Modeling AI Tool Adoption in Higher Education: The Role of Authentic Learning and Prompting Competence

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https://doi.org/10.34190/ejel.24.4.4784

Abstract: As AI tools are increasingly used in higher education, understanding the factors affecting students' adoption intentions has become theoretically and practically important. Previous studies have mainly relied on traditional technology acceptance constructs, while comparatively little attention has been given to pedagogical and competence-based conditions shaping students' cognitive evaluations of AI systems. To address this gap, the current study builds on the technology acceptance model (TAM) by proposing authentic learning (AL) and prompt engineering competence (PEC) as precursors of perceived usefulness (PU), perceived ease of use (PEU), and behavioral intention (BI) to use AI tools. The study was based on data collected from 309 undergraduate students at the University of Ha'il. A two-step structural equation modeling (SEM) approach was employed using AMOS software. Confirmatory factor analysis confirmed construct reliability, convergent validity, and discriminant validity. SEM was then conducted to test the hypotheses. The findings show that AL significantly predicts both PU and PEU, whereas PEC significantly predicts PEU but not PU. Both PU and PEU were found to be important predictors of BI. Bootstrapping results reveal that AL affects BI through PU and PEU, while PEC affects BI entirely through PEU. The results also confirm considerable explanatory power, with an R^2 of .71 for BI. These findings extend TAM by reconceptualizing AL as a foundational pedagogical precursor influencing AI adoption and by clarifying the unique role of PEC in improving PEU. Integrating pedagogical and competence-based determinants into AI-enabled higher education advances technology acceptance theory and explains the AI adoption mechanism more precisely. The findings provide practical guidance for educators and instructional designers by emphasizing the importance of integrating authentic learning tasks and developing students' prompt engineering skills to enhance meaningful AI-supported learning.

Keywords: Artificial intelligence in higher education, Technology acceptance model, Authentic learning, Prompt engineering competence, Behavioral intention

1. Introduction

The swift emergence of AI tools, especially generative AI, has already changed higher education (Kurtz et al., 2024). There is a growing trend of universities utilizing AI for teaching, assessment, administration, and research (Flores-Velásquez et al., 2024). AI-powered systems are being developed to support personalized learning pathways, adaptive feedback, and data-driven decision-making, offering unprecedented opportunities for engagement and improved learning outcomes (Vafadar and Amani, 2024). This potential is enhanced through generative AI allowing students and teachers to create text, code, and visual outputs to enhance creativity, productivity, and problem-solving abilities (Hughes et al., 2025; Özbay, Özbay and Tutkunca ,2025; Alshammari et al., 2026).

The implementation of AI presents numerous opportunities but also poses several teaching and ethical issues. Issues of academic integrity, bias, privacy, and intellectual property have already sparked considerable debate within the academic community (Vafadar and Amani, 2024; Hughes et al., 2025). The rapid creation of complex content by AI poses a threat to the traditional approach to assessment. The use of AI may lead to cognitive dependency and the weakening of critical thinking skills among students (Hughes et al., 2025). Furthermore, not all students have easy access to sophisticated AI programs, thereby creating a digital divide (Özbay, Özbay and Tutkunca, 2025). Finding solutions to these issues will require more than the implementation of regulations governing the use of AI in education. It will also be necessary for educators to gain a deeper understanding of how students intend to use AI (Rughiniș et al., 2025).

It is important, theoretically as well as practically, to discover students' intentions for adopting AI tools, owing to the potential two-edged sword AI technologies represent (Alenezi, 2023; Alshammari and Alshammari, 2024; Alshammari et al., 2025).

Understanding how students judge AI systems and under what conditions constructive and responsible use of AI occurs is key to effective integration. In recent decades, the technology acceptance model (TAM) has provided

Cite this article: Alshammari, S. H. and Alshammari, M.H. 2026. "Modeling AI Tool Adoption in Higher Education: The Role of Authentic Learning and Prompting Competence", *Electronic Journal of e-Learning*, 24(4), pp 44-59, https://doi.org/10.34190/ejel.24.4.4784

a useful lens for understanding technology adoption (Flores-Velásquez et al., 2024). The TAM states that the main determinants of behavioral intention are perceived usefulness (PU), or how much a system enhances performance, and perceived ease of use (PEU), or how effortless a system is perceived to be (Shahzad, Xu and Javed, 2024; Shata and Hartley, 2025). These constructs have shown a strong capacity to predict technology adoption in educational contexts (Alshammari and Alshammari, 2024; Alshammari et al., 2025).

However, the TAM has conceptual limitations in the generative AI environment. The TAM views adoption as perception driven and implicitly assumes that cognitive evaluations occur primarily through individual assessment of system attributes. Interactive intensity, skill conditioning, and educational embedding also characterize AI-enabled learning environments (Zhao, An and Liu, 2025; Roe et al., 2025). Using generative AI involves constantly prompting and evaluating outputs to apply a certain judgment. Under such conditions, perceptions of usefulness and ease may not result simply from internal system characteristics but from instructional design and user effectiveness. The above suggests that the explanatory power of the TAM in AI contexts is dependent on the inclusion of context-sensitive antecedents that serve to actively construct cognitive perceptions rather than merely predicting intention from them.

This research paper argues that students' perceptions of AI tools are co-constructed through pedagogical framing and interactional competence. Specifically, we propose that authentic learning (AL) and prompt engineering competence (PEC) are proposed as predictors of PU and PEU.

Authentic learning is defined as learning that is designed to occur in contexts that approximate as closely as possible the real world (Larng, 2024). It is possible to use AI tools right away as they can be embedded in authentic tasks. As students engage AI to solve real problems and not just theoretical exercises, its usefulness is seen to be relevant (Salinas-Navarro et al., 2024). These alignments should greatly boost PU. Similarly, an authentic learning environment that scaffolds participation aids in reducing ambiguity and clarifying the task objective. A structure of this kind can reduce complexity perception at the time of interaction between humans and AI, enhancing PEU.

To interact with generative AI, PEC is the social interactional competence to utilize. Effective prompt design is crucial in obtaining relevant and high-quality output from AI (Woo et al., 2024). When prompt tactics are used effectively, there is less ambiguity and more predictability, leading to less frustration for readers (Bashardoust et al., 2024). Therefore, students with stronger PEC are likely to find AI tools easier to utilize. While competence may lead to better results, the main theoretical goal of competence is to reduce friction rather than making things seem genuinely more useful.

