Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 10, No. 7, 272-287
2026
Publisher: Learning Gate
DOI: 10.55214/2576-8484.v10i7.13368

Understanding academic performance in generative AI-assisted learning: The roles of cognitive trust, knowledge application, personalization, and playfulness

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Abstract: As generative artificial intelligence (AI) becomes increasingly integrated into higher education, understanding the factors that contribute to effective learning outcomes has emerged as an important research issue. While prior studies have primarily focused on technology adoption and usage intentions, relatively limited attention has been given to the mechanisms through which students translate AI-supported experiences into academic performance. This study investigates the relationships among cognitive trust, knowledge application, personalization, playfulness, and academic performance in the context of generative AI-assisted learning. Data were collected from 306 university students with experience using generative AI for academic purposes. The proposed research model was analyzed using partial least squares structural equation modeling (PLS-SEM). The findings indicate that cognitive trust is positively associated with knowledge application, personalization, playfulness, and academic performance. Knowledge application is also positively associated with academic performance. In contrast, personalization does not show a significant association with academic performance, while playfulness demonstrates a negative association. Additional multi-group analysis reveals a significant gender difference in the relationship between personalization and academic performance. Practical implications for educators, universities, and AI service providers are discussed.
Keywords: *Academic performance, Cognitive trust, Generative AI, Knowledge application, Personalization, Playfulness.*

1. Introduction

The rapid advancement of generative artificial intelligence (AI) has transformed the educational landscape and created new opportunities for teaching and learning. Unlike traditional educational technologies that primarily facilitate information access and communication, generative AI systems can generate original content, provide personalized explanations, deliver real-time feedback, and engage in natural-language interactions with users. The public release and widespread adoption of large language models such as ChatGPT have accelerated the integration of AI into educational settings, fundamentally changing how students search for information, complete assignments, develop ideas, and solve academic problems [1, 2]. As a result, generative AI has become one of the most influential technological developments in higher education.

The growing popularity of generative AI has stimulated considerable academic interest. Previous studies have highlighted its potential to enhance learning effectiveness, promote self-directed learning, improve knowledge acquisition, and support academic productivity [3-5]. Through interactive conversations and adaptive responses, generative AI can function as a virtual learning assistant that supports students in understanding complex concepts, generating ideas, and refining academic work [1, 6]. These capabilities have encouraged educational institutions and instructors to explore ways of integrating generative AI into teaching and learning processes.

History: Received: 4 May 2026; Revised: 2 July 2026; Accepted: 8 July 2026; Published: 24 July 2026
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Despite these promising developments, concerns regarding the educational implications of generative AI continue to emerge. Researchers have raised questions about the reliability and accuracy of AI-generated content, the potential erosion of critical thinking skills, and challenges related to academic integrity [7, 8]. Because generative AI systems may occasionally provide inaccurate or fabricated information, students must evaluate and verify AI-generated outputs rather than accept them uncritically. Consequently, educational outcomes may depend not only on the technological capabilities of generative AI but also on how students perceive, evaluate, and utilize AI-generated information during their learning activities.

Among the various factors that may influence educational outcomes, cognitive trust has emerged as a particularly important consideration. Trust plays a central role in determining whether individuals are willing to rely on technological systems and incorporate their outputs into decision-making processes [9, 10]. In educational contexts, students who perceive generative AI as competent, knowledgeable, and reliable may be more likely to engage with AI-generated information and apply it to academic tasks. Conversely, students who doubt the quality or credibility of AI outputs may be reluctant to incorporate AI-generated knowledge into their learning activities. Although prior research has extensively examined trust in information systems and online environments, relatively limited attention has been devoted to understanding how cognitive trust influences educational outcomes in generative AI contexts.

Furthermore, existing studies have primarily focused on technology adoption intentions, usage behavior, ethical issues, and institutional responses [11-14]. Comparatively fewer studies have investigated the mechanisms through which students translate their interactions with generative AI into academic performance. In particular, limited research has examined how cognitive trust shapes learning-related experiences such as knowledge application, personalization, and playfulness. This omission is important because positive perceptions of AI systems do not necessarily guarantee meaningful learning outcomes. Features that enhance user experience may not always contribute directly to academic success, and some characteristics may even produce unintended consequences in educational settings.

This study addresses these gaps by developing and testing a research model that examines the relationships among cognitive trust, knowledge application, personalization, playfulness, and academic performance in the context of generative AI-assisted learning. Drawing upon trust theory, knowledge-based learning perspectives, and educational technology research, this study investigates how students' trust in generative AI influences their learning experiences and academic outcomes. By focusing on both cognitive and experiential factors, the study provides a more comprehensive understanding of the educational value of generative AI beyond simple adoption or usage intentions.

