Exploring College Students' Behavioral and Continuance Intention to Use AI Tools: A Technology Adoption and Grit Perspective

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Abstract

This study examines the factors shaping college students' adoption and continued use of artificial intelligence (AI) tools, such as ChatGPT, for academic tasks. Drawing on the Unified Theory of Acceptance and Use of Technology (UTAUT), Expectation Confirmation Theory (ECT), and Grit Theory, we propose and test an integrative model in which performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) predict behavioral intention (BI) to use AI tools, which in turn predicts continuance intention (CI), moderated by consistency of interest (COI) and perseverance of effort (POE). Survey data from 187 college students were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Results indicate that PE and FC significantly predict BI, while EE and SI do not; BI significantly predicts CI; and of the two dispositional moderators tested, POE significantly moderates the BI-CI relationship while COI does not. These findings suggest that perceived usefulness and facilitating conditions, rather than ease of use or social influence, drive students' initial adoption of AI tools, and that perseverance plays a greater role than consistency of interest in sustaining continued use. Implications for educators, policymakers, and developers seeking to support effective AI adoption in higher education are discussed.

Keywords: artificial intelligence, technology adoption, UTAUT, expectation confirmation theory, grit theory

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1. INTRODUCTION

Artificial Intelligence (AI) has rapidly emerged as one of the most transformative technologies. AI powered systems such as ChatGPT, Bing Copilot, and Gemini are increasingly used by college students to support writing, coding, problem solving, research, and creative ideation. These tools offer instant feedback, personalized guidance, and adaptive learning opportunities that were previously unavailable in traditional educational environments. As AI becomes more integrated into academic workflows, understanding how students perceive and interact with these tools is essential for designing effective learning experiences and institutional policies.

The adoption of AI tools in higher education is influenced by multiple factors, including perceived usefulness, ease of use, social encouragement, and the availability of resources that support adoption. This study investigates the perceptions of college students regarding the performance expectancy (PE) effort expectancy (EE), and Social Influence (SI) of using AI tools. Additionally, it examines the extent to which these perceptions influence students' behavioral intention (BI) to use AI tools for academic tasks.

Beyond initial adoption, it is equally important to understand what drives students to continue using AI tools over time. Expectation Confirmation Theory (ECT) suggests that continuance intention (CI) is shaped by satisfaction and confirmation of initial expectations (Bhattacherjee, 2001). Meanwhile, Grit Theory introduces the idea that personal characteristics—specifically consistency of interest (COI) and perseverance of effort (POE)—may influence whether students persist in using AI tools despite challenges or learning curves (Duckworth et al., 2007).

It also investigates whether the consistency of interest (COI) and perseverance of effort (POE) in using AI tools moderate the relationship between BI and continuance intention (CI). Through a comprehensive analysis of these hypothesized relationships, this study aims to provide valuable insights into the factors influencing college students' attitudes and behaviors towards AI tools in education.

The Unified Theory of Acceptance and Use of Technology (UTAUT) posits that the intention to use a technology is influenced by PE, EE, SI, and FAC (Venkatesh et al., 2003). PE refers to the performance expectancy of the technology, while EE represents the perceived effort expectancy (Davis, 1989). In other words, PE refers to a user's opinion of how much this will improve their performance on a certain task and EE refers to how easy it is to learn and use the new technology. SI focuses on how much a user's friends might influence the use of AI tools. FC encompasses any external factors that facilitate or hinder its use. Expectation Confirmation Theory suggests that users' satisfaction and intention to continue using a technology are influenced by the confirmation of their initial expectations regarding its performance (Bhattacherjee, 2001). Grit Theory focuses on the perseverance and passion for long-term goals and suggests that individuals with higher levels of grit are more likely to persist in their efforts to achieve their objectives (Duckworth et al., 2007).

Despite extensive application of UTAUT to a wide range of technologies, and growing use of ECT to explain continuance behavior, most technology adoption research in higher education focuses on situational and technology-related antecedents (PE, EE, SI, FC) while overlooking dispositional, individual-difference variables that may explain why some students sustain AI tool use over time despite challenges or learning curves. Few studies have integrated a personality-based framework such as Grit Theory into an AI adoption model to address this gap. This study addresses that gap by integrating UTAUT and ECT with Grit Theory, testing whether consistency of interest (COI) and perseverance of effort (POE) moderate the translation of initial adoption intention (BI) into continuance intention (CI). Its theoretical contribution is to show that a dispositional trait—perseverance—plays a distinct role in sustaining AI tool use beyond the technological and social factors emphasized by UTAUT alone.

