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Prompt Engineering Competence, Knowledge Management, and Technology Fit as Drivers of Educational Sustainability through Generative AI

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Abstract

This study investigated the impact of prompt engineering competence, knowledge management, and task–individual–technology fit on the continued intention to use artificial intelligence (AI), as well as their implications for educational sustainability. Data from 437 undergraduate students who use AI tools for academic purposes were analyzed using PLS-SEM. The results indicated that prompt engineering competence significantly predicts knowledge acquisition and knowledge application, which, in turn, significantly predict both task-technology fit (TTF) and individual-technology fit (ITF). Furthermore, TTF and ITF were found to have significant impacts on the continuous intention, which, in turn, positively predicts educational sustainability through generative AI. The results of the multi-group analysis revealed that the hypotheses were supported in both the female and male samples and that the model maintained a consistent and robust structure across genders. Overall, the findings provide substantial evidence on how generative AI supports sustainable learning in education by developing prompt engineering skills, promoting effective knowledge management practices, and ensuring technology alignment.

Keywords: Artificial intelligence; Knowledge Management; Prompt Engineering; Task-Technology Fit

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1. Introduction

Recent years have witnessed rapid developments in educational technologies, presenting both new opportunities and various challenges for all stakeholders, from university students to Professors. The increasing prevalence of AI-based learning tools, such as chatbots and generative AI applications, has raised questions about how these tools can be effectively implemented and sustainably adopted in education [1]. In contrast to conventional knowledge systems, AI-powered learning technologies, most notably generative AI tools, operate through probabilistic and adaptive mechanisms rather than deterministic, rule-based processes. In contrast to the outputs of traditional educational technologies, which are largely predefined, the outputs of generative artificial intelligence systems emerge dynamically during the human-artificial intelligence interaction process and depend largely on the nature of user input [2,3]. This fundamental difference positions AI-supported learning tools as socio-technical systems in which learning outputs are not solely provided by technology, but rather shaped by human-AI co-production [4]. Sustainability in education refers not only to ensuring the long-term continuity of innovative applications but also to the continuous development of the system in line with changing needs and trends [5]. In this regard, the sustainability of AI-enabled learning environments is contingent not only on the availability of technology, but also on students' capacity to interact meaningfully with AI systems and to generate value from these systems over time continuously [2].

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This study examines the contribution of AI-supported online learning platforms to educational sustainability, focusing on students' intentions to continue using these platforms and the cognitive factors that influence these intentions. In the literature, continued intention is defined as the tendency of individuals to continue using a system in the long term after initially accepting it [6]. While continuance intention has been extensively examined in general IS research, its formation in AI-supported learning environments differs due to the adaptive and user-dependent nature of AI systems. In such environments, continued use is closely linked to users' interaction competencies and their ability to guide AI behavior effectively [7]. It is considered critical that the benefits these tools provide in education be permanent and sustainable, so that students not only adopt a new digital learning tool at the outset but also continue to use it regularly, consistently, and voluntarily [8].

This study proposes a research model to examine the factors influencing university students' use of AI-supported tools in online learning environments. The model assumes that prompt engineering competency, defined as students' ability to use AI tools effectively, enhances the processes of acquiring and applying knowledge. Prompt engineering competence represents a novel, AI-specific interaction capability that differentiates generative AI systems from earlier generations of educational technologies. In contrast to conventional systems that employ predefined command structures, generative AI tools rely on natural language input. Therefore, the quality of user input is a pivotal factor in determining system performance and learning outcomes

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[9,10]. These processes increase students' perceived levels of "task-technology fit" (TTF) and "individual-technology fit" (ITF). In AI-supported learning contexts, perceptions of TTF and ITF are shaped not only by system characteristics but also by the extent to which students can clearly and effectively communicate their goals, constraints, and contextual information to the AI system. Consequently, user competencies assume a pivotal role in establishing perceived fit, superseding the significance traditionally attributed to educational technologies [11–13]. Research findings show that students' high perceptions of TTF and ITF in learning tasks significantly strengthen their continued intentions to use AI tools. A strong intention to continue facilitates the permanent integration of these tools into teaching and learning processes, thereby contributing to the sustainability of education [14,15]. In this context, the sustainable integration of AI-supported learning tools into education is contingent not only on technological capabilities but also on the development of interaction competencies that enable students to engage with AI in a productive, responsible, and critical manner [16]. Based on this theoretical framework, the study develops nine hypotheses from the task–individual–technology fit perspective.

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2. Theoretical Background and Hypotheses

2.1 Research Model

The research model presented in Figure 1 comprehensively addresses the factors predicting students' consistent use of AI-supported online learning tools. In the model, prompt engineering competency is defined as the

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student's ability to provide clear, accurate, and purpose-driven commands to the AI tool [17]. A high level of this competency enables students to acquire knowledge more efficiently from these tools and to translate that knowledge into practice. Here, "knowledge acquisition" refers to the process of learning new content and concepts through technological tools, while knowledge application refers to the degree to which the learned knowledge can be effectively used in practical tasks [18].

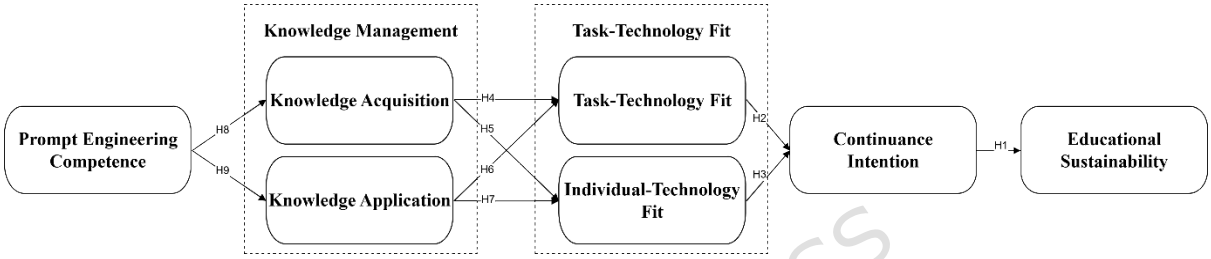


Figure 1. Research Model

The model suggests that the information acquisition and application processes affect technology fit in two dimensions. TTF refers to the extent to which a technology facilitates students' learning tasks. At the same time, ITF refers to the degree to which the technology aligns with students' personal needs, preferences, and skill levels [19]. Continuous intention refers to the student's plan to use the relevant tool regularly and consistently in the future [20]. Sustainability in education, by contrast, refers to the long-term continuity that results from the comprehensive and effective integration of such tools into the learning environment [21].