The findings contribute to the growing literature on generative AI in education in several ways. First, the study extends existing research by identifying the learning-related mechanisms through which cognitive trust is associated with academic performance. Second, it provides empirical evidence regarding the educational roles of personalization and playfulness, two factors that remain insufficiently understood in AI-supported learning environments. Finally, the study offers practical insights for educators, universities, and AI service providers seeking to maximize the educational benefits of generative AI while minimizing potential drawbacks. As generative AI continues to reshape higher education, understanding these relationships is essential for developing effective and responsible AI-supported learning environments.

2. Literature Review

Generative AI has rapidly emerged as one of the most transformative technologies in contemporary education. Unlike traditional educational technologies that primarily deliver information or support communication, generative AI systems can create original content, provide personalized explanations, generate feedback, and engage in interactive conversations with learners [15-17]. The widespread adoption of systems such as ChatGPT has significantly altered how students access information,

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ISSN: 2576-8484
Vol. 10, No. 7: 272-287, 2026
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complete assignments, and support their learning processes. As a result, generative AI has attracted substantial attention from researchers seeking to understand its educational opportunities and challenges [1, 2].

Existing studies have highlighted several educational benefits of generative AI. One of the most frequently discussed advantages is its ability to provide immediate and adaptive learning support. Students can receive explanations, examples, summaries, and feedback tailored to their needs, potentially reducing learning barriers and improving access to educational resources. Research has suggested that generative AI can function as a virtual tutor capable of supporting self-directed learning, problem-solving, and knowledge development across various disciplines [1, 6]. In higher education, students have reported using generative AI to brainstorm ideas, clarify difficult concepts, organize assignments, and improve writing quality [5].

Another important stream of research has examined the role of generative AI in enhancing learning efficiency and productivity. Because these systems can process large amounts of information and generate responses within seconds, students can access learning support more quickly than through traditional information-seeking methods. Generative AI has been found to assist learners in organizing knowledge, synthesizing information, and exploring alternative perspectives during academic tasks [3, 4]. Such capabilities may help students focus more on higher-order thinking activities rather than routine information retrieval processes.

Despite these potential benefits, researchers have also identified several concerns regarding the educational use of generative AI. One major issue involves the reliability and accuracy of AI-generated content. Generative AI systems may occasionally produce incorrect, misleading, or fabricated information while presenting it with a high degree of confidence. This phenomenon creates challenges for learners who may lack sufficient domain knowledge to evaluate the quality of generated outputs [1, 8]. Consequently, scholars have emphasized the importance of critical thinking, fact-checking, and information verification when students use generative AI in educational settings [7].

Academic integrity has emerged as another prominent concern. The ability of generative AI to produce essays, reports, programming code, and other academic materials has generated debate regarding plagiarism, authorship, and assessment validity. Several studies have argued that educational institutions need to reconsider assessment strategies and establish clear guidelines governing responsible AI use rather than relying solely on detection and prohibition approaches [2, 6]. This perspective reflects a broader shift from viewing generative AI as a threat toward understanding how it can be integrated responsibly into teaching and learning processes.

Although the literature has expanded rapidly, much of the existing research remains focused on adoption intentions [12, 13], ethical concerns [14, 18, 19], and user perceptions [16, 20, 21]. Comparatively less attention has been devoted to understanding the psychological and learning-related mechanisms through which generative AI influences academic outcomes. In particular, limited research has examined how students' trust in AI systems shapes knowledge-related behaviors and learning experiences that contribute to academic performance. Furthermore, the educational implications of personalization and playfulness remain insufficiently understood, as these characteristics may not always produce positive learning outcomes. Addressing these gaps is important because the educational value of generative AI ultimately depends not only on access to the technology but also on how students interact with, evaluate, and apply AI-generated knowledge during the learning process.

3. Theoretical Framework and Conceptual Model

This study is grounded in an integrated perspective of trust theory, knowledge-based learning theory, and technology-enabled learning research. The central premise is that students' perceptions of generative AI are shaped by their cognitive trust in the technology, which subsequently influences how they engage with AI-generated resources and ultimately affects academic outcomes. Trust theory suggests that individuals are more likely to rely on a technology when they perceive it as competent, reliable, and capable of supporting task accomplishment [10, 22]. In educational contexts, trust facilitates learners' willingness to adopt and utilize technological support systems [9, 23]. Knowledge-based learning theory further argues that learning outcomes emerge not only from access to information but also from the successful application of acquired knowledge to practical tasks [24, 25]. At the same time, technology-mediated learning experiences are influenced by system characteristics such as personalization and playfulness, which shape learners' engagement and interaction quality [26, 27]. Integrating these perspectives, the proposed model conceptualizes cognitive trust as a foundational belief that promotes productive learning behaviors and experiences, which are reflected in knowledge application, personalization, and playfulness, and subsequently associated with academic performance.

