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Behavioral Pathways Behind Students' Willingness to Pay for GenAI in Higher Education

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Abstract

Generative artificial intelligence (GenAI) tools are rapidly becoming embedded in higher education, yet the mechanisms that facilitate students' willingness to pay (WTP) for these tools remain largely unexplored. Understanding WTP in education is important as it reflects a deeper level of commitment than casual use. This study employs the technology acceptance model to explain students' willingness to pay for GenAI for educational purposes. Using an online survey of 121 undergraduate students at a large public university in the United States, we measured perceived ease of use, perceived usefulness, behavioral intention, and willingness to pay, and analyzed their relationships using partial least squares structural equation modeling. Results show that perceived ease of use positively predicted perceived usefulness, which in turn shaped behavioral intention, and behavioral intention predicted willingness to pay in the same direction. Moreover, perceived ease of use contributed to willingness to pay primarily through perceived usefulness and intention to use (or continue using) GenAI tools. The findings suggest that students invest financially when GenAI tools provide clear academic benefits, developing their intention to use (or continue using) the tools. The research extends theoretical understanding of the technology acceptance model by incorporating economic perspectives in an emerging technological setting and offers guidance for universities, AI service providers, and developers seeking to design pricing and governance policies that reflect student value perceptions.

Keywords: generative AI, willingness to pay, perceived usefulness, technology acceptance model, education

1. INTRODUCTION

Generative artificial intelligence (GenAI) is reshaping higher education, influencing how students learn, complete academic tasks, and interact with digital technologies (Batista et al., 2024). In practice, this transformation is reflected in the growing use of GenAI by both students and instructors across learning, assessment, and academic work (Collie et al., 2024; Collie & Martin, 2024; Sousa & Cardoso, 2025; Tzirides et al., 2024). Several colleges and universities have already begun planning frameworks to support GenAI assisted learning and are outlining initiatives to promote AI literacy and ethical use among faculty, staff, and students (Russell Group, 2023). While generative AI tools have gained rapid visibility in education, existing research documents both the opportunities and the limitations associated with their use in educational contexts (Dimitriadou & Lanitis, 2023). In this regard, gaining insight into how students understand, evaluate, and engage with GenAI tools, as well as how their perceptions of these tools translate into actual behavior, is essential for informing effective institutional policies and governance related to AI in education (Shahzad et al., 2024). However, systematic evidence on the educational value and behavioral implications of generative AI remains limited (Kasneci et al., 2023; Miranda & Chamorro-Mera, 2025).

From a behavioral perspective, research on the adoption of generative AI by students in higher education primarily focuses on usage intentions or self-reported usage as behavioral outcomes, primarily explaining how these outcomes are shaped by student perceptions of these tools (Kanont et al., 2024; Shahzad et al., 2024; Wang et al., 2025). However, usage intentions and self-reported usage do not best reflect students' commitment to using GenAI tools, indicating the need to incorporate a behavioral outcome that better reflects deeper commitment. In broader literature, willingness to pay (WTP) is conceptualized as a distinct behavioral

outcome that typically follows adoption or purchase intention and reflects a higher level of commitment than intention or self-reported use (Cascavilla et al., 2025; Liang et al., 2024; Shi et al., 2022; Yang et al., 2023). For instance, Shi et al. (2022) find that users' trust in the Internet of Things (IoT) technology and their willingness to adopt it are positively associated with their willingness to pay for such systems. Regarding the use of generative AI in education, WTP has received relatively little attention, even though WTP represents a deeper level of commitment than casual use.