Previous studies have investigated AI adoption, pedagogical innovation, and skills related to AI. However, a structural framework that explicitly models pedagogical and competence-based determinants as antecedents of TAM constructs has rarely been the subject of integrated study. Existing research treats perceptions of usefulness and ease as unique cognitive evaluations that are independent from instructional design or skill. A gap therefore exists in understanding how pedagogical structure and AI-specific competence shape perceptions that will influence behavioral intention. As such, this study offers a proposal for, and empirical test of, an extended technology acceptance model that incorporates AL and PEC as predictors of PU and PEU that predict behavioral intention (BI) to use AI tools for learning. Employing structural equation modeling (SEM), the study aims to offer a theoretically enhanced explanation of AI tool adoption in higher education as it demonstrates how pedagogical and competence-based conditions shape students' cognitive evaluations and subsequent adoption intentions.

Accordingly, this study addresses the following research question:

RQ: How do authentic learning and prompt engineering competence influence students' behavioral intention to use AI tools through the mediating mechanisms of perceived usefulness and perceived ease of use within the Technology Acceptance Model framework?

2. Literature Review

2.1 AI Adoption in Higher Education

The quick speed at which generative AI technology is exploding is causing AI to enter more furiously into the higher education sector thereby impacting teaching and learning practices (Adamakis and Rachiotis, 2025; Kurtz et al., 2024). Recent empirical studies increasingly record experimentation with, and adoption of, AI tools among university students, who are embedding these systems in content generation, feedback, data analysis, and problem-solving tasks (Alshammari et al., 2025; Mukhamedkarimova and Umurkulova, 2025).

Two main themes are identified in the literature. First, AI allows for personalization and efficiency. Tools that rely on generative AI, such as adaptive tutoring systems, automated grading systems, and platforms that permit students to innovate and draft in addition to providing iterative feedback in real time, have been found to enhance productivity and perceived academic support (Vieriu and Petrea, 2025; Sallai et al., 2024). However, there is some ethical and pedagogical tension. Concerns about academic integrity, algorithmic bias, overreliance, and digital inequities continue to shape institutional debate (Hughes et al., 2025; Roe et al., 2025).

The use of these systems is determined not by students' exposure to them, but by students' own perceptions. While there are high rates of experimentation with these AI systems, their eventual incorporation into students' educational processes will likely depend on their perceptions of the systems' value (Wahdah, Kurniawan and Irawan, 2025; Flores-Velásquez et al., 2024). Theoretical models are therefore needed to explain students' perceptions of value and usability.

2.2 Technology Acceptance Model in AI Contexts

TAM continues to be utilized to examine technology use in educational environments (Shata and Hartley, 2025). According to TAM, BI is explained by PU, defined as the belief that the technology enhances students' performance, and PEU, defined as the belief that the technology requires minimal effort to use (Flores-Velásquez et al., 2024). The practical use of the TAM in AI contexts supports the theory that PU and PEU predict the acceptance intention of students (Zhao, An and Liu, 2025; Kanont et al., 2024). When students see real academic value and experience smooth and intuitive interactions, they are more likely to include AI into their workflow.

However, current generative AI environments significantly limit the applicability of traditional TAMs. According to this model, perceptions are largely determined by a person's valuation of system characteristics. AI-enabled learning environments depend on skills, more interaction, and enhanced pedagogy (Roe et al., 2025). Generative AI requires frequent prompting, critical assessment, and contextual coordination with learning tasks. In such a context, perceptions of usefulness and ease of use may be affected by instructional design and user competence, not only the features of the system. This indicates that the TAM needs to be enriched with context-sensitive antecedents that are able to account for how perceptions themselves are constructed.

2.3 Authentic Learning as a Pedagogical Predictor

Authentic learning is based on constructivist principles and involves a real, meaningful task that the learner must investigate in collaboration with others, and which requires the learner to apply their knowledge (Lang, 2024; Salinas-Navarro et al., 2024). Rather than focusing on abstract exercises, authentic learning environments ground academic work in realistic contexts, which leads to more engaged learning and higher-order thinking (Kitchen et al., 2025).

Within such scenarios, AI tools are functional. When AI is used for real projects, such as policy analysis or data-driven reports or essays, its usefulness becomes clear. According to Salinas-Navarro et al. (2024), it is likely that the extent to which AI can help students achieve things they value will strengthen PU. Authentic learning may also improve PEU. Specifying prompts, using structured steps, and guided application help reduce ambiguity. When the use of AI is embedded within clearly defined goals, students experience cognitive friction and clarity regarding the appropriate deployment of the technology (Fragkaki et al., 2025; Radović et al., 2021).

Based on the above arguments, the following hypotheses are proposed:

> ***H1:*** *Authentic learning positively influences perceived usefulness.*
>
> ***H2:*** *Authentic learning positively influences perceived ease of use.*

2.4 Prompt Engineering Competence as an AI-Specific Skill

Prompt engineering competence is the ability to make structured, accurate, and iterative prompts in a way that generates accurate and relevant outputs from generative AI systems (Woo et al., 2024; Federiakin et al., 2024). Prompt engineering competence refers to human-centric and operating-focused AI, in comparison to general AI literacy, which is conceptual and ethical (Lee and Palmer, 2025).

Efficiently creating a prompt will eliminate uncertainty during AI interaction. According to Woo et al. (2024), skilled users can harness this ability to tailor their commands strategically, increasing the predictability of responses and reducing trial and error; ultimately reducing perceived effort. Consequently, PEC is theoretically positioned as an antecedent of PEU, suggesting a more complex relationship with PU. While effective prompting may yield higher-quality outputs, proficiency alone does not alter an AI system's functional capabilities. Instead, it simply provides access to these advanced capabilities (Anam, 2025). Therefore, PEC indirectly influence perceptions of usefulness, but its primary theoretical impact lies in enhancing interactional fluency.

Based on the above arguments, the following hypotheses are proposed:

H3: *Prompt engineering competence positively influences perceived ease of use.*

H4: *Prompt engineering competence positively influences perceived usefulness.*

3. Perceived Usefulness, Perceived Ease of Use, and Behavioral Intention

According to the TAM, global task–technology fit (TTF), and information and communication technology (ICT) in traditional schools, recent experiments conducted by Zhao, An and Liu (2025) have demonstrated that PU is the strongest predictor of BI in the field of education. Students' intention to adopt AI tools increases when learning efficiency and academic performance are enhanced, while PEU also influences BI in situations requiring repeated contact (Bayaga, 2025). Interaction that is easier on cognition reduces load and encourages longer usage.

The TAM suggests that PEU could strengthen PU, as both constructs could serve as proximal determinants of intention. In the context of AI, the quality of interaction and the perceived value are closely linked, and these cognitive evaluations jointly influence the adoption of a system.