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According to the research model, students with high-level prompt engineering skills can acquire and apply more comprehensive and sophisticated information by utilizing AI. This process reinforces the perception that the technology is compatible with both learning tasks and students' individual competencies. Implementing the intention to continue ensures the long-term establishment of the relevant technology in the educational environment, thereby supporting sustainability in education [22]. In the following sections of the study, these relationships are summarized in light of the existing literature, and each hypothesis is presented in detail.

2.2 Hypotheses

2.2.1 Educational Sustainability

Educational sustainability can be defined as the education system's ability to consistently meet the needs of current and future generations over the long term by effectively leveraging innovations and technologies [23]. Within the domain of artificial intelligence, the concept of educational sustainability extends beyond the mere continuous utilization of systems. It encompasses the long-term enhancement of learning quality, inclusivity, and adaptability through responsible and meaningful human–artificial intelligence interaction [24]. The contribution of digital learning tools to educational sustainability depends on their adoption and regular use in academic processes, thereby improving long-term learning outcomes [25]. However, sustainable value creation in AI-supported learning environments requires students to actively develop competencies to

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direct, evaluate, and improve AI-generated outputs, rather than passively consuming information [26]. The current literature indicates that the sustainable use of educational technologies relies on users developing intrinsic motivation to utilize the technology regularly over time [27]. For example, research by Samed Al-Adwan and colleagues shows that for e-learning systems to function as a sustainable strategy in education, student participation and appropriate conditions must be ensured, and that this is linked to students' intention to use the system. In this context, students' intentions to continue using a technology are a critical prerequisite for its permanent integration into the educational environment and for providing long-term benefits [28]. Students who demonstrate a strong commitment to continued use of the technology can sustain their learning processes by using it regularly. Nevertheless, educational sustainability is not merely a concept limited to the continuous use of technology; it also encompasses the potential to enhance the quality and inclusivity of learning processes in the long term [29]. In this context, AI-powered learning tools have the potential to improve learning quality by providing personalized feedback, structuring complex learning tasks, and ensuring equal opportunities for students with different learning needs [30,31]. The adaptive learning opportunities offered by generative AI contribute to educational sustainability by supporting students' higher-order cognitive skills, critical thinking capacities, and long-term knowledge retention [32,33]. Accordingly, educational sustainability should be regarded not solely as the sustained presence of technology, but also as a transformative process that enhances learning practices,

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rendering them more effective and equitable [34]. Within this theoretical framework, it is hypothesized that students' intentions to continue using a technology will contribute to the long-term, qualified, and sustainable establishment of productive AI-supported learning tools in educational environments. Based on this rationale, the following hypothesis is proposed:

H1: Continuance intention has a positive impact on educational sustainability.

2.2.2 Continuance Intention

According to Bhattacherjee, the intention to continue refers to individuals' behavioral tendency to continue using a particular information system (IS) or technology after the initial usage period has ended [35]. This concept was developed in the technology acceptance literature to explain users' behaviors after the initial adoption phase. In the context of e-learning, continued intention to use a system is an essential indicator of its success. For example, a study conducted by Salloum and colleagues found that perceived usefulness and satisfaction significantly influenced the continued use of "learning management systems" (LMS) [36]. A more recent study found that, in addition to user satisfaction, perceptions of task-technology fit significantly explain students' intentions to continue using LMSs on new-generation online microlearning platforms [37].

Additionally, using such resources helps students better understand the subject matter and develop their skills. For example, a study in STEM education demonstrates that regular use of resources helps students

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retain knowledge, enhance their critical thinking skills, and strengthen their resilience when solving complex problems [38]. The findings reveal that the intention to continue not only affects technology use but also plays a decisive role in long-term learning outcomes and individual development. Therefore, the intention to continue, which occupies a central position in the research model, is considered an important variable that indirectly affects other factors supporting sustainability in education.

2.2.3 Task-Technology Fit

“Task-Technology Fit” (TTF) is a fundamental concept that describes the degree to which a technology or system aligns with the tasks an individual seeks to accomplish [39]. In AI-assisted learning systems, task-technology fit is not solely determined by predefined system functions; it emerges dynamically from the interaction between task requirements and users' ability to create effective prompts that guide AI responses [10]. The TTF model developed by Goodhue and Thompson suggests that the success of an information technology depends on the extent to which it meets users’ task requirements [40]. This framework emphasizes the alignment between technological features and user needs and is frequently used to assess outcomes such as technology usage rates, user satisfaction, and performance [41]. TTF has also been widely applied in IS research. For instance, studies on digital learning materials (e.g., video-based learning, augmented reality, digital games) have identified positive correlations between TTF levels and learning intention and learning success [42,43]. Prior findings reveal that a high degree of congruence between tasks and technology in e-learning systems fosters students’ perception of the

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system as a sustainable learning tool, thereby enhancing their inclination to utilize it [44]. The incorporation of TTF into technological acceptance models has been shown to have a generally positive effect on perceived ease of use and perceived usefulness, thereby indirectly increasing the intention to use [45]. In light of these findings, as TTF increases, students' willingness to use the system will also increase, and consequently, their intention to continue using it will strengthen.

H2: Task-technology fit positively affects continuance intention.

2.2.4 Individual-Technology Fit

The term "Individual-Technology Fit (ITF)" refers to the level of compatibility between a technology and the user's individual characteristics, preferences, competencies, and needs [46]. In productive artificial intelligence environments, individual-technology compatibility is closely related to students' levels of artificial intelligence literacy, self-efficacy perceptions, and prompt engineering competencies. The extent to which students can interact comfortably and effectively with artificial intelligence systems is determined by these elements[47]. This concept can be viewed as an extension of the TTF model, with a focus on the individual dimension. The ITF's approach requires technology to be "suitable" for both the task and the user [19]. For instance, in the context of a decision support system, the concept of ITF has been defined as the technology's capacity to provide guidance commensurate with the user's level of expertise [48]. Within the context of education, elements such as the degree of comfort students experience when interacting with the

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technology, their perception of self-efficacy with it, and the extent to which it aligns with their personal learning style can be considered components of individual-technology fit [49].