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This study aims to propose an integrative research model, drawing upon the Unified Theory of Acceptance and Use of Technology (UTAUT), Expectation Confirmation Theory, and Grit Theory, to address several key research questions. Firstly, it examines college students' perceptions of the performance expectancy (PE), effort expectancy (EE), and social influence (SI) of using AI tools such as ChatGPT, Bing Copilot, and Gemini and their behavioral intention (BI) to use them for academic tasks. Do all of these factors influence a student's decision to use AI tools to complete classwork? This study also investigates the predictive role of facilitating conditions (FC) in students' BI to use AI tools. Finally, it explores whether the consistency of interest (COI) and perseverance of effort (POE) in using AI tools for learning moderates the relationship between BI and continuance intention (CI). Through these inquiries, this study aims to provide valuable insights into the factors influencing college students' attitudes and behaviors towards using AI tools.

The following is a review of three theories used to formulate our hypothesized relationships: the UTAUT, Expectation Confirmation Model (ECM), and Grit Theory. After reviewing these theories and their relatedness to the use of AI tools by college students in academic environments for learning purposes, a research model will be proposed. Research methods will be discussed regarding how to collect the data needed to validate the proposed hypotheses. Analysis results will be reported, along with academic and practical implications. The paper will conclude with limitations and future research directions.

2. LITERATURE REVIEW

2.1 Understanding AI Adoption Behaviors of Students via the UTAUT

The UTAUT offers a holistic framework for comprehending individuals' attitudes and behaviors toward technology adoption (Venkatesh et al., 2016), and has been applied to study AI adoption across domains such as language and music learning (Zhang, 2020), coding (Jung, 2020), web design (Lively et al., 2023), and cybersecurity (Khan et al., 2024). This study specifically explores college students' adoption of AI tools for learning in higher education. According to UTAUT, four key factors influence users' behavioral intentions: PE, EE, SI, and FC. PE refers to users' perceptions of the benefits and effectiveness of AI tools for learning, while EE relates to their perceived ease of use. SI refers to the influence an individual's family and friends have on their use of AI tools, and FC encompasses external factors—such as access to resources and technical support—that facilitate or hinder use.

From the perspective of college students, the use of AI for learning offers numerous benefits. AI tools can provide personalized and adaptive learning experiences, enhance engagement, and improve academic performance by offering instant feedback and tailored recommendations (Taylor et al., 2021). AI tools can facilitate collaborative learning and provide access to a wealth of educational resources, contributing to a more dynamic and interactive learning environment (Tan & Teo, 2000). However, there are also drawbacks to consider. Some students may perceive AI tools as impersonal or intimidating, leading to concerns about privacy, data security, and algorithmic bias (Fernández Fernández, 2022). Furthermore, reliance on AI tools for learning may diminish critical thinking skills and creativity, as students may become overly dependent on automated solutions (Vincent-Lancrin & Van der Vlies, 2020).

The Impact of Performance Expectancy (PE) on Behavioral Intention (BI) of Using AI Tools for Learning

We propose that PE significantly influences college students' behavioral intentions regarding the use of AI for learning. Positive PE can motivate students to adopt AI tools, as they perceive them as beneficial and effective in enhancing their learning experiences. For example, if students believe that AI tools such as ChatGPT, Bing Copilot, and Gemini can accurately assist them in completing assignments, understanding complex concepts and tasks (Fitria, 2021), solving problems (Yalazi-Dawani, 2023), or generating creative ideas (Bender, 2023), they are more likely to integrate these tools into their learning process. Studies have shown that students who perceive AI tools as useful and capable of improving their academic performance are more inclined to adopt them for educational purposes (Alhumaid et al., 2023). Thus, we propose:

> *H1: Performance expectancy (PE) positively influences students' behavioral intention (BI) to use AI tools.*

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The Impact of Effort Expectancy (EE) on Behavioral Intention (BI) of Using AI Tools for Learning

We believe that EE also plays a crucial role in shaping college students' behavioral intentions towards using AI for learning. Positive EE indicates that students find AI tools easy to navigate, understand, and interact with, which increases their willingness to adopt these tools. For instance, if students perceive that AI tools such as ChatGPT provide user-friendly interfaces (Mantravadi et al., 2020), intuitive functionalities, such as conversational AI-enabled Chatbot (Bharti et al., 2020), and quick responses to their queries, they are more likely to integrate them into their study routine. Research suggests that students' perceptions of EE significantly influence their attitudes and intentions towards using technology for learning purposes (Alhumaid et al., 2023). Therefore, we propose:

H2: Effort expectancy (EE) positively influences students' BI to use AI tools for learning.

