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Habit Before Utility: Understanding Student Acceptance and Use of Generative AI in Higher Education

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ABSTRACT

This quantitative cross-sectional survey study examined the factors influencing student acceptance of ChatGPT and the extent to which UTAUT2 explained behavioral intention and actual use among students enrolled in two-year and four-year programs at Historically Black Colleges and Universities (HBCUs). Using Partial Least Squares Structural Equation Modeling (PLS-SEM), habit, hedonic motivation, performance expectancy, and social influence significantly predicted behavioral intention. Habit emerged as the strongest predictor. Behavioral intention and facilitating conditions significantly predicted actual use. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) explained 75% of the variance in behavioral intention but only 16.7% in actual use. These findings demonstrate that understanding students' acceptance of generative AI (GenAI) does not fully explain actual use and suggests that research and institutional responses to student adoption should consider both intention and use when examining student's engagement with these technologies.

Keywords: behavioral intention, ChatGPT, generative AI, HBCU, higher education, student adoption, technology acceptance, UTAUT2

INTRODUCTION

Since the public release of ChatGPT in late 2022, generative artificial intelligence (GenAI) has become a popular area of inquiry across higher education. The widespread commercialization of GenAI has enabled students to incorporate this technology into a variety of academic activities, including generating written content, summarizing information, brainstorming ideas, and supporting problem-solving tasks. As these technologies became increasingly accessible, educators and institutional leaders were challenged to consider both the educational opportunities they present and the implications for teaching, learning, assessment, and academic integrity. GenAI platforms have demonstrated the potential to enhance learning experiences, improve educational performance, and reduce the time and effort required to complete academic tasks (Abbas et al., 2023; Sandu & Gide, 2019; Zhu et al., 2019). At the same time, concerns have been raised regarding plagiarism, algorithmic bias, misinformation, and the ethical use of AI-generated content within academic environments (Cheng et al., 2023; Mackey & Jacobson, 2019). As higher education institutions continue to navigate these opportunities and challenges, understanding how students perceive and adopt GenAI has become increasingly important in institutional responses as they steward knowledge and center learning in this ever-evolving AI-mediated environment.

Early scholarship examining GenAI in higher education has documented growing interest in the educational applications of these novel technologies. Researchers have explored how GenAI supports student learning, facilitates content generation, and influences instructional practices while also examining its potential impact on assessment, academic writing, and faculty practice (Abbas et al., 2023; Crompton & Song, 2020; Pinzolits, 2023). These studies demonstrate that GenAI is starting to be integrated into higher education in diverse ways. Although these platforms may improve efficiency, support learning, and enhance aspects of student performance (Abbas et al., 2023; Sandu & Gide, 2019; Zhu et al., 2019), what needs to be better understood is how well this technology is accepted and used by students (Strzelecki, 2023).

This need is particularly evident within Historically Black Colleges and Universities (HBCUs). While artificial intelligence has been examined across numerous higher education contexts, little research has focused on two-year and four-year HBCU students. Two systematic reviews examining the application of artificial intelligence in higher education identified hundreds of studies published between 2007 and 2022; however, neither identified studies involving students in two-year or four-year HBCUs (Crompton & Burke, 2023; Zawacki-Richter et al., 2019). This absence is significant because HBCUs have long played a distinctive role in expanding educational opportunity and producing graduates in science, technology, engineering, and mathematics (Knight et al., 2012), while historically Black community colleges continue to provide critical educational pathways for underserved populations (Bailey et al., 2006; DePass & Chubin, 2017; Elliott et al., 2019). Understanding student adoption of GenAI within these institutional contexts represents an opportunity to extend the current body of knowledge.

The purpose of this quantitative cross-sectional survey study was to examine the factors associated with the acceptance and use of ChatGPT among students enrolled at two-year and four-year HBCUs using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework (Venkatesh et al., 2003, 2012). Specifically, this study investigated the relationships among performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and students' behavioral intention to adopt ChatGPT. Applying the UTAUT2 to two-year and four-year HBCU student contexts contributes empirical evidence regarding student acceptance and use of GenAI and provides a foundation for future research examining technology adoption within this important and underrepresented higher education population.