At their core, Generative AI tools present fundamentally different adoption dynamics than traditional educational technologies, and these differences explain why willingness to pay emerges as a critical outcome worthy of investigation. Unlike learning management systems, which institutions license and students access as part of enrollment (Zawacki-Richter et al., 2019), or tutoring systems, which serve supplementary roles (Ma et al., 2014), GenAI tools occupy an ambiguous space where they are simultaneously used as consumer products, academic tools, and infrastructure. Three characteristics distinguish GenAI adoption from prior educational technologies and justify further economic analysis. First, GenAI tools are generative and adaptive, and they produce novel content tailored to individual prompts rather than delivering pre-programmed responses, making each interaction unique and potentially valuable in ways static resources cannot match (Kasneci et al., 2023). Second, they operate with algorithmic opacity, which means students cannot verify how outputs are produced, assess reliability in advance, or predict when tools will succeed or fail, creating uncertainty that complicates value assessment (Dimitriadou & Lanitis, 2023). Third, they exist in dual-tier ecosystems, robust free versions coexist with premium subscriptions, creating active choice points about payment that often do not exist for institutionally licensed software (Jo, 2024; Kuberska & Ruszczyk, 2025).

This combination means that understanding students' willingness to pay is not merely an extension of technology acceptance research, in fact, it speaks directly to whether AI-augmented education will evolve in equitable or stratified ways as free access to these tools becomes increasingly limited.

Prior studies on digital and AI-enabled learning technologies generally frame willingness to pay as a culmination of the adoption process, as it requires users to assign monetary value beyond habitual usage (Jo, 2024). In this context, understanding predictors of WTP can provide insights into how much students value GenAI tools and what determines their willingness to go beyond free versions to paid access. Kasilingam and Krishna (2020) highlight that willingness to commit financially is shaped by users' receptiveness to new technologies, ease of incorporating the tools into daily work, and expected utility. While past research identifies user satisfaction, personal innovativeness, and perceived risk as determinants of WTP (Jo, 2024), limited research has examined whether students' behavioral intention (the individual's conscious readiness to perform a behavior) to use GenAI tools translates into their willingness to pay for these tools. In this research, we address this gap by examining whether behavioral intention to use GenAI predicts students' WTP and whether it acts as the mechanism through which perceived usefulness (perception of how useful a technology is) and perceived ease of use (perception of how easy it is to use a technology) shape payment decisions. The ultimate goal of the research is to generate evidence that can guide universities and policymakers in setting informed, student-centered AI governance and pricing decisions.

2. Theoretical Framework and Literature Review

2.1. Generative Artificial Intelligence (GenAI) and Education

Recent scholarship reflects growing interest in the role of Generative Artificial Intelligence (GenAI) in education (Celik, 2023; Saif et al., 2024; Shoaib et al., 2024), yet the field remains conceptually fragmented and empirically underdeveloped. In one of the earliest efforts to systematize this work, Law's (2024) scoping review of 41 studies in language teaching and learning documents both optimism around GenAI's capacity to provide adaptive, real-time linguistic support and concerns related to ethical risks, uneven teacher preparedness, and limited empirical validation. Notably, most reviewed studies emphasize speculative affordances rather than demonstrating measurable learning gains, underscoring the need for stronger experimental and classroom-based evidence. At the institutional level, adoption remains similarly uncertain. Shailendra et al. (2024) address this gap by proposing a 4E framework, Embrace, Enable, Experiment, and Exploit, to guide universities toward more deliberate GenAI integration, highlighting persistent misalignment among administrators, instructors, and students in contexts where policies remain vague and uptake is inconsistent. A broader set of concerns emerges in Alier et al. (2024) and Mao et al. (2024), who argue that GenAI is simultaneously *deceptive and disruptive*: it introduces significant opportunities (personalization, feedback automation, content creation) while deeply complicating assessment, authorship, and academic integrity. Both works stress that if GenAI use is not carefully scaffolded, learning may shift toward over-reliance rather than knowledge construction.

