p < 0.01$). Similarly, creative inspiration (CR.IN) significantly affects perceived competence (PE.CO) (CR.IN → PE.CO: 0.437; $p < 0.01$). However, the effect of learning engagement (LE.EN) on behavioral intention (BE.IN) was not found to be significant (LE.EN → BE.IN: -0.033; $p = 0.717$). Additionally, the direct effect of relatedness (RELA) on behavioral intention (BE.IN) was also found to be insignificant (RELA → BE.IN: 0.111; $p = 0.105$).

Table 4 presents the standardized path coefficients, t-values, and p-values of the hypothesis tests. H1, H3, H4, and H6 hypotheses were supported, whereas H2, H5, H7, and H8 were not found to be statistically significant.

Accordingly, relatedness (RELA) has a positive and significant effect on learning engagement (LE.EN) (H1 supported). This indicates that stronger relational bonds contribute to increased student engagement in learning. Creative inspiration (CR.IN) has a significant and positive effect on perceived competence (PE.CO) (H3 supported), suggesting that creative inspiration is a key factor in enhancing individuals' sense of self-efficacy. Credibility (TRUST) also has a strong and significant effect on perceived competence (PE.CO) (H4 supported), implying that a trustworthy environment enhances individuals' perception of their own competence. Furthermore, perceived competence (PE.CO) has a strong and positive effect on behavioral intention (BE.IN) (H6 supported), highlighting the importance of individuals' self-perceived abilities in shaping their behavioral intentions.

Notably, perceived competence (PE.CO) emerged as the most influential and significant predictor of behavioral intention (BE.IN). This underscores the critical role of self-efficacy beliefs in the adoption and implementation of specific behaviors.

Table 4.
Standardized parameter estimates, t-values, and direct effect coefficients

Hypothesis	Relationships	Path Coefficient	t- value	p-value	Decision	f2
H1	RELA → LE.EN	0.462	4.761	p < 0.01	Supported	0.189
H2	AU.SU → LE.EN	0.167	1.556	0.120	Not Supported	0.025
H3	CR.IN → PE.CO	0.437	6.311	p < 0.01	Supported	0.341
H4	TRUST→ PE.CO	0.449	7.124	p < 0.01	Supported	0.360
H5	LE.EN → BE.IN	-0.033	0.362	0.717	Not Supported	0.001
H6	PE.CO → BE.IN	0.698	7.438	p < 0.01	Supported	0.550
H7	RELA → BE.IN	0.111	1.621	0.105	Not Supported	0.017
H8	AU.SU → BE.IN	0.118	1.609	0.108	Not Supported	0.023

4.3.1. Indirect Effect

Table 5 presents the findings related to the testing of indirect effects.

H9: Relatedness (RELA) has an indirect effect on behavioral intention (BE.IN) through learning engagement (LE.EN).

H10: Credibility (TRUST) has an indirect effect on behavioral intention (BE.IN) through perceived competence (PE.CO).

H11: Autonomy support (AU.SU) has an indirect effect on behavioral intention (BE.IN) through learning engagement (LE.EN).

H12: Creative inspiration (CR.IN) has an indirect effect on behavioral intention (BE.IN) through perceived competence (PE.CO).

Table 5.
Partial Mediation Effect Results (Indirect effects)

Hypothesis	Relationships	Path Coeff.	t- value	p-value	Decision
H9	RELA -> LE.EN -> BE.IN	-0.015	0.348	0.728	Not Supported
H10	TRUST-> PE.CO -> BE.IN	0.314	4.858	p<0.01	Supported
H11	AU.SU -> LE.EN -> BE.IN	-0.006	0.297	0.767	Not Supported
H12	CR.IN -> PE.CO -> BE.IN	0.305	5.050	p<0.01	Supported

When the results are examined, hypotheses H9 and H11 were not supported, indicating that the indirect effects of relatedness and autonomy support on behavioral intention through learning engagement were not statistically significant. On the other hand, hypotheses H10 and H12 were supported, meaning that the variables of credibility and creative inspiration had a statistically significant indirect effect on behavioral intention through perceived competence. The significance of the indirect effect of credibility (TRUST) on behavioral intention through perceived competence shows that students' trust in the accuracy of the information provided by ChatGPT increases their sense of perceived competence, which positively influences their intention to adopt the technology. This result points to the critical role of trust in the accuracy of the information provided in enabling students to feel competent in effectively using the technology.

Similarly, the significance of the indirect effect of creative inspiration (CR.IN) on behavioral intention through perceived competence indicates that educational environments that support students' creative and innovative thinking skills enhance their perceived competence levels and, in turn, strengthen their intention to use the technology. This finding highlights the importance of environments that foster creativity in enabling students to feel competent in using technology.