The Impact of Social Influence (SI) on Behavioral Intention (BI) of Using AI Tools for Learning

SI also plays a significant role in shaping individuals’ behavioral intentions regarding the adoption of AI tools for learning. SI, which encompasses normative pressure, peer influence, and societal expectations, affects users’ perceptions and willingness to engage with AI-driven educational technologies (Bozan et al. 2016). Research suggests that when students perceive AI tools as widely accepted and endorsed by influential figures such as professors, peers, or educational institutions they are more likely to integrate these tools into their learning practices (An et al., 2023; Chai et al., 2021). Additionally, the perception of AI tools as beneficial and effective, reinforced by social validation, enhances users' confidence in their utility. However, negative societal perceptions, skepticism regarding AI’s capabilities, or concerns about ethical implications can hinder adoption rates (Wang et al., 2024). Ultimately, SI serves as a powerful force that can either accelerate or impede the widespread use of AI tools for learning, depending on collective attitudes and endorsements within academic and social networks.

H3: Social Influence (SI) positively influences students' BI to use AI tools for learning.

The Impact of Facilitating Conditions (FC) on Behavioral Intention (BI) of Using AI Tools for Learning

Beneficial perceptions of FC can significantly facilitate the adoption of AI tools among college students by minimizing barriers to usage and providing necessary support and resources. For example, if students have access to comprehensive technical support, including user guides, tutorials, and troubleshooting assistance, they are much more likely to feel confident and competent in using AI tools (Lin et al., 2022). Additionally, offering training sessions or workshops on how to effectively utilize AI tools in various academic tasks can enhance students' skills and knowledge, further encouraging their adoption (Kuleto et al., 2021). Institutions that invest in robust infrastructure and provide reliable internet connectivity can also contribute to positive perceptions of FC by ensuring seamless access to AI tools and online resources.

Conversely, negative perceptions or experiences related to FC can deter students from using AI tools and diminish their behavioral intentions. For instance, if students encounter technical glitches or experience difficulties in accessing support channels when encountering problems with AI tools, they may become frustrated and reluctant to continue using them. Similarly, if institutions fail to provide adequate training or resources for utilizing AI tools effectively, students may perceive them as burdensome or irrelevant to their academic needs, leading to decreased usage and adoption rates. Thus, we propose:

H4: Facilitating conditions (FC) positively influences students' BI to use AI tools for learning.

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2.2 Understanding AI Adoption Behaviors of Students via Expectation Confirmation Model

The Expectation Confirmation Model (ECM) offers insights into individuals' behaviors and attitudes based on their prior expectations and post-usage experiences (Bhattacherjee, 2008). In the context of college students' adoption of artificial intelligence (AI) tools for learning, ECT provides a valuable framework for understanding the relationship between BI and Continuation Intention (CI). According to ECT, individuals' satisfaction with a technology, based on their pre-existing expectations and actual experiences, influences their intention to continue using it (Bhattacherjee, 2001). In the case of using AI tools for education, students' initial perceptions of the usefulness, ease of use, and overall satisfaction with the tools are likely to shape their behavioral intentions to adopt them (An et al., 2023). Subsequent confirmation of these expectations and the resulting satisfaction are theorized to further shape students' intentions to continue using them (Saqr et al., 2023). Thus, we propose:

> *H5: Behavioral intention (BI) positively influences the continuance intention (CI) of students to use AI tools for learning.*

It is important to clarify how ECT is represented in the tested model. Although confirmation and satisfaction are the constructs that formally mediate the expectation-to-continuance relationship in ECT, this study does not measure them directly; instead, it tests the direct path from BI to CI. This simplification is consistent with parsimonious extensions of technology continuance research that treat behavioral intention as capturing the net effect of prior expectations, allowing continuance intention to be assessed without a second, post-usage measurement wave. As a result, H5 should be understood as a test of ECT's underlying logic—that intentions formed prior to sustained use shape continuance—rather than a full test of the confirmation-satisfaction mediating chain. We revisit this simplification, and its implications for future work, in Section 5.3.