A student who exhibits a high degree of individual-technology compatibility will perceive the learning technology they use as both familiar and suitable for their needs, thereby positively influencing their user experience. The existing literature suggests that approaches such as personalizing technological tools and adaptive learning increase user-individual compatibility, thereby improving educational success and technology engagement [50]. It has been indicated that students are more inclined to persist in using technology if they perceive it as aligning with their learning style and pace. Consequently, a high level of ITF will increase students' intention to continue using the technology by ensuring satisfaction and comfort in their interactions with it. Based on this expectation, the following hypothesis is developed:

H3: The individual-technology fit positively affects continuance intention.

2.2.5 Knowledge Acquisition

"Knowledge acquisition" refers to the extent to which a student gains new knowledge and skills through the learning environment or technological tools [18]. Knowledge acquisition is among the most fundamental impacts of digital platforms on student learning outcomes. The literature highlights several important factors that support effective knowledge acquisition, including ease of access to learning materials, content quality, and the effectiveness of feedback [51]. Research indicates that students'

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knowledge acquisition in e-learning systems significantly influences their perceptions of the system and their intention to continue [52]. For example, integrating knowledge management processes, such as knowledge acquisition, application, and sharing, into the "Technology Acceptance Model" (TAM) significantly increases students' intentions to continue using e-learning systems and their perceived benefits [53,54]. These findings indicate that the extent to which students perceive learning in a digital environment positively influences their likelihood of continued use of that platform.

In the current research model, knowledge acquisition refers to the extent to which students acquire new knowledge by utilizing AI-powered educational tools, such as ChatGPT-based learning assistants. Students with a high level of proficiency in prompt engineering can access the desired information more efficiently and enhance their knowledge acquisition by asking the AI system more descriptive, goal-oriented questions. It is hypothesized that knowledge acquisition has a decisive impact on perceptions of the technology's task performance effectiveness (TTF) and its compatibility with the learning process (ITF). A recent study on the use of AI by adult learners has revealed the practical benefits of information obtained from AI tools and shown that this use improves individual performance [55]. These findings support the idea that information acquisition can shape the perception of technology compatibility. In summary, students' effective knowledge acquisition through e-learning tools will strengthen their perception of the tool's

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suitability for both current tasks and individual learning needs. Within this framework, the following hypotheses have been developed:

H4: Students' level of knowledge acquisition positively affects task-technology fit.

H5: Students' level of knowledge acquisition positively affects individual-technology fit.

2.2.6 Knowledge Application

Knowledge application is defined as students' ability to apply the knowledge they have acquired in practical tasks, problem-solving processes, or real-life scenarios [18]. This concept emphasizes that learning does not remain solely at a theoretical level but is transformed into action, particularly the application of learned knowledge [20]. The fundamental purpose of education is to ensure that knowledge is retained and can be applied in various contexts. Therefore, the effectiveness of learning tools should be evaluated not only by the amount of information conveyed but also by the extent to which students can apply it. The usability and compatibility of an e-learning platform depend on its capacity to support knowledge application through features such as interactive exercises, scenarios, and project-based tasks. Students who interact with such features may perceive the platform as more valuable and compatible [56]. A study by Ahn examined the application of knowledge among individuals using generative AI tools and found that knowledge gained through practical tasks increased both user performance and the frequency of tool use [57]. These findings support the notion that the

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applicability of knowledge functions as a motivational feedback mechanism for technology use.

In the research model under consideration, students' capacity to utilize the knowledge they acquire through AI-powered tools in their academic endeavors, including homework, projects, and problem-solving, will serve as a reliable indicator of the efficacy of technology in their perception. If a student applies a formula learned through AI in their homework and arrives at the correct result, they will consider that tool to be fit for purpose. Conversely, this experience of success can also enhance perceptions of student-technology compatibility, as it demonstrates the contribution of technology to their learning process [58]. As the application of knowledge becomes more straightforward, students' confidence in and adoption of technology is observed to increase. Consequently, the efficacy with which students apply the knowledge acquired through technology will fortify their perception of that technology's suitability for specific tasks and individual needs. With this expectation, the following hypotheses have been proposed:

H6: The level of knowledge application positively affects task-technology fit.

H7: The level of knowledge application positively affects individual-technology fit.

2.2.7 Prompt Engineering Competence

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Prompt engineering competence is defined as the ability to provide accurate and effective commands (prompts) to AI tools, enabling users to obtain the desired outputs [17]. Recent studies conceptualize prompt engineering as a critical cognitive and metacognitive competency in human–artificial intelligence interactions, particularly in educational contexts where learning outcomes depend on the clarity, structure, and purpose of user inputs [9,26,59]. In the context of interaction with AI, the quality of the input provided by the user is a key factor in predicting the accuracy and usefulness of the response received [60].

As posited by Federiakin et al., prompt engineering has been defined as a novel competency necessary for professional and personal learning in the 21st century [9]. The authors emphasize that a few words can dramatically affect the success of AI output [61]. A well-formulated inquiry or directive enables the AI tool to demonstrate its capabilities effectively, whereas an ambiguous or erroneous command can yield undesired or inaccurate outcomes. Consequently, students must cultivate competencies in prompt engineering to ensure the effective utilization of AI tools [62].

Students with a high level of engineering proficiency can delve deeper into AI topics and receive more precise, detailed answers to their questions. For example, a student who asks appropriately structured questions can obtain comprehensive explanations or creative solution suggestions from ChatGPT [60]. This pedagogical approach is expected to increase both the depth and breadth of the knowledge students acquire. Garg et al. suggested that the practical design of prompts can significantly

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impact educational outcomes in interactions with AI [63]. Furthermore, enhancing students' AI interaction capabilities has been shown to enrich the learning experience by facilitating more precise responses [64]. Additionally, a student who has acquired prompt engineering skills can critically evaluate AI-generated outputs and continue to guide them in meeting their needs. Consequently, they have the opportunity to apply what they have learned to their assignments and projects. Cultivating engineering aptitude expedites the application of knowledge. Therefore, students who demonstrate a high level of engineering proficiency are expected to acquire additional knowledge through AI and apply it more effectively in practice. Based on these conclusions, our final two hypotheses are as follows:

H8: Prompt engineering competence positively impacts knowledge acquisition.