2.2. Technology Acceptance and Willingness to Pay (WTP) for Educational AI

Prior research on willingness to pay (WTP) for digital and AI-driven learning technologies frames WTP as the outcome of an adoption process shaped by perceived value, affect, trust, and contextual factors rather than utility alone. In digital services, perceived playfulness, convenience, and personal innovativeness influence attitudes and adoption intentions, which in turn predict users' willingness to pay (Kasilingam & Krishna, 2020). Demographic factors further moderate these relationships, resulting in uneven WTP across user groups. In educational contexts, WTP is further shaped by multi-stakeholder dynamics in which users and payers may differ. Chen et al. (2021) show that while perceived value remains the strongest predictor of parents' WTP for online learning platforms, social influence, such as recommendations and community norms, exerts an independent and amplifying effect, particularly when payers lack direct experience with the tool. This dynamic is especially relevant for GenAI adoption in classrooms, where authorization decisions may be made by non-users. Classic technology adoption research helps explain why perceived value and WTP may emerge unevenly over time. Educators often do not integrate new technologies immediately, not due to rejection, but because meaningful adoption requires training, pedagogical scaffolding, and sustained exposure (Kotrlik & Redmann, 2009). Adoption in educational contexts frequently follows S-shaped diffusion patterns, with benefits such as improved learning outcomes appearing only after consistent use becomes established (Bergman, 2016). These findings suggest that WTP for GenAI may depend on habit formation and demonstrated instructional usefulness rather than short-term trial experiences.

Recent GenAI-focused studies refine these mechanisms. Jo (2024) shows that perceived intelligence and service quality of ChatGPT shape perceived usefulness and knowledge support,

which then drive user satisfaction; critically, in this research, satisfaction rather than usefulness alone predicts willingness to pay for premium access. Similarly, Kuberska and Ruszczyk (2025) find that although GenAI use among students is nearly universal, most rely on free versions, with conversion to paid plans is limited by the high sensitivity to price. Notably, perceived output quality does not significantly predict WTP, suggesting that learners distinguish between educational usefulness and purchase value. Institutional and contextual factors further condition these dynamics: instructors' adoption is guided more by perceived usefulness than by personal cost (Chen et al., 2025), while environmental support and trust shape sustained student use and contribute to persistent access disparities (Li et al., 2025). At the same time, concerns about reliability and accuracy continue to temper full reliance on GenAI tools, potentially limiting WTP unless trust is strengthened (Divekar et al., 2024). Overall, willingness to pay for educational GenAI depends less on access or novelty and more on sustained usefulness, trust, and integration into authentic learning practices.

2.3. Theoretical Framework

We use the Technology Acceptance Model (TAM) to structure our conceptual framework (Figure 1) and research hypotheses. The model, developed by Davis (1986, 1989) explains why people choose to use technology. The model suggests that two beliefs drive acceptance: Perceived Usefulness (PU) and Perceived Ease of Use (PEU). These beliefs shape a person's attitude and intention to use, which then lead to actual usage. A large body of research has validated TAM across different contexts (Lala, 2014; Marangunić & Granić, 2015; Silva, 2015).

In educational settings, TAM has been widely applied and consistently finds that both PU and PEU strongly predict students' and teachers' intentions to use learning technologies (Granić & Marangunić, 2019). However, research also shows that adoption is rarely immediate. Teachers

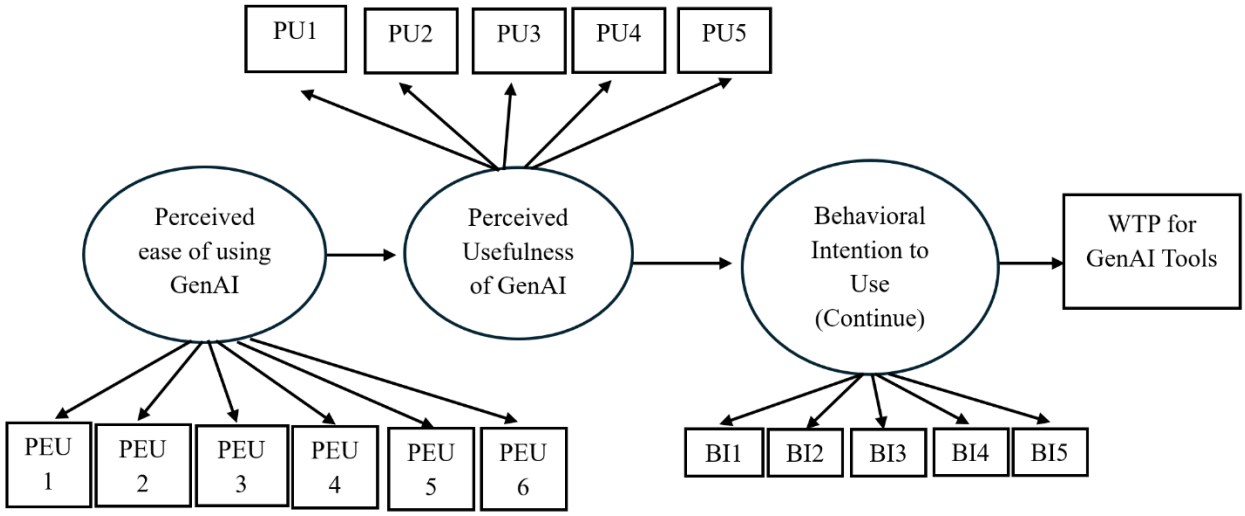
and students often need time, support, and training to integrate new tools effectively (Kotrlik & Redmann, 2009). During the COVID-19 shift to online learning, studies found that when learners perceived online platforms as useful and satisfying, they were more likely to continue using them (Han & Sa, 2022), and that factors such as self-efficacy, personal innovativeness, and social influence can strengthen acceptance (Chahal & Rani, 2022; Dana et al., 2022). These findings emphasize that usefulness must be demonstrated in practice, and the learning environment must endorse the tool, before acceptance becomes stable.