2.3 Understanding AI Adoption Behaviors of Students via Grit Theory

Consistency of Interest (COI)

Grit Theory emphasizes the role of consistency of interest (COI) in achieving long-term goals (Wang et al., 2021). In the context of college students' adoption behaviors towards AI tools, COI reflects the extent to which students maintain a sustained interest in using these tools for learning purposes over time. For example, students who consistently engage with AI tools like ChatGPT, Bing Copilot, or Gemini for various academic tasks, such as homework or exam preparation, demonstrate a high level of COI. This sustained interest motivates them to persist in using these tools despite encountering challenges or setbacks, thereby strengthening their continuance intentions. Therefore, COI serves as a crucial moderator that reinforces the relationship between behavioral intention (BI) and continuance intention (CI), driving students' long-term commitment to integrating AI tools into their learning processes. Thus, we propose:

> *H6: The consistency of interest (COI) in using AI tools for learning moderates the relationship between BI and CI.*

Perseverance of Effort (POE)

Grit Theory also underscores the importance of perseverance of effort (POE) in achieving success (Wang et al., 2021). In the context of college students' adoption behaviors towards AI tools, POE reflects students' ability to maintain effort and resilience in using these tools, even in the face of obstacles or difficulties. For example, students who exhibit perseverance in overcoming technical difficulties or adapting to new features of AI tools demonstrate a high level of POE. Driven by their determination and resilience, these students are more likely to translate their initial BI into continued usage over time. Therefore, POE serves as another critical moderator that strengthens the relationship between BI and CI, reinforcing students' commitment and persistence in utilizing AI tools for learning purposes. Thus, we propose:

> *H7: The perseverance of effort (POE) in utilizing AI tools for learning over time moderates the relationship between BI and CI.*

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2.4 Research Model

The research model (Figure 1) investigates the influence of various factors on college students' adoption of AI tools in their learning process, with a focus on examining how COI and POE moderate the relationship between BI and CI. Independent variables such as PE, EE, SI, and FC are assessed for their impact on students' BI to use AI tools. COI evaluates the consistency of students' interest in using AI tools, while POE examines their perseverance in utilizing these tools over time. The moderating roles of COI and POE are explored to understand their influence on the relationship between BI and CI. Ultimately, CI serves as the dependent variable, reflecting students' intention to continue using AI tools for completing academic tasks.