Based on the above arguments, the following hypotheses are proposed:

H5: *Perceived usefulness positively influences behavioral intention.*

H6: *Perceived ease of use positively influences behavioral intention.*

While the TAM can help establish a foundation for the adoption of new technologies, it is essential to extend the model to AI contexts. The abilities to engage in authentic learning and prompt engineering are expected to serve as key precursors influencing students' PU and PEU. Although TAM suggests a relationship between ease of use and usefulness, these constructs are treated as separate mediators in the present model. The integration of these factors supports the development of a contextually grounded model for AI adoption in higher education. The validation of this model is examined empirically in this study. The proposed research model is presented in Figure 1.

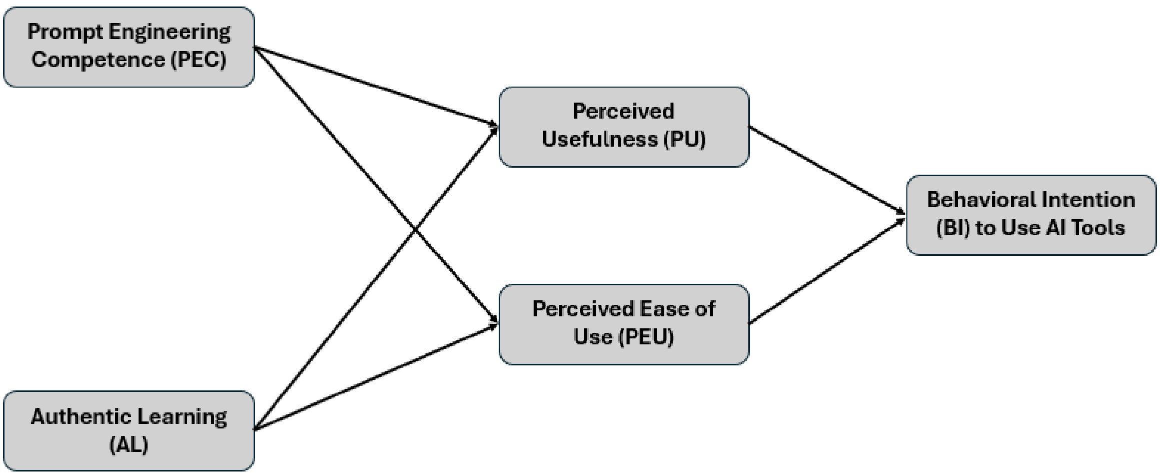

Figure 1: Proposed Research Model

4. Methodology

4.1 Research Design

The study utilized a quantitative cross-sectional research design to investigate the factors influencing students' intention to use AI tools in higher education. To test the posited structural relationships among AL, PEC, PU, PEU, and BI, a survey-based approach was chosen. Many studies in the technology acceptance literature use cross-sectional survey designs, as they are useful to model latent constructs and predictive relationships (Hair et al., 2021; Kline, 2023).

The evaluation of the research model was performed using an AMOS covariance-based SEM test. According to Byrne (2013) and Hair et al. (2021), SEM is particularly useful for testing theoretically specified structural relationships among latent constructs and evaluating the extent to which empirical data support proposed explanatory models.

4.2 Participants and Data Collection

The collection of data took place in the first semester of 2025–2026. Respondents for this study were recruited from among students of various colleges of the University of Ha'il taking the course Introduction to AI. Google Forms was utilized to devise an online questionnaire. The link to the survey was shared with students via Blackboard and the university email, authorized by the institution. Potential participants were briefed about the study objectives, anonymity, and confidentiality. A total of 309 valid responses were collected and analyzed. The sample size is greater than the minimum recommendations for analysis using SEM, which normally requires a minimum of 200 cases or 10 participants per estimated parameter (Hair et al., 2006; Kline, 2023). This sampling frame was intentionally selected because students enrolled in the "Introduction to AI" course have structured and direct exposure to AI tools within an educational context. Such exposure ensures that participants possess sufficient familiarity and interaction experience to meaningfully evaluate perceived usefulness, perceived ease of use, and competence-related factors. Therefore, this context provides a suitable and theoretically relevant setting for examining AI adoption mechanisms in higher education.

However, it is acknowledged that the use of a single institution and course may limit the generalizability of the findings. This limitation is addressed in the limitations and future research section, and future research is encouraged to replicate the study across diverse institutional and disciplinary contexts.

4.3 Instrumentation

The survey tool consisted of five sections based on validated scales. All items were measured using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The nine items used to evaluate PEC were adapted from the research of Gibreel and Arpaci (2025). The items examine students' ability to ask precise questions, improve AI instructions step by step, and communicate with generative AI.

Authentic learning was assessed using nine items adapted from Neo et al. (2012). The scale compares students' perceptions of learning in real life to an active and collaborative inquiry approach. The four items testing PU were adapted from Davis (1989) and measure the extent to which students agree that using AI tools could boost their academic performance and learning ability. The four items used to measure PEU were also adapted from Davis (1989). This scale measures the extent to which students believe that AI tools are easy to learn and use. Behavioral intention was measured using three items (Davis, 1989) that reflect students' intention to continue using AI tools for learning purposes. Prior to distribution, all items were reviewed for clarity and relevance.

4.4 Data Analysis

The data were analyzed in two stages. SPSS was used to help with the demographic and data analysis, examining missing values, normality, and outliers in our study. Statistics were calculated to describe participants' characteristics. All statistical analyses were conducted using IBM SPSS Statistics version 26 and AMOS version 24. Missing data were assessed prior to analysis. The dataset contained no missing values; therefore, no data imputation or deletion procedures were required. The two-step SEM method suggested by Anderson and Gerbing (1988) was used. Initially, confirmatory factor analysis (CFA) was performed to evaluate the measurement model in terms of construct reliability, convergent validity, and discriminant validity. Next, the relationships between constructs were examined using the structural model. Path coefficients, critical ratios, and significance levels were evaluated. Bootstrapping methods were employed for indirect effect and mediation path evaluation using 5,000 resamples with bias-corrected confidence intervals, which provide robust estimates without assuming normality of the sampling distribution (Preacher and Hayes, 2008). By separating measurement validation from structural testing, the two-step SEM procedure improves rigor and reduces bias, thereby enhancing the interpretability of SEM models (Anderson and Gerbing, 1988; Byrne, 2013).

Outliers were examined using boxplots for univariate outliers and Mahalanobis distance for detecting potential multivariate outliers. No significant outliers were identified that required removal.