While the original TAM does not directly include Willingness to Pay as a component, we treat willingness to pay as the behavioral outcome in this study. Building on the literature reviewed above, we conceptualize willingness to pay (WTP) as a post-adoption outcome that follows acceptance and experienced benefit rather than a precursor to use. Research on digital services shows that positive experiences, convenience, and satisfaction increase openness to paying for premium features (Kasilingam & Krishna, 2020), while educational contexts introduce additional complexity because users and payers may differ. In such cases, perceived value and social endorsement play a central role in WTP decisions (Chen et al., 2021).

Our framework (Figure 1) brings these insights together by asking a straightforward question about whether students' acceptance of GenAI tools actually translates into willingness to pay for them. When students find these tools easy to use and helpful for their learning, does that positive experience mean they would support them financially? This matters because most existing research stops at understanding whether students will adopt these tools, not whether they value them enough to pay for continued access. By connecting acceptance to payment willingness, we can better understand what makes educational GenAI worth investing in from the student perspective.

Figure 1

Conceptual Framework of the Study



2.4. Key Predictors and Outcomes

Understanding how users adopt and financially support digital technologies requires examining core constructs from the Technology Acceptance Model (TAM) and related frameworks. This study focuses on four key constructs: i) Perceived Ease of Use (PEU), ii) Perceived Usefulness (PU), iii) Behavioral Intention (BI), and iv) Willingness to Pay (WTP) to explain the adoption and monetization of generative AI (GenAI) tools in educational settings. The following sections briefly review each construct and develop hypotheses based on established theoretical relationships.

2.4.1. Perceived Ease of Use (PEU)

PEU refers to the degree to which individuals believe that using a particular technology will be free of effort (Davis, 1989). Within TAM, PEU is a foundational determinant because it directly shapes users' perceptions of usefulness and their subsequent adoption intentions. Prior research demonstrates that users are more likely to adopt a system when they perceive it as valuable and easy to use (Venkatesh & Davis, 2000). Studies in human-computer interaction (HCI) and information systems emphasize that features such as simple navigation, reduced

complexity, and familiarity reduce perceived effort and increase user satisfaction (Zhang & Li, 2005). In the context of generative AI tools used for academic work, PEU likely plays an especially important role. Research on educational technology adoption shows that meaningful integration requires training and support (Kotrlik & Redmann, 2009), and when tools feel smooth and manageable, students perceive fewer barriers to adoption (Granić & Marangunić, 2019). These principles suggest that ease of use may be critical for GenAI tools that students are adopting rapidly with minimal formal instruction. Therefore, we expect that students who find AI tools easy to use will also view them as more beneficial in their coursework.