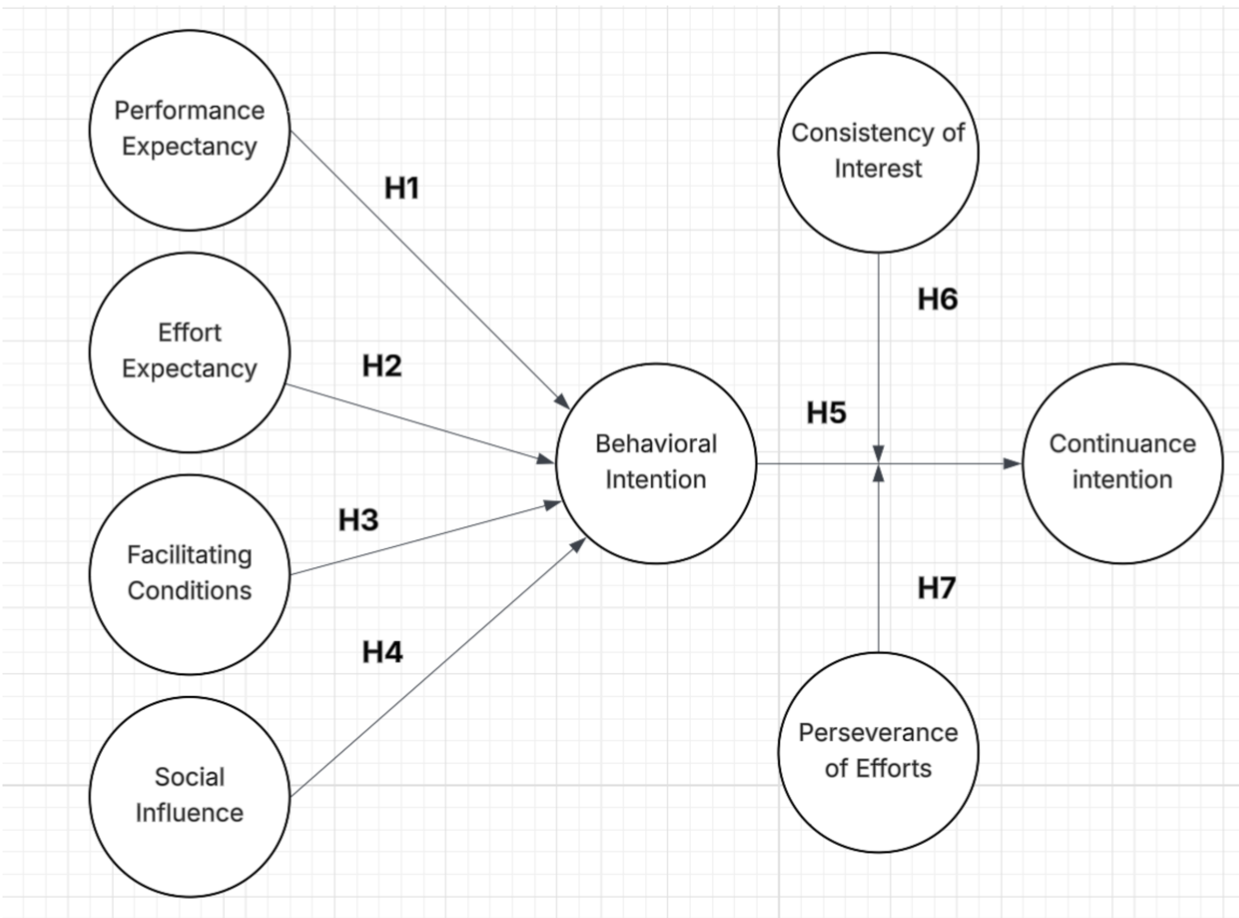

Figure 1. Research Model

3. RESEARCH METHODOLOGY

We designed a survey instrument based on the Unified Theory of Acceptance and Use of Technology (UTAUT), Expectation Confirmation Theory, and Grit Theory to assess our proposed hypotheses. This survey enables us to gather data and empirically examine the theoretical model and hypotheses. We then utilized Partial Least Squares – Structural Equation Modeling (SmartPLS V.4) to analyze the measurement and structural models and validate the hypothesized relationships among the constructs. Specifically, we employed the consistent PLS-SEM algorithm for assessing the correlations among our reflective constructs, ensuring consistency with a factor model (Dijkstra & Henseler, 2015). Partial Least

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Squares – Structural Equation Modeling is particularly suitable for exploratory studies (Hair Jr et al., 2017) and is less restrictive in its assumptions regarding sample sizes, data distribution, and measurement scales (Chin, 1998), thereby minimizing estimation issues (Goh & Sun, 2014).

3.1 Data Collection Method

The primary data were gathered from business students at a state university in North Carolina. Table 1 presents the demographic information of the participants. College students, representing the younger generation, are frequent users of AI for various learning purposes such as completing assignments, preparing for exams, and writing papers. Prior to taking the survey, participants were informed that they would receive extra credit from their instructors by specifying the classes they were enrolled in. Responses were meticulously reviewed for completeness, and surveys with missing information were excluded. Missing data primarily resulted from students who voluntarily chose to discontinue the survey midway through or who reported not having previously used AI tools for learning, in which case they were directed to a "Thank you" page. A total of 187 data points were entered for the path analysis. Table 1 delineates demographical profile of students participating in the survey.

What is your gender?	**Frequency**	**Percent**
Male	129	69%
Female	57	30%
Do not want to answer	1	1%
What is your age?		
18-24	169	90%
25-34	13	7%
35-44	4	2%
missing data	1	1%
What is your education level?		
High school degree	47	25%
College/associate degree	50	27%
Undergraduate degree	76	41%
Graduate degree	14	7%

Table 1. Demographical Profile

How many times a week do you use AI?	**Frequency**	**Percent**
1-2 times	104	56%
3-4 times	53	28%
5-6 times	13	7%
More than 6 times	17	9%
What is the name of the generative AI that you typically use?		
ChatGPT	128	68%
Copilot	5	3%
Gemini	1	1%
Multiple tools mentioned	12	6%
Other	2	1%
Missing/No response	39	21%

Table 2. Use of Generative AI

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3.2 Survey Instruments

The survey instrument utilized in this study was meticulously designed to ensure rigor and validity in measuring the constructs outlined by the UTAUT, ECM, and Grit Theory. Drawing upon these theories, we aimed to assess college students' perceptions and behaviors concerning the use of AI tools for learning. Each construct in our research model was operationalized through multiple measurement questions adapted from prior studies, with careful consideration given to tailoring them to the context of AI usage in education.

We employed multi-item scales to enhance the validity and reliability of the constructs within the research model (MacKenzie et al., 2011). Item responses were gathered using a seven-point Likert scale, ranging from 1 = "strongly disagree" to 7 = "strongly agree." Items for PE, EE, BI, and FC were adapted from Davis (1989); for example, PE was measured with items such as "I find ChatGPT useful in my daily life," while BI was captured through statements such as "I plan to use ChatGPT in the future." Continuance intention (CI) was measured using items such as "I have an intention to continue using ChatGPT" (Wu et al., 2014). The consistency of interest (COI) and perseverance of effort (POE) constructs from Grit Theory were assessed using items adapted from Duckworth et al.'s (2007) Short Grit Scale. Overall, the survey instrument was designed to capture nuanced insights into students' perceptions and behaviors regarding AI tools in education.