5. Results

5.1 Demographic Information

Table 1 presents the demographic characteristics of the 309 respondents in this study. Of this number, the majority were male respondents, namely 66.7% (n = 206), with 33.3% (n = 103) being female. Despite the fact that gender distribution is skewed in favor of male respondents, both groups were adequately represented for meaningful structural modeling.

In terms of their academic programs, most respondents were enrolled in a bachelor's degree program (90.9%; n = 281), while the rest were diploma students (9.1%; n =28). The outcomes mainly reflect those of individuals pursuing undergraduate degrees, which seems justifiable given the effect of increasing AI tool use at bachelor's level.

The study included a variety of participants from different colleges to increase the representation of various disciplines. The highest percentage of respondents came from the health college (25.2%; n = 78), business administration (19.4%; n = 60), science (13.9%; n = 43), arts (11.7%; n = 36), computer science and engineering (9.1%; n = 28), education (8.1%; n = 25), applied college (7.4%; n = 23), and engineering (5.2%; n = 16). The presence of various disciplines strengthens the applicability of the findings across different academic fields. especially as uses of AI increasingly straddle technical and non-technical disciplines.

On the question of previous exposure to AI tools, 94.8% of respondents (n = 293) reported previous use of AI, whereas 5.2% of respondents (n = 16) reported no previous use of AI. The high rate of exposure indicates that students are already using AI. Therefore, it is both timely and relevant to investigate the determinants of AI adoption.

Regarding the duration of utilization of AI tools, approximately half the respondents (47.2%; n = 146) had utilized AI tools for more than six months. Moreover, 20.1% (n = 62) had utilized AI tools for four to six months, while 17.8% (n = 55) and 14.9% (n = 46) had utilized AI for one to three months and for less than one month, respectively. The data shows that a large percentage of respondents had had ongoing experience with the tools, indicating that their answers were more likely based on experience and not on a first-time test.

The demographic indicators of the analyzed sample were heterogeneous in terms of academic discipline, level of AI experience, and gender. Due to the high levels of previous use of AI and extent of use, it would be appropriate to study the community's cognitive and pedagogical reasons for utilizing AI.

Table 1: Demographic and Background Characteristics of the Participants

		Frequency	Percent
Gender	Male	206	66.7
	Female	103	33.3
Academic Program	Bachelor	281	90.9
	Diploma	28	9.1
Colleges	Education	25	8.1
	Science	43	13.9
	Arts	36	11.7
	Business Administration	60	19.4
	Computer Science and Engineering	28	9.1
	Engineering	16	5.2
	Applied College	23	7.4
	Health	78	25.2
Previous_experience_with_AI	Yes	293	94.8
	No	16	5.2

		Frequency	Percent
Period_with_Using_AI_tools	Less than a month	46	14.9
	1-3 Months	55	17.8
	4-6 Months	62	20.1
	More than six months	146	47.2
	Total	**309**	**100.0**

5.2 Confirmatory Factor Analysis

Following the approach advocated by Anderson and Gerbing (1988), a confirmatory factor analysis (CFA) was conducted to assess the measurement model. The initial measurement model did not achieve acceptable fit according to commonly recommended SEM criteria, yielding $\chi^2/df = 3.046$, CFI = .877, IFI = .878, and RMSEA = .082 (Awang, 2015). Figure 2 presents the initial measurement model before refinement.

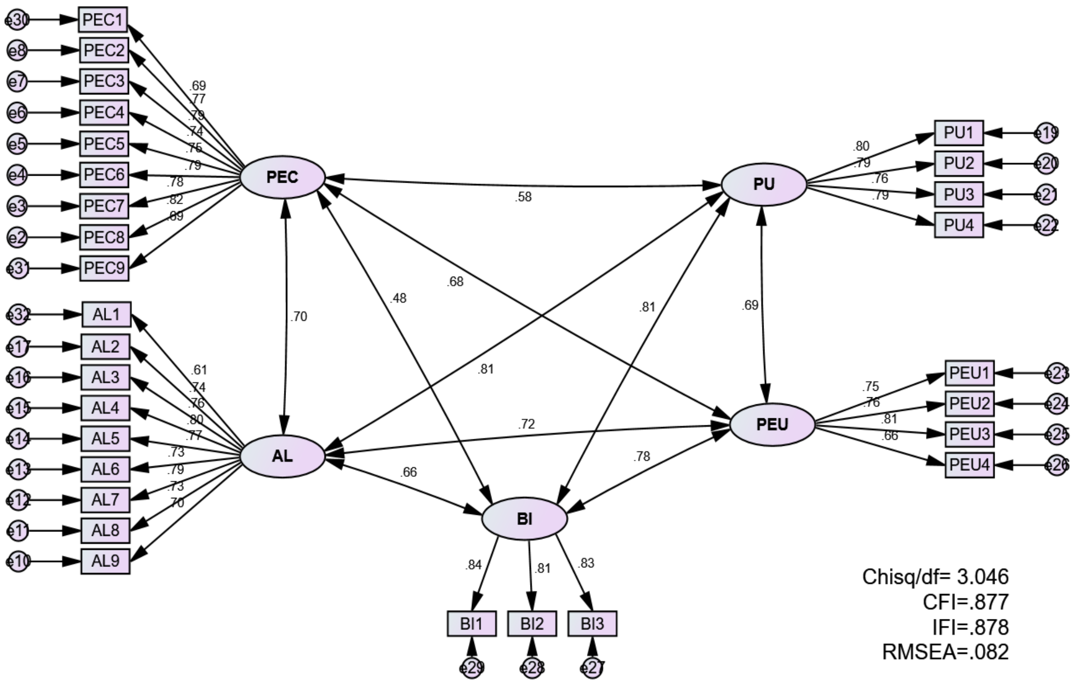

Figure 2: Initial Measurement Model Before Refinement

However, inspection of the factor loadings and modification indices revealed that three items (AL1, PEC1, and PEC9) exhibited relatively low factor loadings and contributed to model misfit. In accordance with SEM guidelines, indicators that do not adequately represent their underlying construct may be removed to improve measurement quality (Hair et al., 2010). Accordingly, these three items were removed from the model.

Furthermore, modification indices suggested correlating residual terms within the same constructs. Specifically, e3 and e2 corresponded to items within the Authentic Learning construct, while e12 and e15 corresponded to items within the Prompt Engineering Competence construct. These covariances were theoretically justified due to similarities in item wording and conceptual overlap. As recommended by Awang (2015), correlated residuals were introduced only when supported by substantive theoretical justification rather than solely to improve statistical fit.