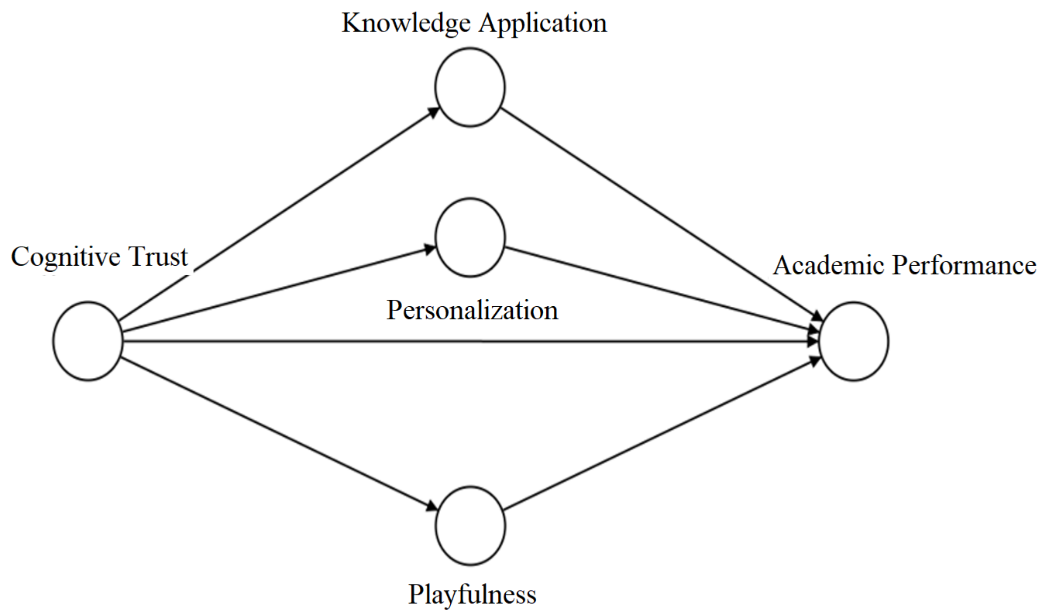

Figure 1.
Research Framework.

3.1. Cognitive Trust

Cognitive trust refers to the belief that a technology or agent has the competence and reliability needed to perform a task effectively [10, 22]. In AI-supported learning, this belief gives students confidence that generated explanations, examples, and suggestions can be used as meaningful academic resources [28, 29]. Trust in digital systems has been associated with stronger acceptance, deeper engagement, and greater willingness to rely on system recommendations [9, 30]. In educational technology, perceived usefulness and credible system information are also closely connected with knowledge-oriented use and learning outcomes [24, 31]. When students believe generative AI is competent, they may be more willing to apply AI-supported knowledge, perceive the service as personalized, enjoy the interaction, and report stronger academic performance. Based on this reasoning, the following associations are proposed.

H_{1a}: Cognitive trust is positively associated with knowledge application.

H_{1b}: Cognitive trust is positively associated with personalization.

H_{1c}: Cognitive trust is positively associated with playfulness.

H_{1d}: Cognitive trust is positively associated with academic performance.

3.2. Knowledge application

Knowledge application refers to the use of acquired knowledge to solve problems, complete tasks, or improve performance in a specific context [24, 25]. From a knowledge-management perspective, learning becomes valuable when students can transform information into practical action. Prior studies on technology-supported learning suggest that digital systems improve learning outcomes when they help learners organize, interpret, and apply knowledge rather than merely access information [23, 32-34]. Generative AI may support this process by offering explanations, examples, drafts, and feedback that help students connect abstract knowledge with academic assignments. When students can apply AI-supported knowledge to real coursework, they are likely to feel more capable, efficient, and confident in academic tasks. Based on this reasoning, the following association is proposed.

H_2: Knowledge application is positively associated with academic performance.

3.3. Personalization

Personalization refers to the degree to which a system adapts content, interaction, or recommendations to users' individual needs, preferences, and prior behavior [27, 35]. In digital learning environments, personalization can make learning experiences more relevant by aligning resources, feedback, and pacing with learner characteristics [36, 37]. Adaptive and personalized learning research shows that customized support can improve learner engagement, satisfaction, and perceived learning value [38, 39]. In the context of generative AI, personalized responses may help students receive explanations that fit their academic level, task purpose, and preferred communication style. Such tailored interaction can reduce unnecessary effort and strengthen students' confidence in using AI for university assignments. Based on this reasoning, the following association is proposed.