LITERATURE REVIEW

Artificial intelligence (AI) has been intimately intertwined with education since its early development. Although this review is not intended to provide an exhaustive history of artificial intelligence or artificial intelligence in education (AIED), it examines the evolution of AI leading to the development of GenAI platforms, specifically ChatGPT. Because AI encompasses a broad range of technologies, a comprehensive historical review is beyond the scope of this study. Instead, this review focuses on the historical development of GenAI, its emergence within higher education, current educational applications, the literature examining student adoption, and the appropriateness of the UTAUT2 as the theoretical framework guiding this study.

The establishment of the field of AI is widely attributed to the 1956 Dartmouth Summer Research Project, during which the term *artificial intelligence* was introduced, and the field emerged as a distinct area of scientific inquiry (McCarthy et al., 2006). Since that time, definitions of AI have continued to evolve as researchers have debated the definition of intelligence and what is deemed intelligent behavior by machines (Kaplan, 2016; Sayler, 2019; Williamson & Eynon, 2020). Early developments including Logic Theorist, ELIZA, the LISP programming language, heuristic problem solving, and expert systems, provided the computational foundations that later supported intelligent educational technologies. Expert systems became the backbone of many intelligent computer-assisted instructional systems and represented an important step toward the application of AI within educational environments (Jones, 1985).

As AI matured, educational applications evolved alongside advances in computing. Early computer-assisted instruction systems such as computer assisted instruction (CAI), SPEEDAC, and PLATO demonstrated the potential for interactive and increasingly individualized learning experiences. Although these early systems were limited by contemporary computing capabilities, they still contributed to AIED by introducing concepts, including adaptive feedback, incorporating learner interaction, and individualized instruction. Continued developments yielded innovations such as the Perceptron and later further advances in machine learning and neural networks enabled the development of large language models. The development of new transformer architecture produced contemporary GenAI platforms such as GPTs. ChatGPT emerged from decades of continued advances in AI research and educational applications and not an isolated technological breakthrough.

Applications of Artificial Intelligence in Higher Education

The application of AIED has expanded considerably over the past two decades, supporting instructional, administrative, and institutional decision-making. As AI has evolved, researchers have increasingly examined how these technologies can enhance teaching, learning, assessment, and institutional operations. Systematic reviews of the literature provide an important foundation for understanding both the breadth of AI applications in higher education and the areas that remain underexplored.

Crompton and Burke (2023) conducted a systematic review of 138 international studies published between 2016 and 2022 and identified five major themes in the application of AI within higher education: assessment and evaluation, predictive AI, intelligent tutoring systems (ITS), and managing student learning. Similarly, Zawacki-Richter et al. (2019) synthesized 146 studies published between 2007 and 2018 and identified four dominant areas of AI research: predictive uses, assessment and evaluation, adaptive systems and educational personalization, and intelligent tutoring systems. Although conducted across different timeframes, both reviews demonstrate remarkable consistency in the ways AI has been applied within higher education and provide a useful framework for understanding the evolution of the field.

Consistent with Crompton and Burke (2023), the literature demonstrates that AI applications in higher education extend beyond a single instructional function and encompass predictive applications, assessment and evaluation, adaptive learning and intelligent tutoring systems, and operational and educational management. These areas illustrate that AI has become embedded across multiple dimensions of institutional practice, creating opportunities to improve educational effectiveness while simultaneously raising new questions about how students interact with increasingly sophisticated technologies.

Among these applications, predictive AI has received substantial scholarly attention. Researchers have applied predictive AI across a variety of higher education contexts. These applications include forecasting energy consumption in university buildings (Sadeghian et al., 2023), predicting student academic performance (Nosseir & Fathy, 2020; Petra et al., 2021), identifying students at risk of attrition (Bello et al., 2020), and evaluating learning strategies through AI-based predictive models (Bressane et al., 2022). These studies demonstrate that predictive AI has primarily been applied to support institutional decision-making, operational planning, and the identification of educational trends rather than to examine students' acceptance or behavioral intention to use AI technologies.