H9: Prompt engineering competence positively impacts knowledge application.

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This study aims to elucidate the utilization patterns of AI-enhanced online learning platforms among undergraduate students and to assess their impact on educational sustainability. The extant literature provides robust theoretical foundations, particularly from studies on information systems continuity [35], task-technology fit [40], and knowledge management processes [65]. However, the impact of one of the new skills of the AI era, such as prompt engineering competence, on students'

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knowledge acquisition and application capacities in their learning processes has not yet been sufficiently investigated [63,64].

This study is among the first to empirically examine the influence of prompt engineering competence on students' knowledge acquisition and application in higher education. The proposed model examines the interaction between TTF and ITF, aiming to determine whether students perceive AI tools primarily as task-focused support or as technologies that align with their individual characteristics. Furthermore, the study demonstrates that students' interaction skills with AI support sustainability in education through a unique mechanism, highlighting the relationship between prompt engineering competence and continuance intention. Moreover, integrating the discourse on AI literacy with research on sustainability in education provides practical implications for "higher education institutions" (HEIs) and policymakers regarding the design of AI-integrated courses and curricula.

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The research model is evaluated based on nine hypotheses. The findings are expected to indicate that the development of students' prompt engineering competence will strengthen their knowledge acquisition and application processes, thereby increasing both TTF and ITF. The concept of perceived fit plays a pivotal role in reinforcing students' propensity to use technology, thereby contributing to the consistent pursuit of educational sustainability. This comprehensive model makes an essential contribution to theoretical literature and offers practical implications for

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HEIs and policymakers regarding the effective integration of AI-enabled learning tools.

3. Research Methodology

3.1 Sampling and Procedure

The study was based on 437 responses from undergraduate students who use at least one AI tool for academic purposes, collected via purposive sampling. It received ethical approval from the University's IRB. The survey responses were collected using a web-based survey tool, Google Forms. Informed consent was obtained from each respondent prior to answering the questions. To determine the required sample size for our study, we employed G*Power 3.1 [66]. We followed the standard procedure and recommendations for using the PLS-SEM sample size assessment [67]. We selected a maximum number of predictors as (K=6) and chose the medium effect size (f^2 = 0.15), at a significance level of (0.05), along with a statistical power of (1 – β = 0.80). The assessment results indicated that, under the specified parameters, our study requires 98 respondents. Our study, however, has 437 respondents, which exceeds the required threshold.

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The mean age of the respondents was 21.5 years (SD = 4.57). Their ages ranged from 16 to 56. The respondents consisted of 25.5% first-year students, 32% sophomores, 22.4% juniors, and 20.1% seniors. According to the AI tool used, 97% of respondents reported using ChatGPT, 22% reported using Gemini, and 8% reported using Bing AI. A small sample of students used Co-pilot and Jasper. Regarding usage frequency, 30.6% of

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respondents used AI tools daily, 42.7% weekly, 13.5% monthly, and 13.2% as needed.

3.2 Data Collection

The data were collected using an online survey. The survey consisted of three parts: the informed consent section, the demographic questions section, and the constructs section, which included 25 items corresponding to each of the five constructs employed in this study. All items were collected using a "Likert scale," in which respondents answered the questions according to a scale of "1 (strongly disagree)" to "5 (strongly agree)." The constructs employed were Educational Sustainability [68], Continuance Intention [69], Task-Technology Fit (TTF) and Individual-Technology Fit (ITF) [19], and the "Prompt Engineering Competence Scale" [17]. Knowledge Acquisition and Knowledge Application [18]. The construct items employed in this research are stated in Appendix A.

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3.3 Data Analysis

The study employed "Partial Least Squares Structural Equation Modeling" (PLS-SEM) by using SmartPLS4 to study the relationship between the proposed constructs in the research model. Other than the advantage that PLS-SEM allows in exploring small sample sizes [67]. It also yields better results when studying models with more than one independent and dependent variable [70]. We employed PLS-SEM because it is well-suited to analyzing models similar to those examined in this study.

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4. Results

4.1 Measurement Model

To assess composite and internal reliability, we examined the "composite reliability" (CR), rho_c, and Cronbach's alpha (CA). The results for all constructs exceed the threshold of 0.70 [71]. Additionally, to test convergent validity, we calculated the "Average Variance Explained" (AVE) score for each construct, and all were above the necessary threshold of 0.50 [72]. Table 1 shows the results for both convergent validity and internal reliability.

Table 1. Construct Validity and Reliability

Constructs	Items	VIF	Outer Loadings	CA	CR	AVE
Educational Sustainability	ES1	2.280	0.854	0.888	0.923	0.749
	ES2	2.855	0.901			
	ES3	2.520	0.877			
	ES4	2.007	0.827			
Continuance Intention	CI1	1.957	0.862			
	CI2	2.432	0.899			
	CI3	2.336	0.893			
Task-Technology Fit	TTF1	2.379	0.845			
	TTF2	2.439	0.849			
	TTF3	1.905	0.796			
	TTF4	2.441	0.859			
	TTF5	1.759	0.780			
Individual-Technology Fit	ITF1	1.777	0.808			
	ITF2	1.908	0.824			

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		ITF3	1.986	0.808			
		ITF4	2.083	0.841			
		ITF5	1.318	0.577			
Knowledge Acquisition		KAc1	2.028	0.839	0.878	0.916	0.732
		KAc2	2.082	0.841			
		KAc3	2.579	0.877			
		KAc4	2.393	0.866			
Knowledge Application		KAp1	2.249	0.860	0.865	0.908	0.712
		KAp2	2.207	0.852			
		KAp3	2.058	0.839			
		KAp4	1.817	0.825			
Prompt Competence	Engineering	PEC1	2.375	0.745	0.927	0.939	0.632
		PEC2	2.78	0.780			
		PEC3	2.666	0.809			
		PEC4	2.197	0.776			
		PEC5	3.038	0.853			
		PEC6	2.20	0.776			
		PEC7	2.484	0.805			
		PEC8	2.551	0.797			
		PEC9	2.622	0.807			

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To evaluate discriminant validity, the “Heterotrait-Monotrait Ratio” (HTMT) was analyzed as shown in Table 2. HTMT scores were below the required threshold, confirming discriminant validity [73]. We also checked for possible multicollinearity by calculating the “Variance Inflation Factor” (VIF). Values of 5 or less indicate no multicollinearity issues [67]. The

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highest VIF in our study is 3.038, supporting the conclusion that multicollinearity is not a concern.