H_3: Personalization is positively associated with academic performance.

3.4. Playfulness

Playfulness refers to the degree of cognitive spontaneity, enjoyment, and curiosity experienced during interaction with a technology [26, 40]. In information systems research, playfulness has often been discussed as an intrinsic motivational factor that increases enjoyment and voluntary use of digital technologies [30, 41-43]. However, in academic settings, highly playful interaction may not always support task-focused learning. When students use generative AI mainly because the interaction feels entertaining, they may spend more time exploring amusing responses than completing academic work. Prior research on digital distraction suggests that enjoyable media use can compete with attention, self-regulation, and study time [44, 45]. Based on this reasoning, the following association is proposed.

H_4: Playfulness is negatively associated with academic performance.

4. Empirical Methodology

4.1. Instrument

The measurement instrument was developed based on previously validated scales reported in the literature. The constructs of cognitive trust, knowledge application, personalization, playfulness, and academic performance were adapted from established studies and modified slightly to reflect the context of generative AI-assisted learning (Table A1). Such adaptation is recommended when applying existing scales to emerging technological contexts while preserving conceptual consistency and measurement validity [46].

All measurement items were assessed using a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). A seven-point scale was selected because it provides greater response sensitivity and improves measurement precision in behavioral research [47].

To ensure linguistic and conceptual equivalence, a rigorous translation procedure was employed. The original questionnaire was initially developed in English by the author. Subsequently, a professional language expert translated the instrument into Korean. A separate bilingual expert then conducted a back-translation from Korean into English. The original and back-translated versions were compared carefully, and minor wording discrepancies were resolved through discussion to ensure semantic consistency and translation validity.

To establish content validity, the preliminary questionnaire was reviewed by a panel consisting of university faculty members with expertise in information systems and educational technology, as well as industry professionals familiar with generative AI applications. Their feedback focused on item clarity, contextual appropriateness, and conceptual relevance. Based on their recommendations, several wording modifications were made to improve readability and comprehensibility.

A pilot test was subsequently conducted with voluntary participants who had prior experience using generative AI in educational or professional settings. The pilot study confirmed that respondents were able to understand the questionnaire items without difficulty and complete the survey within a reasonable time frame. Feedback obtained during this stage resulted in minor refinements to item wording and survey instructions before the full-scale data collection.

4.2. Data Collection

This study employed a survey-based research design to examine students' perceptions and experiences regarding the use of generative AI for academic purposes. Survey methods are particularly appropriate for collecting standardized responses from a large number of individuals and for investigating latent perceptions, attitudes, and behaviors that cannot be directly observed [48, 49].

The target population consisted of university students in South Korea who had prior experience using generative AI for academic activities. A purposive sampling technique was employed because the study required respondents who possessed direct experience with generative AI in learning contexts. This approach is appropriate when participants must satisfy specific eligibility criteria relevant to the research objectives [50]. To reach eligible respondents, the survey link was distributed through nationwide networks of university professors who shared the questionnaire with their students across multiple academic disciplines and institutions.

The purpose of the study was clearly explained at the beginning of the survey. Participation was entirely voluntary, and respondents were informed that they could discontinue participation at any time without penalty. Anonymity and confidentiality were guaranteed, and no personally identifiable information was collected. Before participation, all respondents provided informed consent after reviewing the study information and participation guidelines.

The questionnaire consisted of three sections. The first section assessed respondents' generative AI usage patterns, including their experience and frequency of use. The second section measured perceptions related to the main constructs examined in this study. The final section collected demographic information such as gender, age, and academic background.

Data collection was conducted throughout April 2026. Following the completion of data collection, the dataset underwent a preprocessing procedure to improve data quality. Responses containing substantial missing data were removed. In addition, questionnaires completed by respondents without prior experience using generative AI were excluded from the analysis. Responses exhibiting straight-lining patterns, excessively short completion times, or obvious response inconsistencies were also screened and removed. After the data-cleaning process, the remaining valid responses were retained for subsequent statistical analyses. Table 1 describes the sample information.

Table 1.
Profile of the Respondents.

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	180	58.8
	Female	126	41.2
Age	18 years	43	14.1
	19 years	62	20.3
	20 years	45	14.7
	21 years	37	12.1
	22 years	34	11.1
	23 years	25	8.2
	24 years	29	9.5
	25 years or older	31	10.1
Major	Engineering and Technology	114	37.3
	Arts and Physical Education	96	31.4
	Humanities and Social Sciences	90	29.4
	Other	6	2.0
Primary Generative AI Model Used	ChatGPT (Free)	131	42.8
	ChatGPT (Paid)	72	23.5
	Gemini (Free)	60	19.6
	Gemini (Paid)	17	5.6
	Claude (Paid)	8	2.6
	Claude (Free)	2	0.7
	Other	16	5.2
Purpose of Use*	Learning and assignments	245	80.1
	Research and information search	172	56.2
	Writing and report preparation	141	46.1
	Language learning and translation	101	33.0
	Creative activities/content creation	73	23.9
	Programming and software development	41	13.4

Note: *Respondents were allowed to select multiple purposes; therefore, percentages for purposes of use exceed 100% when summed.