Despite the breadth of predictive AI research, the literature provides limited insight into students' adoption of GenAI tools and reveals a notable absence of empirical studies examining students attending two-year and four-year HBCUs. These applications primarily focus on institutional outcomes rather than students' acceptance of AI technologies themselves. Likewise, the literature provides little insight into students' behavioral intention to adopt GenAI tools and reveals a notable absence of research involving students attending two-year and four-year HBCUs.

The Emergence of Generative AI in Higher Education

The commercial release of GenAI fundamentally altered the landscape of higher education by expanding access to AI technologies capable of producing human-like text, images, code, and other forms of content. Unlike earlier educational AI applications that primarily supported institutional decision-making, adaptive learning, or intelligent tutoring, generative AI shifted the focus toward direct interaction between students, faculty, and AI systems. As a result, scholarly attention rapidly expanded from examining how institutions used AI to exploring how generative AI could influence teaching, learning, research, academic writing, and knowledge creation. At the time of the systematic reviews conducted by Zawacki-Richter et al. (2019) and Crompton and Burke (2023), research specifically examining GenAI in higher education was largely absent or identified as an emerging area requiring further investigation.

The earliest literature consisted primarily of conceptual and commentary papers exploring the opportunities and implications of GenAI for higher education. Researchers examined the potential for GenAI to support teaching and learning (Eager & Bruton, 2023), academic writing and information systems education (Craig et al., 2023), medical education and research (Shoja et al., 2023), bioinformatics instruction (Shue et al., 2023), AI assistants in higher education (Schön et al., 2023), and broader institutional opportunities and challenges associated with integrating ChatGPT into academic environments (Meyer et al., 2023; Walczak & Cellary, 2023). These studies report GenAI as a transformative educational technology capable of supporting learning, improving productivity, and augmenting academic work while simultaneously recognizing the need for further research to evaluate its educational impact.

As additional research began to emerge, researchers shifted from examining what GenAI might accomplish to investigating how students and faculty experienced these technologies. Early studies reported positive educational outcomes, including enhanced creativity, increased efficiency, support for academic writing, and improved learning experiences, while also identifying concerns related to academic integrity, response accuracy, overreliance, and ethical use. Strzelecki (2023) extended this emerging literature by examining the determinants influencing higher education students' intention to adopt ChatGPT using the UTAUT2 framework, providing one of the earliest empirical investigations of GenAI acceptance in higher education. Although these studies substantially advanced understanding of GenAI in educational settings, the literature remained limited in both scope and context, with little empirical attention given to students attending two-year and four-year HBCUs.

Technology Acceptance and the UTAUT2 Framework

Technology acceptance is an important component of adoption because an individual's intention to use a technology can influence whether it is ultimately used. Understanding students' acceptance of GenAI requires a theoretical framework capable of explaining both behavioral intention and technology use. Technology acceptance theories have been widely applied to examine the adoption of emerging technologies across educational, organizational, and consumer settings. Among these models, the Technology Acceptance Model (TAM), TAM2, the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) have been the most frequently employed to explain technology adoption behavior.

While TAM and its subsequent extensions established perceived usefulness and perceived ease of use as important determinants of technology acceptance, UTAUT2 expanded these earlier models by incorporating additional behavioral and experiential constructs that more comprehensively explain voluntary technology use (Venkatesh et al., 2012). Because GenAI platforms such as ChatGPT represent a rapidly evolving technology that students voluntarily adopt to support academic work, UTAUT2 provides an appropriate framework for examining the factors influencing students' behavioral intention and use. UTAUT2 distinguishes between behavioral intention and use behavior, recognizing that the factors influencing an individual’s intention to use a technology may differ from those influencing actual use (Venkatesh et al., 2012). The model has demonstrated strong explanatory and predictive capability across diverse technological contexts and has recently been adapted to investigate GenAI acceptance in higher education.

Consistent with Venkatesh et al. (2012), UTAUT2 proposes that behavioral intention is influenced by performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. However, because ChatGPT was available to students at no cost during the period in which this study was conducted, recent investigations of GenAI acceptance have appropriately omitted the price value construct (Strzelecki, 2023). The present study adopts this modified UTAUT2 framework to examine the factors influencing ChatGPT acceptance and use among students attending two-year and four-year HBCUs, extending one of the earliest empirical applications of UTAUT2 within the context of GenAI.