4. DATA ANALYSIS AND RESULTS

4.1 Measurement Model Estimation: Construct Validity and Reliability

Measurement model estimation is a critical step in assessing the validity and reliability of the constructs within the research model. Table 3 presents several key indicators, including Cronbach's alpha, composite reliability (rho_a and rho_c), and average variance extracted (AVE), for each construct. Cronbach's alpha values above 0.7 indicate good internal consistency reliability (Hair et al., 2009), suggesting that the items within each construct are measuring the same underlying concept consistently. The composite reliability values (rho_a and rho_c) exceed the recommended threshold of 0.7 (Fornell & Larcker, 1981), indicating high reliability of the constructs. Additionally, the average variance extracted (AVE) values, which measure the amount of variance captured by the construct in relation to the variance due to measurement error, exceed 0.5 for all constructs except Social Influence (SI), suggesting adequate convergent validity for most of the model (Hair Jr et al., 2017; Fornell & Larcker, 1981). The SI construct exhibited a below-threshold AVE (0.418) and an anomalous negative rho_a (-0.165), despite an acceptable Cronbach's alpha (0.704) and composite reliability rho_c (0.731); this issue is discussed further in the Research Limitations section. Overall, the measurement model estimation results indicate strong reliability and validity for the constructs other than SI, providing reasonable confidence in the measurement model used for subsequent analyses.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	0.967	0.968	0.978	0.938
COI	0.756	0.776	0.857	0.666
CI	0.822	0.823	0.918	0.849
EE	0.841	0.864	0.893	0.677
FC	0.834	0.839	0.901	0.753
PE	0.861	0.871	0.915	0.783
POE	0.757	0.830	0.844	0.578
SI	0.704	-0.165	0.731	0.418

Table 3. Construct Measurement Validity and Reliability

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4.2 Discriminant Validity Analysis

The Fornell-Larcker criterion is employed to assess the discriminant validity of the constructs in the research model. This criterion compares the square root of the average variance extracted (AVE) for each construct with the correlations between that construct and all other constructs. If the square root of the AVE for a particular construct is greater than the correlation between that construct and any other construct, then discriminant validity is supported (Fornell & Larcker, 1981). Table 4 presents the correlations between constructs along the diagonal and the correlations between constructs in the off-diagonal cells. Upon examination, the square root of the AVE for each construct (presented along the diagonal) is greater than the correlations between that construct and all other constructs, providing evidence of discriminant validity. These results suggest that each construct in the research model measures a distinct and unique concept, thus supporting the discriminant validity of the measurement model.

	BI	COI	CI	EE	FC	PE	POE	SI
BI	0.968							
COI	0.070	0.816						
CI	0.707	0.114	0.921					
EE	0.475	0.159	0.391	0.823				
FC	0.487	0.150	0.459	0.537	0.868			
PE	0.651	0.115	0.575	0.531	0.452	0.885		
POE	0.316	-0.208	0.244	0.287	0.206	0.311	0.760	
SI	0.172	0.172	0.184	0.100	0.070	0.166	-0.019	0.647

Table 4. Discriminant Validity – Fornell-Larcker Criterion

4.3 Path Model and Hypothesis Estimation

The analysis results (Table 5) offer valuable insights into the relationships between various factors in the adoption of AI tools. Hypothesis 1 (H1) indicates a strong positive relationship between PE and students' BI to use AI tools, with a path coefficient of 0.497 ($p < 0.001$). This suggests that students who perceive AI tools as useful are more likely to intend to use them. However, Hypothesis 2 (H2) is not supported, as evidenced by a small path coefficient of 0.093 ($p = 0.350$), indicating that improved EE or ease of use does not necessarily contribute to increased BI among students to use AI tools. Similarly, Hypothesis 3 (H3) is not supported, as SI shows a small, non-significant path coefficient of 0.065 ($p = 0.435$), suggesting that peer or social endorsement does not significantly predict students' BI to use AI tools. Conversely, Hypothesis 4 (H4) demonstrates that FC significantly predicts students' BI to use AI tools, with a path coefficient of 0.208 ($p = 0.001$), indicating a positive influence. Moreover, Hypothesis 5 (H5) confirms a strong positive relationship between BI and CI, evidenced by a path coefficient of 0.719 ($p < 0.001$). However, Hypothesis 6 (H6) regarding the moderating effect of COI on the relationship between BI and CI does not exhibit a significant relationship, with a path coefficient of 0.042 ($p = 0.515$). Furthermore, Hypothesis 7 (H7) suggests that the moderating effect of POE on the relationship between BI and CI is statistically significant, with a path coefficient of 0.139 ($p = 0.015$). These two moderation tests appear alongside the main-effect hypotheses in Table 5 (as the COI x BI -> CI and POE x BI -> CI interaction rows) and are summarized with the accept/reject decisions for all seven hypotheses in Table 6.