Model fit was evaluated using multiple goodness-of-fit indices, including the chi-square to degrees of freedom ratio (χ^2/df), Comparative Fit Index (CFI), Incremental Fit Index (IFI), and Root Mean Square Error of Approximation (RMSEA). Following established SEM guidelines, χ^2/df values below 3.0, CFI and IFI values of .90 or higher, and RMSEA values of .08 or lower indicate acceptable model fit (Hair et al., 2010; Awang, 2015).

Following these theoretically justified modifications, the revised measurement model achieved acceptable fit (χ^2/df = 2.906, CFI = .901, IFI = .901, RMSEA = .079). Compared with the initial model, the revised model demonstrated improved fit across all major indices, indicating a more adequate representation of the observed data. The limited and theoretically justified nature of the modifications ensured model parsimony and avoided excessive post-hoc adjustments. Accordingly, the revised measurement model was deemed suitable for subsequent structural analysis. Figure 3 presents the revised measurement model after refinement.

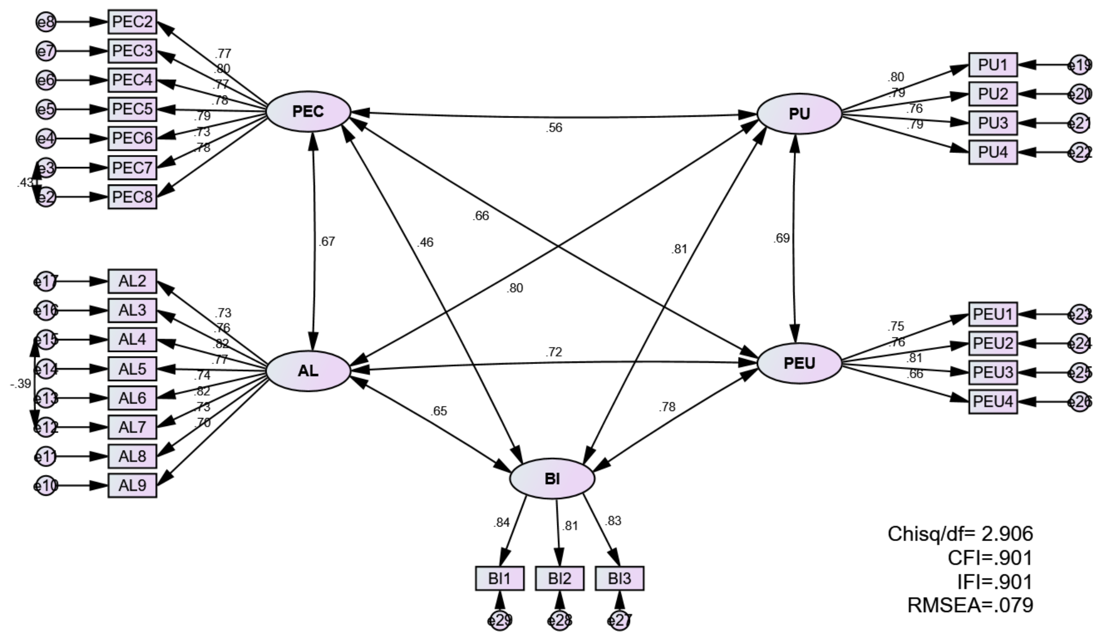

Figure 3: Revised Measurement Model After Refinement

To facilitate evaluation of the model refinement process and enhance methodological transparency, Table 2 compares the goodness-of-fit indices of the initial and revised measurement models.

Table 2: Comparison of Fit Indices for the Initial and Revised Measurement Models

Model	χ^2/df	CFI	IFI	RMSEA
Initial CFA Model	3.046	.877	.878	.082
Revised CFA Model	2.906	.901	.901	.079

As shown in Table 2, the revised model demonstrated improved fit across all major indices, supporting the adequacy of the measurement model for subsequent structural analysis.

Composite reliability (CR) and average variance extracted (AVE) were used to determine the convergent validity after the CFA verified the model fit. The SEM literature suggests that CR values should be higher than .60 to show adequate internal consistency. According to Hair et al. (2010), it is indicated by AVE values which should be more than .50 to show that the latent construct can explain half or more variance of that indicator. All constructs met all of these criteria (see Table 3). The observed CR values were between .834 and .915, all greater than .60. Likewise, the ranges of AVE values varied from .558 to .683, exceeding .50. The results show that the indicators sufficiently converge on their latent constructs. The overall CR and AVE statistics confirm that all the measurement model's constructs have satisfactory convergent validity (Awang, 2015; Hair et al., 2010).

Table 3: Composite Reliability and Convergent Validity of the Measurement Model

	CR	AVE
PEU	0.834	0.558
PEC	0.913	0.601
AL	0.915	0.575
PU	0.866	0.617
BI	0.866	0.683

The discriminant validity was assessed using the heterotrait–monotrait (HTMT) ratio of correlations, a more reliable and sensitive measure than the traditional method (Henseler, Ringle, and Sarstedt. 2015). According to Henseler, Ringle, and Sarstedt (2015), HTMT values less than .85 (conservative threshold) or .90 (liberal threshold) are considered ideal. Similarly, Hair et al. (2021) suggest that the HTMT value should not exceed .90 to ensure the constructs are conceptually distinct.

The HTMT values as shown in Table 4, range from .450 to .810. The highest value (PU and BI = .810) is below the conservative benchmark of .85 indicating that the constructs are empirically distinct. The inter-construct HTMT ratios did not approach, let alone exceed, the critical threshold of .90. Therefore, the model's latent constructs are sufficiently distinct from one another, as each one is expected to represent a particular concept (Henseler, Ringle, and Sarstedt 2015; Hair et al. 2021).

Table 4: Heterotrait–Monotrait Ratio (HTMT) for Discriminant Validity Assessment

Construct	PEC	AL	PU	PEU	BI
PEC	—	0.620	0.550	0.590	0.450
AL	0.620	—	0.780	0.720	0.670
PU	0.550	0.780	—	0.630	0.810
PEU	0.590	0.720	0.630	—	0.740
BI	0.450	0.670	0.810	0.740	—

5.3 Standarized Estimate

As suggested by Awang (2015), the strength of the factor loadings, structural paths, and coefficient of determination (R^2) were assessed by examining standardized estimates. Figure 4 illustrates that all the retained indicators, having standardized loadings over .60, add up to effective indicator reliability, indicating that the indicators adequately represent their constructs. The standardized structural coefficients show significant effect sizes, which allow for comparison of the weights of the predictors of the model. Significantly, this model was able to explain 71% of the variance in BI (R^2 = .71). According to Cohen (2013), R^2 estimates above .26 represent a large effect size for behavioral research. Thus, R^2 result demonstrates that the proposed model offers an adequate and practically significant representation of students' intention to adopt AI tools for higher education.