RESEARCH METHOD

To effectively address the research question, a quantitative, nonexperimental, cross-sectional survey design was employed. A quantitative approach was selected because it enabled the measurement of relationships among established technology acceptance constructs and facilitated statistical testing of the factors influencing students' behavioral intention and technology use. Guided by the UTAUT2, the study examined the following research question: What factors influence students’ acceptance of ChatGPT in higher education, and to what extent does UTAUT2 explain their acceptance and use behaviors? Inquiry provides deeper understanding into the extent to which performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and behavioral intention explained students' acceptance and use of ChatGPT. This design provides an appropriate framework for examining both technology acceptance and students' perceptions of GenAI.

Participants

Participants in this study consisted of undergraduate students enrolled in two-year and four-year academic programs at a southern HBCU. Eligibility was limited to currently enrolled students who voluntarily participated in the study. A convenience sampling approach was used to recruit participants. Although convenience sampling limits the generalizability of findings, it provided access to a population that has been largely underrepresented in prior research examining GenAI adoption in higher education.

Data were analyzed using IBM SPSS Statistics and SmartPLS 4. Descriptive statistics were first computed to summarize participant characteristics and patterns of ChatGPT use. To evaluate the UTAUT2 model, Gerbing and Anderson’s (1988) two-step Partial Least Squares Structural Equation Modeling (PLS-SEM) approach was employed. The measurement model assessment examined indicator reliability, internal consistency reliability, convergent validity, and discriminant validity before evaluating the structural model. The structural model assessment included analyses of collinearity, coefficients of determination (R^2), effect sizes (f^2), path coefficients, and hypothesis testing.

RESULTS

This study examined the factors influencing students' acceptance and use of ChatGPT and the UTAUT2 explained these behaviors among students enrolled in two-year and four-year programs at an HBCU. Following Gerbing and Anderson's (1988) two-step approach, the measurement model was evaluated before assessment of the structural model. The results presented include participant characteristics, measurement model assessment, and structural model assessment. Findings associated with the qualitative research question on perceived benefits and risks of GenAI are not included in this analysis.

A total of 480 survey responses were initially collected. Following data cleansing, 152 responses that did not meet the study criteria were removed, resulting in a final sample of 328 participants. Of the participants, 61.6% (*n* = 202) were male, 36.9% (*n* = 121) were female, and 1.5% (*n* = 5) identified as non-binary. The sample was predominantly between 18 and 24 years of age (84.1%, *n* = 276), followed by participants between 25 and 34 years of age (9.5%, *n* = 31). Participants between 35 and 44 years of age represented 3.4% (*n* = 11), followed by 2.1% (*n* = 7) between 45 and 64 years and .9% (*n* = 3) between 55 and 64 years.

Table 1
Sample Age and Gender Demographics

Description	Frequency	%	Valid %	Cumulative %
Gender				
Male	202	61.6	61.6	61.6
Female	121	36.9	36.9	98.5
Non-Binary	5	1.5	1.5	100
Total	328	100	100	
Age				
18 to 24	276	84.1	84.1	84.1
25 to 34	31	9.5	9.5	93.6
35 to 44	11	3.4	3.4	97.0
45 to 64	7	2.1	2.1	99.1
55 to 64	3	0.9	.9	100
Total	328	100	100	

Participants represented a range of academic disciplines. Other disciplines represented the largest group (33.0%, *n* = 108), followed by business and management (29.6%, *n* = 97), health sciences (14.9%, *n* = 49), social sciences (8.8%, *n* = 29), STEM and engineering (8.8%, *n* = 29), and humanities (4.9%, *n* = 16). The sample was heavily represented by students enrolled in four-year programs. According to the demographic table, 93.9% (*n* = 308) were enrolled in four-year programs and 6.1% (*n* = 20) were enrolled in two-year programs.

ChatGPT use was reported by 33.2% (*n* = 109) of participants, while 66.8% (*n* = 219) reported that they did not use ChatGPT. The frequency data further showed that most participants reported never using the platform. Among those reporting some level of use, frequency ranged from once a month to several times a day. These usage patterns provide additional context for examining behavioral intention and actual technology use within the UTAUT2 model.