Overall, the strongest relationships in the model are BI's association with CI (0.719) and PE's association with BI (0.497). EE and SI showed small, non-significant direct effects on BI, and COI showed a small, non-significant moderating effect on the BI-CI relationship, while FC and POE showed smaller but significant effects. These findings provide valuable insights into the determinants and moderators influencing college students' adoption and continuation intentions regarding AI tools in education. Table

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6 summarizes the results of hypothesis testing, indicating that 4 out of 7 hypotheses (H1, H4, H5 & H7) are supported, while the other 3 hypotheses (H2, H3 & H6) are rejected.

Hypotheses	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	Coefficient	T statistics (|O/STDEV|)	P value
H1: PE -> BI	0.497	0.495	0.112	0.497	4.434	0.000
H2: EE -> BI	0.093	0.093	0.099	0.093	0.935	0.350
H3: SI -> BI	0.065	0.063	0.084	0.065	0.780	0.435
H4: FC -> BI	0.208	0.213	0.062	0.208	3.360	0.001
H5: BI -> CI	0.719	0.720	0.062	0.719	11.563	0.000
H6: COI x BI -> CI	0.042	0.048	0.064	0.042	0.651	0.515
H7: POE x BI -> CI	0.139	0.120	0.057	0.139	2.422	0.015

Table 5. Hypothesis Test Results

Hypothesis	Result
H1: Performance expectancy (PE) positively influences students' behavioral intention (BI) to use AI tools for learning.	Supported
H2: Effort expectancy (EE) positively influences students' BI to use AI tools for learning.	Rejected
H3: Social Influence (SI) positively influences students' BI to use AI tools for learning.	Rejected
H4: Facilitating conditions (FC) positively influences students' BI to use AI tools for learning.	Supported
H5: Behavioral intention (BI) positively influences the continuance intention (CI) of students to use AI tools for learning.	Supported
H6: The consistency of interest (COI) in using AI tools for learning moderates the relationship between BI and CI.	Rejected
H7: The perseverance of effort (POE) in utilizing AI tools for learning over time moderates the relationship between BI and CI.	Supported

Table 6. Summary of Hypothesis Test Results

5. DISCUSSION

As the integration of AI tools into educational settings continues to evolve, understanding the factors that influence college students' perceptions and behaviors towards these tools is essential. This research paper explores college students' adoption and continuance intentions regarding AI tools from the perspectives of UTAUT and Grit Theory. By examining the interplay between students' perceptions, intentions, and persistence in using AI tools, this study aims to provide valuable insights into the theoretical and practical implications for educators, policymakers, and developers involved in supporting effective and sustained AI tool adoption through technology integration.

5.1 Theoretical Implications

The findings of this research paper carry significant theoretical implications for understanding the factors influencing college students' adoption and continuation intentions regarding AI tools in education. The supported hypothesis for PE's influence on BI aligns with UTAUT, underscoring perceived usefulness as a crucial determinant of AI tool adoption (Venkatesh et al., 2011). In contrast, the non-significant relationship between SI and BI suggests that peer or social endorsement played less of a role in shaping students' intentions than prior UTAUT research would suggest (Venkatesh et al., 2003), an inconsistency that may reflect the highly individualized, self-directed way students use tools such as ChatGPT for academic tasks. Similarly, the supported hypothesis for FC's positive impact on BI corroborates UTAUT's emphasis on external facilitating factors (Venkatesh et al., 2016). The finding that BI positively influences CI aligns with expectation confirmation theory, indicating that users' satisfaction and

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continued use are shaped by initial expectations (Davis, 1989). The supported moderating effect of POE further underscores the relevance of grit theory in understanding students' persistence in using AI tools over time. Together, these findings contribute to a more comprehensive understanding of the theoretical underpinnings guiding college students' behaviors and attitudes toward AI tools in educational settings.

5.2 Practical Implications

The practical implications of this research are noteworthy for educators, policymakers, and developers integrating AI tools into educational environments. Emphasizing the perceived usefulness of AI tools—by highlighting practical benefits and efficiency gains for academic tasks—can strengthen student adoption. Similarly, ensuring facilitating conditions such as access to resources and technical support helps institutions promote effective use of AI tools among students.