4.3. Analysis

The study followed a systematic analytical procedure using partial least squares structural equation modeling (PLS-SEM). PLS-SEM was selected because it is well-suited for prediction-oriented research, theory development, and the simultaneous examination of complex relationships among latent constructs [51]. The analysis was conducted using SmartPLS 4. First, the measurement model was evaluated by assessing reliability, convergent validity, and discriminant validity. Subsequently, the structural model was examined to evaluate the proposed relationships among constructs. Finally, bootstrapping procedures were performed to assess the significance and robustness of the hypothesized paths [52].

5. Research Results

5.1. Measurement Model

The measurement model was assessed by examining internal consistency reliability, convergent validity, and discriminant validity following established PLS-SEM guidelines [51]. As shown in Table 2, all item loadings exceeded the recommended threshold of 0.70, ranging from 0.853 to 0.978, indicating satisfactory indicator reliability. The values of Cronbach's alpha ranged from 0.863 to 0.963, while composite reliability (ρa) ranged from 0.863 to 0.970 and composite reliability (ρc) ranged from 0.916 to 0.976. These values exceeded the recommended cutoff of 0.70, demonstrating strong internal consistency [53]. Furthermore, the average variance extracted (AVE) values ranged from 0.785 to 0.931, surpassing the recommended threshold of 0.50 and confirming convergent validity [54] (Table 2).

Table 2.
Construct Reliability and Validity

Construct	Item	Mean	SD	Factor Loading	Cronbach's Alpha	Composite Reliability (ρ_a)	Composite Reliability (ρ_c)	AVE
Cognitive Trust	CGT1	5.209	1.332	0.895	0.863	0.863	0.916	0.785
	CGT2	4.977	1.329	0.871				
	CGT3	5.036	1.339	0.892				
Knowledge Application	KAP1	5.007	1.442	0.928	0.920	0.921	0.949	0.862
	KAP2	5.137	1.353	0.923				
	KAP3	5.134	1.495	0.935				
Personalization	PSN1	4.886	1.498	0.919	0.878	0.882	0.924	0.803
	PSN2	4.605	1.548	0.892				
	PSN3	4.833	1.324	0.878				
Playfulness	PLF1	4.052	1.722	0.962	0.963	0.970	0.976	0.931
	PLF2	3.944	1.694	0.978				
	PLF3	3.696	1.708	0.955				
Academic Performance	ACP1	4.634	1.503	0.853	0.868	0.867	0.919	0.792
	ACP2	5.294	1.427	0.917				
	ACP3	5.281	1.482	0.898				

Discriminant validity was evaluated using both the heterotrait–monotrait ratio and the Fornell–Larcker criterion. As reported in Table 3, all heterotrait–monotrait ratio (HTMT) values were below the conservative threshold of 0.90, ranging from 0.371 to 0.860, indicating adequate discriminant validity [55]. In addition, the square root of the AVE for each construct exceeded its correlations with other constructs, further supporting discriminant validity according to the Fornell–Larcker criterion (Table 4) [54]. Collectively, these results confirm that the measurement model demonstrates satisfactory reliability and validity.

Table 3.
HTMT Ratio.

Construct	1	2	3	4	5
1. Cognitive Trust					
2. Knowledge Application	0.754				
3. Personalization	0.627	0.654			
4. Playfulness	0.608	0.532	0.631		
5. Academic Performance	0.860	0.678	0.452	0.371	

Table 4.
Correlation Matrix and Discriminant Assessment.

Construct	1	2	3	4	5
1. Cognitive Trust	0.886				
2. Knowledge Application	0.673	0.928			
3. Personalization	0.548	0.586	0.896		
4. Playfulness	0.557	0.500	0.576	0.965	
5. Academic Performance	0.745	0.608	0.397	0.343	0.890

Note: Diagonal elements are the square roots of AVE.