Table 2
ChatGPT Usage and Frequency

Description	Frequency	%	Valid %	Cumulative %
Usage				
Not Using ChatGPT	219	66.8	66.8	66.8
Using ChatGPT	109	33.2	33.2	100
Total	328	100	100	
Frequency				
Never	190	57.9	57.9	57.9
Once a Day	11	3.4	3.4	61.3
Once a Month	49	14.9	14.9	76.2
Once a Week	31	9.5	9.5	85.7
Several Times a Day	2	0.6	0.6	86.3
Several Times a Month	23	7.0	7.0	93.3
Several Times a Week	22	6.7	6.7	100
Total	328	100	100	

Measurement Model Assessment

The measurement model was evaluated for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity before assessment of the structural model. Outer loadings for all indicators ranged from .870 to .975, exceeding the established .70 threshold. Indicator reliability values ranged from .756 to .950. These results supported indicator reliability across the constructs included in the model.

Internal consistency reliability and convergent validity were assessed using Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). Cronbach's alpha values ranged from .938 to .966, while composite reliability values ranged from .957 to .978. AVE values ranged from .849 to .937. All constructs exceeded the established thresholds used in the study for internal consistency reliability and convergent validity.

Table 3
Construct Reliability and Validity

Construct	Cronbach Alpha	Composite Reliability	AVE
Behavioral Intention	.938	.961	.891
Performance Expectancy	.953	.966	.876
Effort Expectancy	.961	.972	.896
Social Influence	.953	.970	.914
Hedonic Motivation	.966	.978	.937
Habit	.950	.963	.868
Facilitating Conditions	.940	.957	.849

Discriminant validity was evaluated using the Heterotrait-Monotrait Ratio (HTMT). HTMT values generally remained below the .85 threshold. The relationship between effort expectancy and facilitating conditions produced an HTMT value of .864, slightly exceeding .85 but remaining below .90. The measurement model assessment therefore provided support for proceeding to evaluation of the structural model.

Structural Model Assessment

The structural model was assessed through inner collinearity, coefficient of determination, model fit, effect size, and path coefficient and significance testing. Inner collinearity was examined using variance inflation factor (VIF) values. For predictors of actual technology use, VIF values ranged from 1.715 to 2.738. For predictors of behavioral intention, VIF values ranged from 1.587 to 4.468. All values remained below the threshold of five used in the study, indicating that multicollinearity did not present a significant concern.

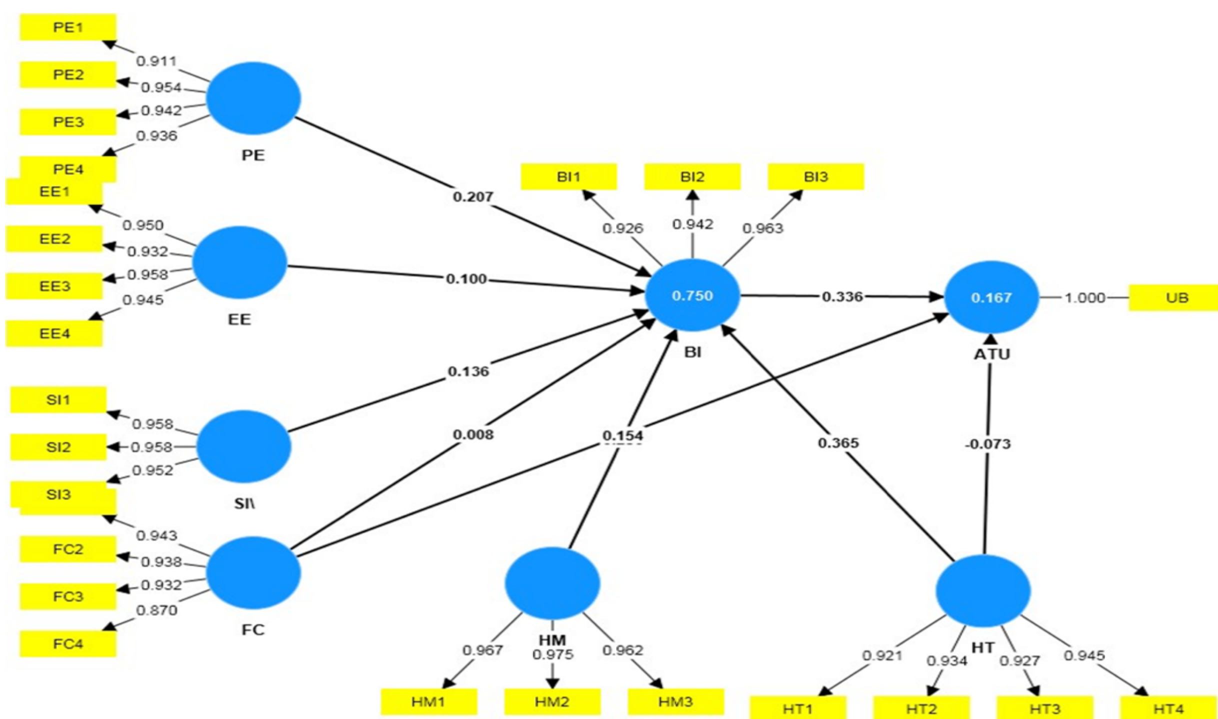
The coefficient of determination demonstrated considerably different explanatory power for behavioral intention and actual technology use. Behavioral intention had an R^2 of .750 and an adjusted R^2 of .746. Thus, the UTAUT2 constructs included in the model explained 75% of the variance in students' behavioral intention to use ChatGPT. Actual technology use had an R^2 of .167 and an adjusted R^2 of .159, indicating that the model explained 16.7% of the variance in actual ChatGPT use.