- *H1 = Perceived ease of using generative AI tools positively influences perceived usefulness of these tools in education.*

2.4.2. Perceived Usefulness (PU)

Perceived Usefulness (PU) is defined as the extent to which a user believes that a system will improve their performance or help them accomplish relevant tasks (Davis,1989; Karahanna & Straub, 1999). PU is widely recognized as the strongest predictor of technology adoption across the TAM, TAM2, and Unified Theory of Acceptance and Use of Technology (UTAUT) models (Venkatesh et al., 2003). In addition, credibility and relevance judgments shape whether a system is seen as genuinely supportive of task performance and decision-making (Davis,1989; Sundar, 2008). Beyond purely instrumental considerations, prior work also suggests that affective qualities of a system, such as enjoyment, comfort, and reduced anxiety, play an important role in shaping usefulness perceptions. Although empirical evidence on affective antecedents of PU has historically been limited, existing studies show that emotions and intrinsic motivation influence how users evaluate both ease of use and usefulness (Venkatesh & Davis, 2000). For example, enjoyment has been shown to positively affect both PU and PEU, while

computer anxiety influences PU indirectly through its effect on PEU (Venkatesh & Davis, 2000). These findings show that usefulness judgments emerge from a combination of cognitive evaluations and affective experience.

Research in information systems further demonstrates that PU often serves as the primary mechanism through which ease-of-use perceptions translate into behavioral outcomes. Gefen and Straub (2000) show that while PEU influences adoption primarily by enhancing PU, PU itself consistently predicts users' intentions to engage with online systems. Consistent with this evidence, we conceptualize PU as the central mediator between ease of use and behavioral intention in our model. Accordingly, we do not include a direct path from PEU to behavioral intention; instead, we focus on how ease of use shapes intention through perceived usefulness. In educational GenAI contexts, perceived usefulness reflects beliefs that these tools enhance academic performance and efficiency, which has been shown to drive continued adoption and integration in higher education settings (Khlaif et al., 2024).

- *H2. Perceived usefulness positively influences behavioral intention to use generative AI tools in education.*

2.4.3. Behavioral Intention (BI)

Behavioral Intention (BI) refers to an individual's conscious readiness or motivation to perform a specific behavior, such as using a technology (Fishbein & Ajzen, 1977). Within the Technology Acceptance Model (TAM), BI is conceptualized as the immediate antecedent of actual system use and is shaped primarily by perceived usefulness and users' attitudes toward the system (Davis et al., 1989). Users are therefore more likely to intend to use a technology when they believe it will enhance their performance and can be used with minimal effort. Subsequent

extensions of TAM, including UTAUT, consistently reaffirm BI as the strongest predictor of technology use across contexts (Venkatesh et al., 2003).

Technology adoption research identifies intention as the most proximal determinant of behavior, even when external opportunities or incentives are present (Fishbein & Ajzen, 1977). Kim et al. (2007) demonstrate that users evaluate the benefits and costs of a technology, and their intention to adopt is driven primarily by perceived value, especially because they personally bear subscription and usage costs. Extending this value-driven perspective, a recent systematic review of video streaming platforms finds that cognitive factors such as perceived quality, content relevance, enjoyment, and cost–benefit assessments strongly shape users' value perceptions and, in turn, their subscription intentions (Wu et al., 2024). In our context, behavioral intention thus serves as a key bridge linking academic value perceptions (PEU and PU) to financial commitment (WTP). Accordingly, we propose:

- *H3. Behavioral intention toward generative AI tools positively influences willingness to pay for educational purposes.*

2.4.4. Willingness to Pay (WTP)

Willingness to Pay (WTP) refers to the maximum monetary amount an individual is prepared to pay to obtain a good or service or to avoid an undesired outcome (Vock et al., 2013). Originating in economics, WTP is commonly used to quantify how individuals value benefits in cost–benefit analyses across domains such as healthcare, public policy, and consumer services (Mariani et al., 2014). In digital platforms and mobile applications, WTP is shaped by perceived value, trust, and expectations of usefulness and compatibility (Tang et al., 2020), as well as broader value perceptions such as emotional, social, and convenience value, which can motivate

users to accept higher costs when the experience feels enjoyable, meaningful, or beneficial (Kashani & Kasmani, 2015).