Table 2. Discriminant Validity

	ES	CI	TTF	ITF	KAc	KAp	PEC
ES							
CI	0.694						
TTF	0.767	0.834					
ITF	0.557	0.726	0.812				
KAc	0.749	0.788	0.851	0.613			
KAp	0.747	0.737	0.836	0.616	0.860		
PEC	0.666	0.732	0.765	0.624	0.723	0.725	

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4.2 Hypothesis Testing

Table 3 presents the hypothesis-testing results, indicating significant positive relationships for all proposed links. The proposed independent variable, continuance intention, explains 36% of the variance in educational sustainability ($R^2 = 0.369$), whereas TTF and ITF account for 55% of the variance in Continuance Intention ($R^2 = 0.558$). Knowledge application and knowledge acquisition explain 33% of the variation in ITF ($R^2 = 0.338$) and 62% of the variation in TTF ($R^2 = 0.629$). Lastly, Prompt Engineering competence accounts for 42% of the variation in Knowledge acquisition ($R^2 = 0.458$) and 42% in Knowledge application ($R^2 = 0.424$).

Table 3. Hypothesis Testing

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H	Path	f^2	β	T	P	Support
H1	Continuance Intention → Educational Sustainability	0.584	0.607	16.687	***	Yes
H2	Task-Technology Fit → Continuance Intention	0.353	0.559	9.963	***	Yes
H3	Individual-Technology Fit → Continuance Intention	0.064	0.239	4.437	***	Yes
H4	Knowledge Acquisition → Task-Technology Fit	0.242	0.455	9.023	***	Yes
H5	Knowledge Acquisition → Individual-Technology Fit	0.062	0.306	4.649	***	Yes
H6	Knowledge Application → Task-Technology Fit	0.180	0.392	7.702	***	Yes
H7	Knowledge Application → Individual-Technology Fit	0.065	0.315	5.002	***	Yes
H8	Prompt Engineering Competence → Knowledge Acquisition	0.747	0.654	19.169	***	Yes
H9	Prompt Engineering Competence → Knowledge Application	0.737	0.651	18.216	***	Yes

***$p < 0.001$.

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The study's results were evaluated using path coefficients (β), t-values, p-values, and effect size (f^2). Our results indicated that continuous intention has a strong and significant influence on educational sustainability (H1: $\beta = 0.607$, $t = 16.687$, $p < 0.001$, $f^2 = 0.584$), emphasizing that sustained and consistent use of Gen AI systems by learners significantly supports educational sustainability. Both TTF (H2: $\beta = 0.559$, $t = 9.963$, $p < 0.001$, $f^2 = 0.353$) and ITF (H3: $\beta = 0.239$, $t = 4.437$, $p < 0.001$, $f^2 = 0.064$) proved to be positive and significant predictors of continuance intention, with task-technology fit showing a noticeably stronger effect size compared to individual technology fit on continuance intention.

Knowledge acquisition has a positive and significant influence on TTF (H4: $\beta = 0.455$, $t = 9.023$, $p < 0.001$, $f^2 = 0.242$) and on ITF (H5: $\beta = 0.306$, $t = 4.649$, $p < 0.001$, $f^2 = 0.062$). Conversely, knowledge application had a significantly positive impact on TTF (H6: $\beta = 0.392$, $t = 7.702$, $p < 0.001$, $f^2 = 0.180$) and on individual-technology fit (H7: $\beta = 0.315$, $t = 5.002$, $p < 0.001$, $f^2 = 0.065$). These findings highlighted the pivotal role of knowledge acquisition and knowledge application in determining how effectively learners align their AI tools with their tasks and personal needs throughout their learning journey.

Lastly, prompt engineering competence (PEC) emerged as the strongest predictor in the model, showing a huge effect size on knowledge acquisition (H8: $\beta = 0.654$, $t = 19.169$, $p < 0.001$, $f^2 = 0.747$) and knowledge application (H9: $\beta = 0.651$, $t = 18.260$, $p < 0.001$, $f^2 = 0.737$).

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These results highlight the crucial role of prompt engineering competence in learners' ability to craft, design, and refine prompts that enhance their capacity to apply and acquire knowledge in AI-mediated learning contexts. In conclusion, these results support all nine hypotheses, thereby validating the proposed model, which posits that engineering competence drives and supports the two main knowledge processes: knowledge acquisition and knowledge application. These, in turn, influence task and individual technology fit, which leads to continuance intention and ultimately to educational sustainability.

4.3 Multigroup Analysis

To investigate gender differences in the structural model results, the study employed a multigroup analysis that included both within- and between-group differences, as shown in Tables 4 and 5. Table 4 shows standardized path coefficients, the *t*-values, and significance levels for both male and female groups. Table 5 highlights the differences between them and indicates whether each is significant.

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Within-group structural relationship results indicate that all hypothesized relationships (H1-H9) were significant for both male and female groups. The comparison reveals that continuance intention (CI) has a strong and positive relationship with educational sustainability (ES). In both groups, the effect is stronger for women ($\beta = 0.626$, $p < 0.001$) than for men ($\beta = 0.539$, $p < 0.001$), supporting H1. TTF also has a significant and robust relationship with continuance intention for both males ($\beta = 0.502$, $p < 0.001$) and females ($\beta = 0.574$, $p < 0.001$), supporting H2. For

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H3, the relationship between ITF and continuance intention (CI) is also supported for both males ($\beta = 0.248$, $p < 0.01$) and females ($\beta = 0.234$, $p < 0.001$). Both "Knowledge Acquisition" (KAc) and "Knowledge Application" (KAp) are essential antecedents of both ITF and TTF. H4 indicates that the effect of "Knowledge Acquisition" on TTF is strong and significant for both males ($\beta = 0.595$, $p < 0.001$) and females ($\beta = 0.410$, $p < 0.001$). H5 shows that "Knowledge Acquisition" also has a strong and significant effect on "Individual-Technology Fit" (ITF) for both males ($\beta = 0.375$, $p < 0.01$) and females ($\beta = 0.275$, $p < 0.001$). Conversely, H6 finds that Knowledge Application significantly predicts TTF in both males ($\beta = 0.214$, $p < 0.05$) and females ($\beta = 0.451$, $p < 0.001$). H7 examines the impact of Knowledge Application on ITF and reveals a strong, significant relationship for both men ($\beta = 0.216$, $p < 0.05$) and women ($\beta = 0.358$, $p < 0.001$).