Effect-size analysis further identified differences in the relative contribution of the UTAUT2 constructs. Habit demonstrated the largest effect on behavioral intention (f^2 = .336). Hedonic motivation had an effect size of f^2 = .077, performance expectancy had an effect size of f^2 = .054, and social influence had an effect size of f^2 = .033 on behavioral intention. Effort expectancy demonstrated an effect size of f^2 = .009 on behavioral intention. Facilitating conditions had no effect on behavioral intention (f^2 = .000) but a small effect on actual technology use (f^2 = .017). Habit demonstrated a very small effect on actual technology use (f^2 = .003).

Path coefficient and significance testing identified the relationships among the UTAUT2 constructs. Behavioral intention significantly predicted actual technology use (β = .336, t = 3.710, p = .000). Facilitating conditions also demonstrated a statistically significant positive relationship with actual technology use (β = .154, t = 2.308, p = .021). Habit did not significantly predict actual technology use (β = −.073, t = .867, p = .386).

Figure 1

Path Coefficient Model



For behavioral intention, habit demonstrated the strongest statistically significant relationship (β = .365, t = 6.698, p = .000), followed by hedonic motivation (β = .256, t = 3.346, p = .001), performance expectancy (β = .207, t = 3.205, p = .001), and social influence (β = .136, t = 2.001, p = .045). Effort expectancy did not significantly predict behavioral intention (β = .100, t = 1.509, p = .131), and facilitating conditions did not demonstrate a significant relationship with behavioral intention (β = .008, t = .121, p = .904).

Table 4
Path Coefficient, SD, T, and p-Value

Path	Path Coefficient (β)	Standard Deviation	T-Statistics	*p*-Value
BI → ATU	.336	.091	3.710	.000
EE → BI	.100	.066	1.509	.131
FC → ATU	.154	.067	2.308	.021
FC → BI	.008	.064	.121	.904
HM → BI	.256	.077	3.346	.001
HT →ATU	-.073	.085	.867	.386
HT → BI	.365	.055	6.698	.000
PE → BI	.207	.064	3.205	.001
SI → BI	.136	.068	2.001	.045

The results identified habit, hedonic motivation, performance expectancy, and social influence as significant predictors of behavioral intention to use ChatGPT among the students in the study. Habit demonstrated the strongest relationship with behavioral intention. Behavioral intention significantly predicted actual technology use, while facilitating conditions also demonstrated a significant direct relationship with actual use. Habit, however, did not significantly predict actual technology use. The model explained 75% of the variance in behavioral intention and 16.7% of the variance in actual technology use, demonstrating substantially greater explanatory power for students' intention to use ChatGPT than for their reported actual use.