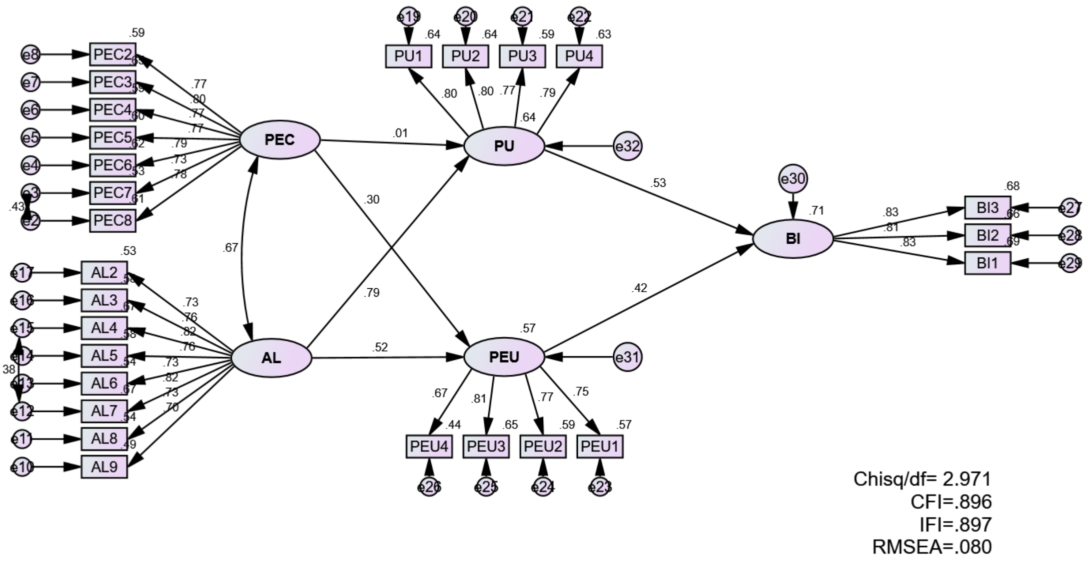

Figure 4: Final Structural Equation Model with Standardized Path Coefficients

5.4 Unstandardized Estimate

To evaluate the structural relationships and test the research hypotheses, the unstandardized estimates were examined. Unstandardized estimates, or actual regression weights (B), represent the relationship between variables in their true measurement units. To calculate the critical ratio (CR), the estimate is divided by its standard error. Awang (2015) notes that the unstandardized estimate is crucial for determining the statistical significance of relationships between variables. CR values are comparable to t-values; values greater than ±1.96 are considered statistically significant. By analyzing the unstandardized estimates, their standard errors, CR values, and corresponding p-values, researchers can gain valuable insights into the statistical significance and validity of relationships in covariance-based SEM models. Standardized estimates reveal the strength of the relative effect, while unstandardized estimates help assess parameter significance for the acceptance or rejection of hypotheses. Figure 5 presents the unstandardized SEM estimates.

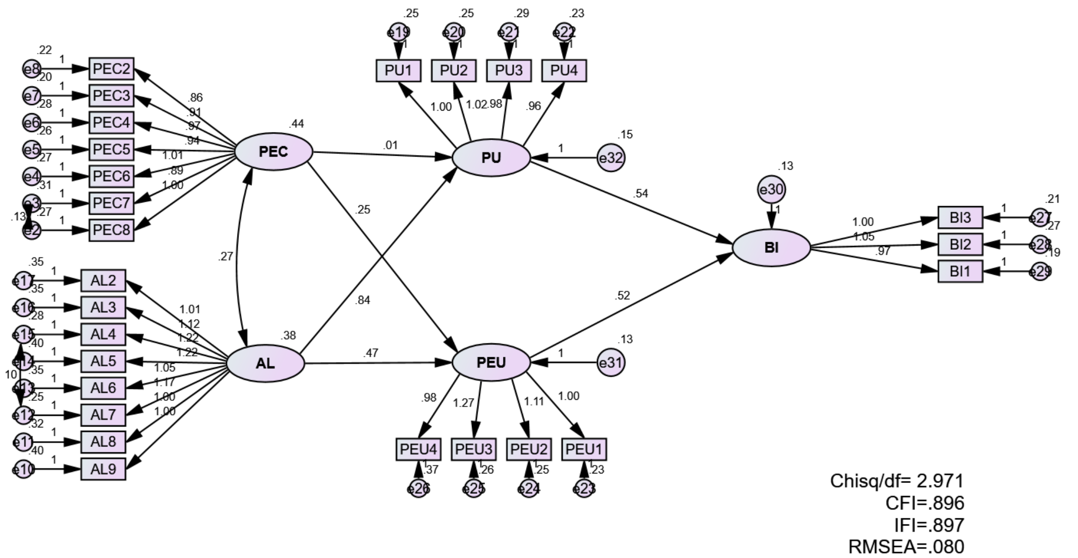

Figure 5: Unstandardized Structural Equation Model Estimates

6. Structural Model and Hypothesis Testing

The structural relationships were evaluated using unstandardized regression estimates with standard errors with CRs and p-values. According to Awang (2015), a value greater than ±1.96 is significant at .05.

As indicated in Table 5, AL significantly predicted PU (B = .844; CR = 9.360; p < .001). Consequently, H1 is accepted. AL was positively associated with PEU (B = .466; CR = 6.647; p < .001), supporting H2. The current research establishes the importance of pedagogical design in affecting students' cognitive perception of AI tools.

The effect of PEC on PEU is positive and significant (B = .247; CR = 4.180; p < .001), supporting H3. However, PEC was not significantly associated with PU (B = .013; CR = .206; p = .837). Therefore, H4 is not supported. As the findings suggest, prompt engineering helps lower the level of effort to interact with AI tools, but prompt engineering skills do not enhance the PEU of the tool to achieve learning outcomes.

In accordance with the main propositions of the TAM, PU significantly predicted BI (B = .544; CR = 8.144, p < .001). Therefore, H5 is supported. In the same way, PEU was found to significantly predict BI (B = .516; CR = 6.564; p < .001), thus confirming H6.

Consequently, five of the six hypotheses were confirmed. According to the findings, AL plays a central role in determining the perceptions of usefulness and ease of use. However, PEC enhances only PEU. The cognitive perceptions (PU and PEU) appear as significant predictors of students' intention to use AI tools in higher education.