Finally, "Prompt Engineering Competence" (PEC) shows the strongest influence across all proposed relationships in the model. For Knowledge Acquisition (KAc), the results show a strong and significant effect for males ($\beta = 0.708$, $p < 0.001$) and females ($\beta = 0.633$, $p < 0.001$). The impact of PEC on Knowledge Application is the second strongest and significant across both genders, with males ($\beta = 0.677$, $p < 0.001$) and females ($\beta = 0.639$, $p < 0.001$).

Table 4. Within-Multigroup analysis

		Male				Female			
H	**Path**	***β***	***T***	***P***	**Support**	***β***	***T***	***P***	**Support**

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H1	Continuance Intention → Educational Sustainability	0.539	6.553	***	Yes	0.626	15.965	***	Yes
H2	Task-Technology Fit → Continuance Intention	0.502	4.214	***	Yes	0.574	9.225	***	Yes
H3	Individual-Technology Fit → Continuance Intention	0.248	2.582	**	Yes	0.234	3.611	***	Yes
H4	Knowledge Acquisition → Task-Technology Fit	0.595	5.950	***	Yes	0.410	7.364	***	Yes
H5	Knowledge Acquisition → Individual-Technology Fit	0.375	2.940	**	Yes	0.275	3.626	***	Yes
H6	Knowledge Application → Task-Technology Fit	0.214	2.146	*	Yes	0.451	8.196	***	Yes
H7	Knowledge Application → Individual-Technology Fit	0.216	1.740	*	Yes	0.358	4.948	***	Yes
H8	Prompt Engineering Competence → Knowledge Acquisition	0.708	10.972	***	Yes	0.633	16.339	***	Yes
H9	Prompt Engineering Competence → Knowledge Application	0.677	8.768	***	Yes	0.639	16.557	***	Yes

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

As shown in Table 5, the results indicate that the structural model is consistent across male and female groups for all hypotheses (H1–H5, H7–H9), with no statistically significant differences in path coefficients between the groups ($p > 0.05$). This suggests that gender does not moderate any of the relationships examined in the proposed model and that the structural and relationship models are similar for both groups. However, for hypothesis H6, the results demonstrate a significant

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difference between the groups in the relationship between knowledge application and Task-Technology Fit (H6), with females showing a larger effect than males, as evidenced by a Δβ of 0.238 ($p = 0.021$). These findings suggest that females rely more on knowledge application to support their approach to the task than males do. In summary, these findings indicate that the overall model structure is robust across both male and female groups, except for knowledge application and its impact on task-technology fit in the female group.

Table 5. Between-Group Differences

H	Path	Difference (Female -Male)	*p*	Result
H1	Continuance Intention → Educational Sustainability	0.088	0.167	NS
H2	Task-Technology Fit → Continuance Intention	-0.014	0.453	NS
H3	Individual-Technology Fit → Continuance Intention	-0.100	0.248	NS
H4	Knowledge Acquisition → Task-Technology Fit	-0.185	0.056	NS
H5	Knowledge Acquisition → Individual-Technology Fit	0.141	0.163	NS
H6	Knowledge Application → Task-Technology Fit	0.238	0.021	Significant
H7	Knowledge Application → Individual-Technology Fit	-0.075	0.158	NS
H8	Prompt Engineering Competence → Knowledge Acquisition	-0.038	0.312	NS
H9	Prompt Engineering Competence → Knowledge Application	0.072	0.304	NS

NS: Not Significant

5. Discussion

The theoretical foundation of this study is built on the “Task-Technology Fit” (TTF) and “Knowledge Management” (KM) theories [40]. While TTF

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theory suggests that the fit of technological tools to users' task requirements increases usage efficiency and intention to continue, KM theory supports sustainability in education through effective management of knowledge acquisition and knowledge application processes [74]. AI-based technologies can enhance both knowledge management processes and the quality of learning outcomes by adapting to users' individual needs and tasks [75].

Educational sustainability refers to AI-supported learning processes that enable students to effectively acquire concepts presented in AI tools and apply them to practical situations [76]. Thus, AI-based education not only facilitates students' access to knowledge but also ensures that this knowledge is long-lasting, applicable, and transformative [77]. This study hypothesized that continuance intention would positively affect educational sustainability (H1). The results indicate that the continued intention to use AI tools positively influences their educational sustainability. A recent study investigated the impact of actual use on educational sustainability [65]. Their findings indicated that knowledge acquisition, knowledge application, perceived animacy, perceived anthropomorphism, and perceived intelligence positively influenced the actual use of AI. In contrast, knowledge sharing has no significant effect on usage. Additionally, it was found that the actual use significantly increases educational sustainability.

Strengthening the task and individual-technology fit can play a key role in increasing intentions to use AI tools [11]. When "task-technology

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fit" (TTF) is high, specifically when AI technologies fit the user's requirements, individuals' intention to continue using the technology increases. Accordingly, it is hypothesized that TTF would positively impact continuance intention (H2). The results confirm this hypothesis and align with other findings. For example, a recent study investigated the impact of TTF on scientific creativity among Chinese scholars [78]. Their findings suggest that while TTF promotes creativity by increasing AI literacy, it also reinforces dependency and inhibits creativity, which can be explained within the framework of the "AI Empowerment-Inhibit Paradox." Another study combined the TTF model with the "Technology Acceptance Model" (TAM) to examine the factors predicting STEM teachers' intention to use AI for instructional innovation [79]. The findings suggest that TTF and attitude towards innovation are determinants of teachers' behavioral intentions to use AI in innovative teaching practices.