DISCUSSION AND CONCLUSIONS

This study examined the factors influencing students' acceptance and use of ChatGPT and the extent to which UTAUT2 explains these behaviors among two-year and four-year HBCU students. Habit, hedonic motivation, performance expectancy, and social influence emerged as significant predictors of behavioral intention to use ChatGPT. These findings are consistent with recent literature examining student adoption of technology in educational settings (Abu Elnasr et al., 2024; Arthur et al., 2023; Strzelecki, 2023).

Habit emerged as the strongest predictor of behavioral intention. Habit represents the extent to which technology use becomes routine or automatic and has been identified as an important factor in continued technology use (Limayem et al., 2007; Venkatesh et al., 2012). Hedonic motivation, or the enjoyment derived from using ChatGPT, was also a significant predictor of behavioral intention. This finding is consistent with prior studies demonstrating the importance of hedonic motivation in students' acceptance of technologies, including ChatGPT (Arthur et al., 2023; Strzelecki, 2023). As noted by Venkatesh et al. (2012), however, the influence of hedonic motivation may shift as users gain experience with a technology.

Performance expectancy was also a significant predictor, demonstrating that students' perceptions of ChatGPT's usefulness and its ability to enhance performance influenced their intention to use the technology. Performance expectancy has consistently been identified as an important predictor of technology acceptance within UTAUT2 research (Tamilmani et al., 2021; Venkatesh et al., 2012). Social influence was also statistically significant, indicating that the perceptions and attitudes of those within students' circles of influence, including the academic community, are associated with their intention to use ChatGPT. Together, these findings demonstrate that students' intentions are influenced by habitual use, enjoyment, perceived utility, and their social environment.

The UTAUT2 demonstrated considerable explanatory power for behavioral intention, explaining 75% of its variance. Behavioral intention was also a statistically significant predictor of actual ChatGPT usage. Facilitating conditions significantly predicted actual technology use but did not significantly predict behavioral intention. The UTAUT2 explained only 16.7% of the variance in actual technology use, demonstrating weaker explanatory power for usage than for behavioral intention. This distinction is important because students' acceptance of ChatGPT does not necessarily explain the full range of factors that determine whether the technology is actually used.

The findings support UTAUT2 as a useful framework for understanding ChatGPT behavioral intention among two-year and four-year HBCU students. The study adds to the limited research examining technology acceptance within this student population and provides an empirical basis for understanding the factors associated with students' adoption of GenAI. The findings also demonstrate the need to distinguish between behavioral intention and actual use when examining how students engage with emerging technologies.

IMPLICATIONS

The findings of this study have implications for how higher education institutions understand and respond to student adoption of GenAI. Behavioral intention and actual use are related, but they do not represent the same outcome. Understanding the contributing factors for students intention to use GenAI provides only part of the picture. Additionally, it is important to understand how students are actually using these GenAI technologies, what they need to use them effectively, and what conditions may support or limit their use.

Creating a supportive academic environment is an important part of this work. Faculty can help students understand how generative AI can be used appropriately in their academic work while reinforcing the need for human oversight. This requires institutions to provide faculty with opportunities to develop their own knowledge and understanding of GenAI so they are prepared to support students as these technologies continue to evolve. Institutions should also ensure that students and faculty have access to the resources and support needed to engage with emerging technologies effectively.

Clear institutional guidance is also needed. As GenAI becomes increasingly embedded in technologies students already use, institutions should establish guidance that addresses appropriate and ethical use while supporting AI literacy and critical thinking. Students should have a role in this process. Collaboration between students and faculty can help institutions better understand how GenAI is being used and develop approaches that reflect student experiences while maintaining expectations for academic integrity and appropriate use.

Future research should continue to examine the relationship between students' intentions and their actual use of GenAI. Longitudinal studies can provide greater insight into whether behavioral intention results in sustained use over time. Needs assessments can also help identify what students need to use these technologies effectively. Future studies should move beyond whether students use GenAI and examine the efficacy of that use, including whether it supports the academic tasks for which students are using it. Comparative research across student populations and institutional settings can further contribute to understanding GenAI adoption in higher education.

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