5.2. Structural Model

The structural model was evaluated using the bootstrapping procedure with 5,000 resamples. The model explained 57.6% of the variance in academic performance, indicating substantial explanatory power. As presented in Table 5, cognitive trust positively influenced knowledge application ($\beta = 0.673$, $p < 0.001$), personalization ($\beta = 0.548$, $p < 0.001$), playfulness ($\beta = 0.557$, $p < 0.001$), and academic performance ($\beta = 0.678$, $p < 0.001$). Knowledge application also had a positive effect on academic

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 10, No. 7: 272-287, 2026
DOI: 10.55214/2576-8484.v10i7.13368

performance ($\beta = 0.240$, $p < 0.001$). However, personalization did not significantly affect academic performance ($\beta = -0.038$, $p = 0.417$). Playfulness showed a significant negative relationship with academic performance ($\beta = -0.133$, $p = 0.001$) (Table 5).

Table 5.
Hypothesis Testing Results.

H	Predictor	Outcome	β	t	p	Result
H1a	Cognitive Trust	Knowledge Application	0.673	17.051	<0.001	Supported
H1b	Cognitive Trust	Personalization	0.548	12.459	<0.001	Supported
H1c	Cognitive Trust	Playfulness	0.557	13.544	<0.001	Supported
H1d	Cognitive Trust	Academic Performance	0.678	11.961	<0.001	Supported
H2	Knowledge Application	Academic Performance	0.240	3.894	<0.001	Supported
H3	Personalization	Academic Performance	-0.038	0.812	0.417	Not Supported
H4	Playfulness	Academic Performance	-0.133	3.182	0.001	Supported

To provide a more nuanced understanding of the proposed relationships, a multi-group analysis (MGA) was conducted to examine whether the structural relationships differed according to gender (male = Group 1; female = Group 2). Following the bootstrapping MGA procedure in PLS-SEM, path coefficients were compared across groups to identify significant differences in the strength and direction of the hypothesized relationships.

The results are presented in Table 6. Most structural paths did not differ significantly between male and female students, indicating that the effects of cognitive trust on knowledge application, personalization, playfulness, and academic performance were generally stable across gender groups. Likewise, the relationships between knowledge application and academic performance and between playfulness and academic performance did not show statistically significant gender differences. However, a significant gender difference was observed for the relationship between personalization and academic performance ($\Delta\beta = -0.285$, $p = 0.003$).

Table 6.
MGA by Gender.

Path	Male (β)	Female (β)	Difference (Female − Male)	p-value (Two-tailed)	Result
Cognitive trust → Knowledge application	0.749	0.591	-0.158	0.051	Not Significant
Cognitive trust → Personalization	0.586	0.555	-0.031	0.677	Not Significant
Cognitive trust → Playfulness	0.546	0.576	0.031	0.708	Not Significant
Cognitive trust → Academic performance	0.648	0.774	0.125	0.302	Not Significant
Knowledge application → Academic performance	0.174	0.311	0.137	0.306	Not Significant
Personalization → Academic performance	0.090	-0.196	-0.285	0.003	Significant
Playfulness → Academic performance	-0.157	-0.175	-0.018	0.824	Not Significant

Note: Male = Group 1; Female = Group 2. Difference values represent Group 2 minus Group 1. Statistical significance was assessed using the bootstrap MGA procedure. A p-value below 0.05 indicates a significant difference between groups.

6. Discussion

The findings show that cognitive trust plays the most central role in explaining students' generative AI-based learning experiences. Students who perceive generative AI as competent, knowledgeable, and reliable appear more willing to use its outputs for knowledge application, to interpret the system as personalized, to experience the interaction as playful, and to evaluate their academic performance more positively. This result is consistent with trust theory, which argues that perceived ability is a key foundation of reliance on another actor or system [10, 22]. It also aligns with prior information systems research showing that trust strengthens users' acceptance of digital systems and increases their willingness to depend on system-generated recommendations [9, 30]. In the context of generative AI, this finding suggests that students do not simply use AI because it is available or fashionable. Rather, they seem to engage with it academically when they believe that its responses are sufficiently accurate, relevant, and useful. A more critical interpretation is that cognitive trust may function as a gateway perception: without believing in the system's competence, students may not meaningfully apply AI-generated knowledge, perceive responses as personally relevant, or enjoy the interaction in a productive way. However, this also implies a potential risk. If students overestimate the competence of generative AI, trust may encourage excessive reliance on AI-generated content even when the output contains errors, bias, or unsupported claims.

Knowledge application was also positively associated with academic performance. This result supports the knowledge management perspective that knowledge becomes valuable when it is applied to actual tasks rather than merely acquired or stored [24, 25]. It is also consistent with studies on e-learning and technology-supported education, which suggest that digital tools contribute to learning outcomes when they help learners organize, interpret, and use information for academic purposes [32, 33]. In this study, generative AI seems to support academic performance by helping students connect abstract knowledge with coursework, assignments, and problem-solving activities. The result implies that the educational value of generative AI lies less in providing quick answers and more in enabling students to translate information into usable knowledge. More specifically, students may benefit when AI assists them in restructuring ideas, generating examples, comparing alternatives, and applying concepts to concrete academic tasks. This finding also suggests that educators should not evaluate generative AI use only as a threat to academic integrity. Instead, the key issue is whether students are guided to use AI as a knowledge application tool rather than as a substitute for learning.