Table 5: Results of Structural Equation Modeling and Hypothesis Testing

Hypothesis	Path	B	S.E.	C.R.	P	Decision
H1	AL → PU	.844	.090	9.360	<.001	Supported
H2	AL → PEU	.466	.070	6.647	<.001	Supported
H3	PEC → PEU	.247	.059	4.180	<.001	Supported
H4	PEC → PU	.013	.063	.206	.837	Not Supported
H5	PU → BI	.544	.067	8.144	<.001	Supported
H6	PEU → BI	.516	.079	6.564	<.001	Supported

7. Indirect Effects Analysis

The indirect effects assessment of AL and PEC on BI was done using bootstrapping techniques. Both Awang (2015) and Hair et al. (2010) recommend using bootstrapping to analyze the indirect effects in SEM because bootstrapping does not require any assumption of normality of the sampling distribution. Additionally, bootstrapping provides bias-corrected (BC) confidence estimates for the indirect paths.

Table 6 shows that AL has a significant indirect influence on BI through PU and PEU. The corresponding values were found to be (B = .700; p < .001), confirming that the effect of AL on students' intention to use AI tools occurs through a cognitive evaluation mechanism. AI appears to be more useful and easier to use for students when embedded in real-world learning situations, resulting in a stronger intention to use the technologies.

Similarly, PEC has a significant indirect effect on BI through PEU (B = .135; p = .044). This result means that prompt engineering skills enhance students' intention to use AI tools. The path from PEC to PU was found to be non-significant, indicating that the mediation was only valid for PEU.

The bootstrapping results reflect that both the pedagogical determinant (AL) and the competence-based determinant (PEC) have an indirect effect on BI via cognitive perceptions. This shows that PU and PEU reinforce each other in the extended TAM framework.

Table 6: Bootstrapped Indirect Effects on Behavioral Intention (BI)

Predictor	Indirect Path(s)	Indirect Effect (B)	p-value	Decision
AL	AL → PU → BI; AL → PEU → BI	0.700	<.001	Supported
PEC	PEC → PEU → BI	0.135	.044	Supported

8. Discussion

The study extends the TAM by adding AL and PEC as upstream determinants of the adoption of AI tools in higher education. Using SEM in a staged approach on data from 309 undergraduate students, the results shed light on how pedagogical design and AI-specific interactional skills affect cognitive assessments of AI tools, which, in turn, leads to use intention. The model explains 71% of the variance in BI. This indicates that the proposed extensions have a significant impact on the explanatory ability of TAM in AI-enabled learning.

The results show that AL is a significant predictor of PU and PEU. As a result, the design of instructions influence the beliefs students have about AI technologies. Students who engage with AI tools that are embedded in authentic, problem-oriented and contextually relevant tasks are more likely to use them as tools for achieving real academic and professional results (Kitchen et al., 2025; Lang, 2024; Salinas-Navarro et al., 2024). When learners enter a workplace or classroom-like context, AI is no longer experienced as a technological artefact but as a resource that contributes towards better performance. When technology delivers visible and consequential benefits, it is perceived as being useful.

At the same time, structured and scaffolded AL appears to lessen interactional levels of perceived difficulty. Fragkaki et al. (2025) and Radović et al. (2021) argue that interacting with AI is made easier through guided engagement, having a clear task objective, and working as a team. Students do not see AI as a standalone tool but as part of a goal-directed learning ecology. As a result, it requires less effort and is easy to use. Seemingly, usability is not only dependent on interface features but also on pedagogical embedding.

Another important finding is that PEC was significantly associated with PEU but not PU. The underlying rationale for this distinction lies in the nature of skill-based interaction with AI systems, where students' perceptions are shaped by their ability to effectively engage with prompt creation rather than by the perceived value of the outcomes. Students who can create effective prompts often experience smoother interactions with AI, leading to less friction and frustration with the application (Anam, 2025; Bashardoust et al., 2024; Woo et al., 2024). Thus, students are more likely to perceive AI tools as user-friendly and easier to use.

However, skilled prompting alone does not increase perceptions of usefulness. Perceived usefulness, rather than the user's ability to use AI, seems to be based on the belief that AI systems can lead to significant improvements in learning outcomes. In other words, leveraging AI operationally allows organizations to make use of it but does not necessarily make AI valuable. Even if a student is skilled at crafting prompts, the fact that AI outputs do not significantly advance learning tasks will not change usefulness perceptions (Lee and Palmer, 2025; Federiakin et al., 2024). The non-significant effect of prompt engineering competence on perceived usefulness can be interpreted through expectancy–value theory. While competence enhances students' ability to interact effectively with AI systems, perceived usefulness depends on the extent to which students believe that the technology contributes to meaningful learning outcomes. Thus, operational proficiency alone may not translate into higher perceived value unless it is aligned with task relevance and learning goals. This distinction highlights that competence reduces interactional effort but does not necessarily shape outcome-based evaluations. Our understanding of competence-based determinants is refined by this finding, which highlights that interactional skills primarily affect effort-related beliefs and not outcome-related ones.

As indicated by TAM, PU and PEU significantly predict BI (Chukwuere, 2024; Flores-Velásquez et al., 2024; Ali et al., 2025; Zhao, An and Liu, 2025). Overall, students are more likely to adopt AI tools in a learning context when they perceive them as useful and easy to use. Furthermore, the R^2 value of .71 indicates that the model explains a substantial proportion of the variance in AI adoption. Finally, the findings indicate that PU and PEU demonstrate strong explanatory power within the model, alongside the additional antecedent variables introduced in this study.

9. Theoretical Implications

Unlike prior TAM extensions that primarily introduce additional perceptual or attitudinal variables, this study advances the model by integrating pedagogical and competence-based antecedents as upstream antecedents of cognitive evaluations. This reconceptualization positions perceived usefulness and perceived ease of use as outcomes of learning design and interactional capability, rather than solely as evaluations of system characteristics. In doing so, the study contributes to a more context-sensitive understanding of AI adoption in educational environments. This study improves the TAM in three ways. First of all, cognitive beliefs that are core to the TAM are pedagogically constructed and not merely individually, influencer, or technology based. Conventional use of the TAM assumes that PU and PEU emanate from user-technology interaction in isolation. According to the present findings, learning contexts shape authenticity perceptions. By linking pedagogical design to the TAM's core elements and locating technology acceptance to the educational context's broader learning ecology, this study improves the TAM's contextual validity, especially in educational contexts.

Prompt engineering competence exerts a distinct influence that enhances the understanding of competence-based determinants. The reduction of user effort appears to drive the value of AI-specific operational skills. The distinction between operational and functional skills provides a more nuanced understanding of how competence in specific skills influences the decision to adopt AI applications. However, this finding suggests that not all forms of AI literacy equally enhance perceptions of usefulness and ease of use.