A recent study examined the factors predicting individuals' intention to use AI-based customer services in Malaysia within the framework of the "Stimulus-Organization-Response" (SOR) model and TTF theory [80]. The results highlighted the critical role of TTF on technology adoption intention. Another study integrated the TTF and the "Expectancy-Confirmation Model" (ECM) to explain post-adoption intentions for the continued use of AI chatbots in the tourism industry [81]. Their findings showed that TTF directly and significantly increases users' approval and perceived utility. Perceived usefulness and expectation confirmation positively affect customer satisfaction, which is the strongest predictor of continued intention to use chatbots. A recent study conducted at higher

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education institutions in India examined students' intentions to continue using ChatGPT [82]. The findings revealed that TTF and attitudes toward technology had a strong impact on the intentions.

The concept of "individual-technology fit" (ITF) suggests that individuals have distinct psychological needs, and the impact of AI on users is maximized when technologies are tailored to meet these needs [83]. Within this framework, the hypothesis (H3) that ITF would have a positive impact on users' intention to continue using AI has been formulated. The findings support the hypothesis and indicate a significant, positive relationship between ITF and intention to continue. Previous studies have similarly found that ITF has positive impacts on the perceived ease of use and usefulness of "massive open online courses" (MOOCs), which, in turn, increase the intention to continue [45]. Furthermore, another study proposed an integrated theoretical model combining the "technology acceptance model" (TAM), social motivation, perceived risks, and TTF. This model was tested to explain intentions to use drones for public health emergencies [84]. The findings indicated that ITF, TTF, ease of use, attitudes, and social impact directly shaped users' intentions to use drones.

Users with greater knowledge understand which technology features support which tasks; thus, significantly positive relationships between task requirements and technology capabilities are anticipated [39]. The results showed that "knowledge acquisition" positively influences TTF (H4). As users acquire knowledge, they become more

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comfortable, confident, and competent with technology, thus fostering a positive association between the individual and technology [20]. The results showed that knowledge acquisition has a significantly positive influence on ITF (H5).

When users apply knowledge to solve problems or make decisions, they actively adapt their use of technology to task requirements, thereby strengthening task-technology fit. Therefore, a hypothesis is proposed that the application of knowledge will have a significantly positive impact on task-technology fit (H6). The results indicated that knowledge application has a significantly positive impact on the task-technology fit. Recent findings showed that when AI-based tools are aligned with tasks, they enhance users' ability to apply knowledge effectively [85]. When TTF is high on generative AI platforms, users can apply the knowledge they gain more effectively in decision-support systems and project applications.

The results indicated that the application of knowledge has a significantly positive impact on individual-technology fit (H7). This implies that personalization may enhance the alignment between individuals and technology over time. Recent studies support these findings, showing that using AI to personalize learning content according to students' career goals increases student satisfaction, participation, and learning efficiency [86].

A recent study examined the relationships between task and technology characteristics and EDP using TTF theory to explain "employee digital performance" (EDP) [87]. The results show that "enterprise social

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media” (ESM) functions produce different effects on TTF: work-oriented functions yield a U-shaped effect, while socialization functions have a direct positive effect. TTF increases both digital innovative performance and digital task performance. Digital literacy moderates the relationship between TTF and task performance. Digital culture enhances TTF’s effect on both performance dimensions. Another study integrates TTF and “Theory of Planned Behavior” (TPB) to explain the adoption of generative AI tools in supply chain management [88]. They find that task requirements and AI’s technical capabilities significantly affect TTF.

Prompt engineering is the process of designing prompts or inputs to obtain the most accurate and effective output from an AI model [17]. Prompt engineering enables users to acquire and apply information more accurately and effectively by optimizing their interaction with AI systems [89]. Within this framework, the study hypothesized that individuals’ prompt engineering competence would positively affect their information acquisition via AI (H8). Similarly, it was assumed that this competency would also contribute to the application of information through AI (H9). The analysis results confirmed both hypotheses and showed that prompt engineering competency has a significant and positive impact on AI-based information acquisition and application. Likewise, prior findings suggested that archivists also need to develop specific skills in digital curation processes, such as data collection and access with AI assistance [90]. However, many topics related to competency and data management, particularly in the context of digital curation, remain underexplored in the literature. In the same vein, another study emphasizes that archivists need

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to be literate in AI to effectively utilize this technology for archiving, as well as to ensure the ethical use of AI for effective information management and adaptation to new technologies [91]. Similarly, a recent review study argues that skills such as AI ethics literacy, AI-related computer literacy, and user-centered and organizational AI literacy are essential for archivists and records managers [92].

A prior study examined the impact of the senior management team's AI literacy on the company's AI orientation and its ability to implement AI [93]. The results showed that AI literacy of senior management had a positive influence on both AI orientation and AI implementation ability. Another study conducted among Gen-Z in Thailand examines the relationships among AI literacy, diagnostic and predictive capabilities, and risk management skills [94]. The research results demonstrated that AI literacy has a significant positive influence on both diagnostic and predictive abilities, and that these abilities substantially enhance risk management skills.

The results of the within-group analysis indicate that all hypotheses (H1–H9) are significant in both men and women. This confirms that the proposed model is robust for both groups. Although effect sizes reveal some differences (e.g., the impact of knowledge application on task–technology fit is stronger in women), most are not statistically significant. The group comparison in Table 5 confirms this; only H6 (Knowledge Application → Task–Technology Fit) shows a significant gender difference ($\Delta\beta = 0.238$, $p = 0.021$). This result indicates that knowledge application

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has a stronger influence on task-technology fit in women than in men. All other paths remain unchanged across groups, demonstrating structural consistency.

The findings indicate that the structural model is generally consistent across both male and female groups, with a significant gender difference only in the knowledge application–TTF relationship (H6). Application-based learning approaches and contextual cognitive engagement perspectives can explain the greater effect of knowledge application on TTF among female participants. The literature indicates that female users may focus more on how the knowledge acquired when evaluating technologies translates into concrete task performance, problem-solving processes, and improved learning outcomes [95]. Therefore, it is understood that aligning GenAI with task requirements gains meaning for female users through direct application experience.

6. Conclusion

6.1 Theoretical Implications

The findings show that knowledge management processes (knowledge application and acquisition) are not merely outcome variables; they mediate behavioral outcomes, such as sustained intention, through “task-technology fit” (TTF) and “individual-technology fit” (ITF). This result makes an essential contribution to the IS literature by integrating TTF with KM theory through a functional mediation model.