Personalization was not significantly associated with academic performance, which is an important and somewhat unexpected finding. Previous research has generally suggested that personalization can improve user engagement, information relevance, satisfaction, and learning experience by adapting content to individual needs and preferences [27, 38, 39]. In the context of generative AI, personalized responses may be expected to support students by adjusting explanations to their level, interests, or task requirements. However, the present result suggests that personalization alone may not be sufficient to improve academic performance. One possible interpretation is that students may appreciate personalized interaction, but such interaction does not automatically lead to better learning unless it is connected to deeper cognitive processing or actual knowledge application. Another possibility is that students may define personalization in terms of conversational convenience or preference matching, rather than academic usefulness. This distinction is important because a response that feels personally tailored may still be shallow, inaccurate, or insufficient for demanding academic work. Therefore, the finding challenges the common assumption that personalization is inherently beneficial in educational AI systems and suggests that personalization should be designed around learning goals, feedback quality, and task relevance.

Playfulness showed a negative association with academic performance, which offers a critical insight into the role of enjoyable AI interaction in academic settings. Prior technology acceptance research has often treated playfulness as a positive intrinsic motivation that increases enjoyment, engagement, and voluntary technology use [26, 40, 43]. However, the present finding suggests that in academic use of generative AI, playfulness may have a double-edged effect. While enjoyable interaction can make students more willing to use the system, excessive playfulness may shift attention away from disciplined study, task completion, and critical evaluation. This interpretation is consistent with research on digital distraction, which shows that enjoyable media use can interfere with attention, self-regulation, and academic performance [44, 45]. In practical terms, students who experience generative AI mainly as fun may spend more time exploring entertaining conversations, asking non-task-related questions, or relying on AI for effortless responses. This does not mean that enjoyment is always harmful. Rather, the result suggests that playfulness must be balanced with academic purpose. Generative AI may be most beneficial when it is engaging enough to sustain motivation but not so entertaining that it weakens concentration, independent thinking, or learning discipline.

According to the results of the MGA, personalization showed a small positive association with academic performance among male students, whereas the relationship was negative among female students. This finding suggests that male and female students may evaluate and utilize personalized AI-generated responses differently in academic contexts. Female students may place greater emphasis on the quality, accuracy, and task relevance of AI-generated content than on the personalized nature of the interaction itself. In contrast, personalized responses may provide additional value for male students by enhancing the perceived relevance and usefulness of AI during academic activities.

7. Conclusion

7.1. Theoretical Implications

This study contributes to the emerging literature on generative AI in higher education by providing a theoretically integrated explanation of how students' trust perceptions are translated into academic outcomes through multiple learning-related mechanisms. First, this study extends trust research by positioning cognitive trust as a foundational belief that simultaneously shapes knowledge application, personalization perceptions, playfulness, and academic performance. Previous studies have primarily examined trust as a predictor of technology acceptance, continuance intention, or usage behavior [9, 10, 30]. While these studies established the importance of trust for technology adoption, they provided limited insight into how trust influences educational outcomes after adoption occurs. The present study demonstrates that cognitive trust is not merely an antecedent of system use but also an important factor associated with students' learning experiences and academic achievements. This finding broadens the theoretical role of trust within AI-supported learning environments.

Second, this study contributes to knowledge-based learning theory by showing that knowledge application remains an important pathway linking generative AI use to academic performance. Recent discussions surrounding generative AI have often focused on content generation, productivity enhancement, or ethical concerns [23, 56]. However, relatively little attention has been given to whether students can transform AI-generated information into practical academic knowledge. The findings suggest that educational value emerges not from information access itself but from the ability to apply generated knowledge to academic tasks. This perspective reinforces the argument that learning outcomes depend on active knowledge utilization rather than passive information consumption [24, 25].

Third, the study provides a more differentiated understanding of personalization and playfulness in generative AI contexts. Prior studies generally portray personalization as beneficial and playfulness as a positive motivational factor [26, 27, 43]. However, the findings reveal that personalization was not associated with academic performance, while playfulness demonstrated a negative association. These results challenge assumptions commonly found in technology adoption research. The findings suggest that characteristics that improve user experience do not necessarily improve learning outcomes. For scholars, this highlights the need to distinguish between factors that encourage interaction and factors that facilitate meaningful learning. Future theoretical models of educational AI should therefore separate hedonic experiences from academic effectiveness rather than assuming that positive user experiences automatically translate into better educational outcomes.