The positive influence of behavioral intention on continuance intention highlights the importance of fostering students' initial engagement and satisfaction, for example through interactive learning activities and personalized feedback. The moderating effect of perseverance of effort indicates that students who report higher perseverance also report stronger continuance intentions; however, this study did not test any grit-building intervention, so this finding should not be read as evidence that resilience-building strategies or growth-mindset training would in fact increase continuance intention. That causal claim would require controlled, experimental testing and is offered here only as a direction for future research, not as a demonstrated outcome. This caution is reinforced by the study's reliance on single-source, self-reported data collected at a single point in time, which raises the possibility that common method bias inflated the observed relationship between POE and CI (see Section 5.3); the true strength of this relationship, and therefore the potential value of any grit-focused intervention, should be confirmed with objective or multi-wave data before it informs institutional practice. Together, these findings tentatively suggest that addressing students' perceptions, providing adequate support, and fostering resilience can help educators and policymakers encourage broader and more sustained adoption of AI tools among students.

5.3 Research Limitations

Despite the valuable insights gained from this study, several limitations should be acknowledged. Firstly, the data were collected from a single state university in North Carolina, which may limit the generalizability of the findings to other student populations or educational contexts. Additionally, the survey instrument relied on self-reported measures, which could be subject to social desirability bias or recall errors. Because all constructs were measured using self-reported data collected from the same respondents at a single point in time, the results may also be subject to common method bias; no formal statistical test (e.g., Harman's single-factor test or a full collinearity-based assessment) was conducted to evaluate this possibility, and future work should incorporate such tests. Relatedly, participants were student volunteers who received extra credit for completing the survey, which may introduce self-selection bias not fully captured by the demographic profile in Table 1. Moreover, the study focused on the perceptions and behaviors of college students, overlooking the perspectives of educators or administrators who play crucial roles in implementing AI tools in educational settings. Furthermore, the cross-sectional nature of the study design precludes causal inferences, highlighting the need for longitudinal research to examine the long-term effects of AI tool adoption on student learning outcomes. It is also important to note that this study measures students' behavioral intention and continuance intention to use AI tools, not learning experience, learning outcomes, academic performance, or critical thinking directly; whether sustained AI tool use translates into measurable learning gains remains an open empirical question that this design cannot address. Relatedly, the model tests the direct path from BI to CI rather than measuring confirmation and satisfaction as separate mediating constructs, so it captures ECT's underlying logic but not its full mediating chain; future studies should collect post-usage confirmation and satisfaction measures to test that chain explicitly.

A further limitation concerns the measurement of Social Influence (SI). Although the four-item SI construct demonstrated acceptable Cronbach's alpha (0.704) and composite reliability rho_c (0.731), it exhibited an anomalous negative rho_a (Dijkstra & Henseler, 2015) and an average variance extracted below the conventional 0.5 threshold (0.418). Item-level diagnostics ruled out outlier respondents or careless responding as the cause; systematic testing of alternative three-item subsets did not resolve

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the issue and in some cases worsened the reliability indices, suggesting the instability reflects the correlational structure among the SI indicators rather than a data quality problem. Given the adequate alpha and rho_c, results involving SI should be interpreted with appropriate caution, and future research should consider re-developing or expanding the SI item pool.

5.4 Future Research Directions

Building on the findings and limitations of this study, several future research directions are proposed. Longitudinal studies could explore how students' perceptions and behaviors toward AI tools evolve over time, offering insight into the sustainability of adoption. Comparative studies across institutions or cultural contexts could clarify how context shapes AI tool adoption and effectiveness. Mixed-methods approaches incorporating qualitative interviews could enrich understanding of the interplay between students, educators, and AI technologies. Experimental studies could help establish causal relationships between AI tool interventions and learning outcomes, informing evidence-based practice. Finally, future work should evaluate AI-driven interventions tailored to specific learning needs, supporting more personalized and adaptive learning experiences in higher education.

6. CONCLUSION

This study has shed light on the complex dynamics of college students' perceptions and behaviors regarding the adoption of AI tools in educational settings. Drawing on the Unified Theory of Acceptance and Use of Technology (UTAUT), Expectation Confirmation Theory, and Grit Theory, we proposed an integrative research model to investigate the factors associated with students' intentions to use AI tools for learning purposes. Because the data are cross-sectional and self-reported, and the outcomes measured are behavioral and continuance intentions rather than observed continued use or learning outcomes, the findings should be interpreted as associations rather than causal effects. With that caveat, the analysis results have provided valuable insights into the relationships between various constructs: PE and FC were significantly associated with BI, and BI was significantly associated with CI; EE and SI were not significant direct predictors of BI, and of the two dispositional moderators, POE significantly moderated the BI-CI relationship while COI did not. Overall, this study underscores the transformative potential of AI technologies in higher education and underscores the importance of collaborative efforts among stakeholders to harness these tools effectively for the benefit of students and society as a whole.

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