In conclusion, the significance of the indirect effects reveals that users' perceptions of cognitive competence play a central role in the adoption process of ChatGPT. It is observed that, in the adoption process of educational technologies, it is necessary to strengthen the factors that increase students' perceived competence. In this context, educators and technology developers can increase the adoption rates and effectiveness of technological tools by providing information that students find reliable and by creating learning environments that encourage creativity.

5. CONCLUSIONS AND RECOMMENDATIONS

This study presented a comprehensive research model by examining the individual, cognitive, and motivational factors affecting the adoption of ChatGPT in higher education through the PLS-SEM method. In this model, which tested which tested twelve hypotheses (eight direct and four indirect hypotheses), the perceived competence variable exhibited the strongest direct effect on behavioral intention, while the engagement in learning variable did not significantly affect behavioral intention. These findings indicate that individual approaches to using ChatGPT are shaped more by how competent users feel rather than the functionality of the technology itself.

The relatedness variable was found to have a significant effect only on engagement in learning. This result shows that how closely students perceive ChatGPT to be related to their educational processes affects the extent to which they incorporate this tool into their learning. Similarly, the study by Tiwari et al. (2023) indicated that students' interest and participation levels in lessons increased while using ChatGPT, but excessive use of the technology could negatively affect critical thinking. This finding points to the need for balance in the effective use of technology in educational environments.

The autonomy support variable did not show a significant effect on either engagement in learning or behavioral intention. However, in the literature, autonomy support is defined as an important motivational element, especially in terms of individuals feeling in control of their own learning processes. For example, Zhang (2023) emphasized that AI-based tools provide students with freedom in learning and that this autonomy could enhance their commitment to technology. The weak effect of autonomy support in our study may be associated with students not yet fully perceiving ChatGPT as a personal learning tool.

The creative inspiration variable had a significant effect on perceived competence. This finding shows that ChatGPT, as a technology that stimulates students' creativity, also fosters a sense of "I can succeed" in individuals. The study by Alfaisal et al. (2024) also supports this result, revealing that ChatGPT positively affects students' individual learning experiences by offering opportunities for creative problem-solving.

Similarly, the credibility variable had a significant effect on perceived competence. This indicates that individuals prioritize the reliability of technology in their decision to use it. The study by Shahzad et al. (2024) also found that trust is the strongest determinant of students' adoption of AI-based systems. Accordingly, perceiving ChatGPT as a reliable source of information facilitates students' effective use of this tool. To strengthen the adoption of AI-based tools like ChatGPT, transparency about how the AI generates responses and accuracy verification methods should be clearly communicated to users.

The perceived competence variable had the strongest effect on behavioral intention. This result clearly demonstrates that individuals are more inclined to use technology when they feel competent. Likewise, the study by Foroughi et al. (2024) reported that the more positive students' self-perceptions (self-efficacy) were, the stronger their intention to use tools like ChatGPT. Consequently, training sessions or instructional guidelines designed to boost students' self-efficacy with ChatGPT can significantly increase its effective use.

The engagement in learning variable did not directly and significantly affect behavioral intention. This suggests that students' participation in a technology is not sufficient by itself to determine their intention to use it. Participation seems to function more as an intermediate step shaped by intrinsic motivation or external support. The study by Polyportis and Pahos (2023) also showed that students' adoption of technology depends not only on participation level but also on individual attitudes and environmental factors.

The behavioral intention variable represents the main outcome of technology adoption as the dependent variable of this study. The absence of any variable other than perceived competence having a direct effect in the model suggests that this variable is shaped directly by cognitive processes. The study by Tiwari et al. (2023) also emphasized that individual motivations, learning needs, and the sense of trust are key determinants of behavioral intention. Therefore, in the adoption of AI-based tools such as ChatGPT, the user's internal perceptions and sense of individual competence play a critical role.

The study by Balaskas et al. (2025) examined in detail the impact of trust and especially perceived risk as external factors in the adoption process of ChatGPT. Their research showed that students' perceptions of risk towards AI-supported technologies like ChatGPT had a direct negative effect on their intention to adopt. In the current study, it was determined that the element of trust positively affected behavioral intention by increasing perceived competence;

however, the risk factor was not included in the model. This can be considered one of the limitations of the study. In this context, including perceived risk in future research models may contribute to a more comprehensive analysis of individuals' technology adoption behaviors.

In general, this study reveals that the factors affecting the adoption of ChatGPT in education are closely related not only to technological competence but also to psychological, trust-based, and cognitive factors. The fact that some variables in the research model did not turn out to be significant also indicates the need to re-evaluate this issue with larger sample sizes and by considering contextual differences. Further studies with diverse and larger populations could enhance the generalizability and robustness of these findings. Additionally, exploring contextual or demographic differences might uncover further insights into the nuanced ways students adopt AI-supported educational tools.

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