7.2. Practical Implications

The findings provide several practical implications for educational institutions, generative AI service providers, instructors, and policymakers seeking to maximize the educational value of generative AI. The most important implication is that building students' cognitive trust should be prioritized over simply increasing system functionality. Students appear to benefit academically when they perceive AI-generated responses as reliable, knowledgeable, and academically useful. Therefore, AI developers should focus on improving transparency, source attribution, factual verification, and explanation quality. For example, AI systems could provide confidence indicators, supporting references, or alternative viewpoints to help students evaluate the credibility of generated content.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 10, No. 7: 272-287, 2026
DOI: 10.55214/2576-8484.v10i7.13368

Universities and instructors should also emphasize knowledge application rather than mere AI usage. Many institutions currently focus on whether students use generative AI, yet the findings suggest that educational outcomes depend more on how students apply AI-generated knowledge. Classroom activities can therefore be redesigned to require students to compare AI outputs, justify decisions, solve real-world problems, and critically evaluate generated information rather than simply submit AI-assisted assignments.

The results concerning personalization offer another important lesson. Personalized responses alone may not improve academic outcomes. Consequently, developers should avoid assuming that highly individualized interactions automatically create educational value. Instead, personalization features should be aligned with learning objectives. For instance, AI systems could adapt explanations according to students' prior knowledge levels, assignment requirements, or learning progress rather than merely matching conversational preferences.

Finally, the negative association between playfulness and academic performance suggests that educational AI systems should balance engagement with academic focus. While enjoyable interaction can attract users, excessive entertainment-oriented features may distract students from learning objectives. Service providers should therefore design interfaces that encourage sustained concentration, reflective thinking, and task completion. Features such as structured learning modes, guided problem-solving workflows, and progress-monitoring dashboards may help students maintain academic focus while still benefiting from engaging AI interactions.

7.3. Limitation and Future Research

This study opens several opportunities for future research beyond the limitations commonly discussed in educational technology studies. One noteworthy issue concerns the evolving nature of generative AI itself. Students' perceptions of trust, personalization, and playfulness are likely influenced by the rapidly changing capabilities of AI systems. Relationships observed today may differ substantially as models become more accurate, personalized, and autonomous. Future longitudinal studies could examine how these relationships change across different generations of AI technologies. Another important direction involves investigating the quality of AI-supported learning behaviors rather than relying solely on outcome-based measures. Two students may report similar academic performance while using generative AI in fundamentally different ways. Future studies could explore prompting strategies, critical evaluation behaviors, fact-checking practices, and collaborative learning processes to better understand how students interact with AI during learning activities. Finally, future research could examine discipline-specific contexts. The educational value of generative AI may differ considerably across fields such as engineering, business, medicine, and the humanities. Exploring these contextual differences may provide a more comprehensive understanding of how generative AI supports learning across diverse educational environments.

Funding:

This study was supported by the 2026 In-House Research Grant Program of Hanseo University.

Institutional Review Board Statement:

This study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki and was reviewed and approved by the Institutional Review Board (IRB) of Hanseo University, Republic of Korea (Approval No. HS26-0506-01, approved on 6 May 2026).

Transparency:

The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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Appendix

Table A1.
List of Constructs and Items.

Construct	Item	Description	Source
Cognitive Trust	CGT1	Generative AI has sufficient ability to provide useful advice or information.	Kyung and Kwon [28]
	CGT2	Generative AI understands users' needs and situations well.	
	CGT3	Generative AI is knowledgeable about relevant information and subject matter.	
Knowledge Application	KAP1	Using generative AI enables me to apply what I have learned to actual academic tasks.	Al-Sharafi, et al. [57]
	KAP2	Generative AI helps me integrate different types of knowledge.	
	KAP3	Generative AI helps me better understand the knowledge taught at university.	

Personalization	PSN1	Generative AI provides personalized responses based on my previous conversations or preferences.	Liu and Tao [58]
	PSN2	Generative AI personalizes my conversational experience.	
	PSN3	Generative AI adjusts its responses according to my personal preferences.	
Playfulness	PLF1	Interacting with generative AI is fun.	Mishra, et al. [59]
	PLF2	Interacting with generative AI is enjoyable.	
	PLF3	I feel good when interacting with generative AI.	
Academic Performance	ACP1	I am confident in the knowledge and skills I have acquired through using generative AI.	Maqableh, et al. [60]
	ACP2	I can competently complete university assignments using generative AI.	
	ACP3	I have learned how to complete university assignments more efficiently through generative AI.	