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It has been confirmed that “Prompt Engineering Competence” (PEC) is a competency-based precursor that positively influences the cognitive components of KM (knowledge acquisition/application). Thus, prompt engineering can be conceptualized as a competency embedded in the chain of transformation from knowledge acquisition to application, not limited to AI literacy studies.

Confirmation of the positive impact of knowledge acquisition and application on TTF/ITF underscores the importance of aligning content with users’ goals. The findings emphasized the important role of aligning services with individuals’ expectations and demonstrated that AI personalization can bridge the gap between practical application and theoretical knowledge.

6.2 Practical Implications

Findings reveal that prompt engineering competence positively influences knowledge management practices, including knowledge application and acquisition. This implies that adding practical lessons to the curriculum that develop students’ prompt engineering competence (specifying objectives, assigning roles, setting constraints, guiding with examples, and iterative improvement) and incorporating prompt engineering achievements can strengthen the knowledge management process. Developing prompt engineering competence should be a strategic priority for institutions, as it is essential to achieving sustainability alongside effective knowledge management.

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To integrate prompt engineering into curriculum design, applied learning approaches such as iterative improvement, critical output evaluation, and context-based prompt design can be recommended. In this context, students can be encouraged to develop multiple prompts for the same task, analyze the differences in the quality and appropriateness of GenAI outputs, evaluate the generated content for academic accuracy and contextual consistency, and provide reflective feedback on the prompt strategies used. This pedagogical framework enables the systematic development of the competencies measured by PECS through classroom applications, while supporting the sustainable and purpose-driven use of GenAI in education.

The findings indicated that TTF and ITF have a significantly positive influence on the continuance intention. This suggests that developing AI tools tailored to a specific task yields much more effective results than using a general-purpose AI model. On the other hand, leveraging prompt engineering expertise to refine prompts can be a more cost-effective approach. However, providing adaptable interfaces and personalized command templates tailored to user requirements can increase ITF and thus strengthen continuance intention.

Although new technologies such as GenAI initially generate high interest in educational settings, the gradual decline of this “novelty effect” can be mitigated only by positioning GenAI as a functional, routine learning support tool aligned with pedagogical objectives. Therefore, as users develop their prompt engineering and knowledge management

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skills, the use of GenAI can evolve from superficial experimentation into purpose-driven, efficient, and sustainable applications. Furthermore, within the technology fit concept, if GenAI is used in ways that align with pedagogical needs, the novelty effect can give way to long-term adoption and institutionalized use.

Finally, it has been emphasized that while GenAI serves as a supportive and empowering tool for learning, its use without rigorous and critical scrutiny can weaken students' critical thinking, problem-solving, and cognitive depth [96]. In particular, it is thought that GenAI's provision of ready-made solutions that reduce cognitive load may lead students to become passive consumers of information without developing metacognitive awareness. In this context, it is predicted that the AI Empowerment-Inhibit Paradox necessitates a pedagogically structured, guided, and critical use of GenAI for educational sustainability; otherwise, short-term gains in efficiency may have negative effects on learning quality and long-term cognitive development.

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6.3 Limitations and Future Directions

The study has several limitations. Firstly, this cross-sectional study was conducted within a specific sample group and time frame, limiting the generalizability of its findings. Secondly, the measurement tools rely on self-reports, and participants' perceptual biases may have influenced the results. Although powerful analytical techniques, such as SEM and AI-based methods, were employed, the study primarily yielded correlational rather than causal relationships.

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Finally, the scope of the variables addressed in the study is limited. While unique factors such as ITF, TTF, prompt engineering competence, and knowledge management components were examined, cultural differences or, more importantly, ethical dimensions were not investigated in this research. Future studies could yield comparative results by working with broader and more diverse samples, and experimental or longitudinal designs could be used to test causal relationships more robustly.

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Declarations

Institutional Review Board: "The study was conducted in accordance with the Declaration of Helsinki and approved by the Gulf University for Science and Technology (GUST) Institutional Review Board (IRB-41/2024-25)."

Informed Consent Statement: "Informed consent was obtained from all subjects involved in the study."

Data Availability Statement: "Data are available from the corresponding author upon request."

AI Declaration: "In this study, Grammarly Pro was only used for routine tasks such as enhancing language and readability, with caution."

Conflicts of Interest: "The authors declare no conflicts of interest."

Author Contribution: "The Authors (Omer Gibreel, Kasım Karataş, and Ibrahim Arpaci) equally contributed to each section."

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Appendix A: Constructs and Items

Continuance Intention [43]

CI1: “I am likely to continue to use Generative AI in the future.”

CI2: “I intend to continue to use Generative AI in my daily life.”

CI3: “I have a strong desire to continue to use Generative AI in the future.”

Prompt Engineering Competence Scale [17]

PECS1. “I can conduct effective research by crafting prompts that specify key details, adapt to different AI models, and optimize response accuracy.”

PECS2. “I can break down complex tasks into well-structured prompts, guiding AI step by step while minimizing trial and error.”

PECS3. “I can adjust my prompts using different formats (e.g., structured lists, open-ended questions, scenario-based instructions) to enhance response quality and relevance.”

PECS4. “I can improve AI-generated responses by specifying constraints such as role, tone, length, format, or other contextual factors.”

PECS5. “I can enhance AI output by incorporating relevant background information while recognizing and mitigating potential biases or limitations.”

PECS6. “I can strategically prompt AI to perform higher-order thinking tasks (e.g., analysis, synthesis, evaluation) and refine responses for greater depth.”

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PECS7. “I can improve response relevance by incorporating real-world examples, hypothetical scenarios, or case studies tailored to different AI tools.”

PECS8. “I can iteratively refine my prompts based on AI responses to improve response accuracy and efficiency.”

PECS9. “I can critically evaluate AI-generated responses for reliability, factual accuracy, and bias.”

Knowledge Acquisition [18]

KA1.“Generative AI always enables me to access information anytime and anywhere.”

KA2. “Generative AI facilitates my access to information.”

KA3. “Generative AI enables me to have quick access to knowledge.”

KA4. “Generative AI helps me obtain knowledge that suits my needs.”

Knowledge Application [18]

KA1. “Generative AI enables me to learn new concepts.”

KA2. “Generative AI helps me expand my knowledge.”

KA3. “Generative AI can be used in problem-solving.”

KA4. “Generative AI allows me to apply knowledge in performing my assignments.”