Furthermore, by integrating both pedagogical and competence-based influences on AI adoption, the TAM framework can better account for the role of educational context in shaping adoption decisions, particularly for technologies that require advanced skills, such as generative AI in higher education. Cognitive evaluations related to AI adoption are not formed in isolation; rather, they are shaped by the learner's educational environment and their competence in relevant skills.

10. Practical Implications

The findings offer valuable insights for higher education stakeholders, especially for curriculum designers in terms of integrating AI with real-world authentic tasks. According to the study results, the use of AI was relevant and useful for respondents when using project-based and solution-based activities. This strengthens the PU of users. Classroom use of AI is therefore a more meaningful application than incidental exposure to AI (Kitchen et al., 2025; Salinas-Navarro et al., 2024). Instructors should deliberately scaffold how learners interact with AI. Mzwri and Turcsányi-Szabó (2025) highlight that through structured opportunities to practice creating prompts, revising outputs and evaluating AI responses can reduce perceived difficulty, ultimately leading to increased confidence in utilizing AI. However, tasks should be devised in a way that shows how AI contributes to learning outcomes. This is important, because developing competence is not enough for PU. The policy-makers of educational institutions should note the high explanatory power, that is, the predictability, of the model for integrated AI strategy design. Concurrent investment in innovation in teaching methodologies and AI-specific skills is the way forward with regard to adopting AI. According to Adamakis and Rachiotis (2025), Kurtz et al. (2024), and others, policies should not be limited to frameworks restricting integrities. Competences should be responsibly and effectively trained to engage in AI.

11. Limitations of the Study and Future Research

The study has several limitations. Because it is cross-sectional in nature, it is not possible to establish causality or to assess how these variables may evolve over time. Therefore, longitudinal research is needed to examine the evolution of these variables. Another limitation of the study is the generalizability of the findings. The sample was drawn from a single institution, and institutional culture may influence the variables examined in this study. Consequently, the study should be replicated across multiple institutions and diverse cultural contexts. All variables were measured through self-reporting, introducing the potential for common method bias. Future studies could incorporate objective measures of these variables. As the extended model suggests, AI adoption is a multilevel phenomenon. Therefore, future research should examine the influence of additional factors, such as trust in AI technologies, ethical considerations, social influence, and AI anxiety.

12. Conclusion

This study provides a theoretically grounded extension of the Technology Acceptance Model by demonstrating that students' adoption of AI tools in higher education is not solely driven by traditional cognitive evaluations of usefulness and ease of use but is significantly shaped by pedagogical context and interactional competence. Specifically, authentic learning emerges as a foundational antecedent that enhances both perceived usefulness and perceived ease of use, while prompt engineering competence primarily reduces interactional effort rather than influencing outcome-based evaluations. These findings highlight that AI adoption is a contextually constructed process, where meaningful integration into real-world learning tasks plays a critical role in shaping students' perceptions and intentions. The study thus contributes to the refinement of TAM by positioning pedagogical design and competence as upstream factors influencing cognitive evaluations. Future research should extend this model across different institutional and cultural contexts to enhance generalizability. Longitudinal designs are also needed to examine how perceptions and competencies evolve over time. In addition, further studies may incorporate additional variables such as AI literacy, trust, ethical awareness, and social influence to provide a more comprehensive understanding of AI adoption in higher education. Overall, the findings suggest that maximizing the educational value of AI requires not only accessible technologies but also thoughtfully designed learning environments and targeted development of students' interactional competencies.

AI Statement: AI tools were used solely for language refinement during the preparation of this manuscript. The authors wrote, reviewed, and approved all manuscript content and take full responsibility for the accuracy, integrity, and originality of the work.

Ethics statement: All participants provided informed consent prior to participation in the study. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki. Ethical approval was obtained from the Research Ethics Committee (REC) at the University of Hail, Saudi Arabia (Approval No. H-2026-090). Participation was voluntary, and all responses were collected anonymously and analyzed in aggregated form

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Appendix A: Measurement Items

Prompt Engineering Competence for Learning with ChatGPT

PEC1: I can write academic prompts that help ChatGPT provide accurate and relevant information for my learning.

PEC2: I can break down academic tasks into clear steps and write prompts that guide ChatGPT through each step.

PEC3: I can adjust my prompts using different formats (such as questions, lists, or scenarios) to improve the quality of ChatGPT's academic responses.

PEC4: I can improve ChatGPT's answers by specifying requirements such as role, tone, length, or academic format.

PEC5: I can enhance ChatGPT's responses by adding background information and recognizing possible limitations or biases in its output.

PEC6: I can write prompts that encourage ChatGPT to perform higher-order thinking, such as analyzing, comparing, or evaluating academic concepts.

PEC7: I can use real examples or academic scenarios in my prompts to make ChatGPT's responses more relevant for my learning.

PEC8: I can improve ChatGPT's answers by refining my prompts based on previous responses.

PEC9: I can evaluate ChatGPT's responses for accuracy and credibility when completing academic tasks.

Perceived Authentic Learning with ChatGPT

AL1: I feel that the information generated by ChatGPT is relevant to my learning.

AL2: The activities I do using ChatGPT feel authentic and relevant to my academic tasks.

AL3: I enjoy using ChatGPT as a tool to learn academic topics.

AL4: The examples and explanations provided by ChatGPT help me understand course content better.

AL5: ChatGPT helps me reflect more deeply on the topics I am studying.

AL6: The information suggested by ChatGPT (such as references or resources) is useful for my learning.

AL7: The explanations and content generated by ChatGPT are relevant to my academic needs.

AL8: I like that ChatGPT helps me explore additional sources and external information while learning.

AL9: I can apply what I learn from using ChatGPT in real academic tasks or real-life situations.

Perceived Usefulness of ChatGPT for Learning

PU1: Using ChatGPT improves my learning performance.

PU2: Using ChatGPT enhances my effectiveness in studying academic topics.

PU3: Using ChatGPT increases my learning productivity.

PU4: I find ChatGPT useful for my academic learning.

Perceived Ease of Use of ChatGPT

PEU1: Learning to use ChatGPT is easy for me.

PEU2: I find it easy to get ChatGPT to do what I want for my learning.

PEU3: My interaction with ChatGPT is clear and understandable.

PEU4: It is easy for me to become skillful in using ChatGPT.

Behavioral Intention to Use ChatGPT

BI1: Assuming I have access to ChatGPT, I intend to use it for my learning.

BI2: Given that I have access to ChatGPT, I predict that I will use it for academic purposes.

BI3: I plan to continue using ChatGPT in the future for my learning.