Although traditional Technology Acceptance Model (TAM) formulations do not explicitly include willingness to pay, research in the digital economy and consumer behavior literature positions WTP as a downstream outcome of behavioral intention, showing that perceived value and satisfaction formed through use lead individuals to accept higher prices, while perceived risk can weaken this effect (Demirgüneş, 2015). Users who intend to continue using a service are more likely to perceive sufficient value to justify paying for premium features or subscriptions, particularly when the service is viewed as convenient, essential, and offering added value, and when expected benefits are clearly communicated (Lopes & Galletta, 2006; Ugras, 2025; Wang et al., 2005). In educational generative AI contexts, WTP therefore extends TAM beyond adoption to capture real-world economic commitment. To address gaps in prior research, which rarely models economic outcomes or the full mediation pathway from perceptions to payment decisions, our study addresses these limitations by extending TAM to include Willingness to Pay (WTP) as a novel downstream outcome and by empirically testing the full influence chain, PEU to PU to BI to WTP, using partial least squares structural equation modeling (PLS-SEM). Accordingly, we propose the following hypotheses for indirect effects:

- *H4 = Perceived usefulness of generative AI mediates the relationship between perceived ease and behavioral intention to use these tools in education.*
- *H5 = Behavioral intention to use generative AI tools in education mediates the relationship between perceived usefulness and willingness to pay.*
- *H6 = Perceived usefulness and behavioral intention mediate the relationship between perceived ease of use and willingness to pay.*

3. Methods

Using a convenience sampling method (Golzar et al., 2022), we conducted cross-sectional online surveys with undergraduate students of all levels aged 18 years or older at [university] in the United States. Convenience sampling was deemed appropriate for this study as the total student population was difficult to access, making probability sampling less practical (Etikan et al., 2016). After receiving study approval from the university's institutional review board (IRB), we contacted the instructors and/or teaching assistants of several undergraduate courses across the university, asking them to share our survey link with their students. The survey, created using the Qualtrics platform, was sent with recruitment emails approved by the [university] IRB. A panel of experts consisting of three university faculty members validated the instrument. To establish instrument reliability, we conducted a pilot test with 32 graduate students at the same university before the main data collection. Cronbach's alpha values calculated based on the pilot test satisfied the reliability requirements for each variable (Carmines & Zeller, 1979), signaling us to move forward with the main data collection.

3.1. Participant Characteristics

We obtained a usable sample size of 121 ($N = 121$). Participants' mean age was 21 years ($M = 20.78$, $SD = 3.43$), with nearly three-fourths ($n = 88$, 72.7%) identifying as female (Table 1). Most students ($n = 113$, 93.4%) reported prior experience with GenAI tools, with ChatGPT being the most commonly used tool ($n = 105$, 86.8%). The mean willingness to pay was $5.71 per month for all platforms combined, with only 43.0% of the participants willing to pay for GenAI.

Table 1

Participant Characteristics (N = 121)

Characteristics	
Age (years), M (SD)	20.78 (3.43)
Gender, n (%)	
Female	88 (72.7%)
Male	31 (25.6%)
Others	2 (1.7%)
Academic Year, n (%)	
Freshman	8 (6.6%)
Sophomore	14 (11.5%)
Junior	24 (19.8%)
Senior	17 (14.1%)
Unsure/Other	58 (48%)
Prior GenAI Experience	
Used any GenAI tool, n (%)	113 (93.4%)
Used ChatGPT, n (%)	105 (86.8%)
Used Grammarly, n (%)	51 (42.1%)
Frequency of GenAI use in classes, n (%)	
Do not use	12 (9.9%)
Some classes	65 (53.7%)
Half of classes	14 (11.6%)
Majority of classes	21 (17.4%)
Every class	9 (7.4%)
Willingness to Pay (USD/month)	
WTP, M (SD)	5.71 (9.73)
Range	0.00 - 50.00
Reporting $0 (unwilling to pay), n (%)	69 (57.0%)
Reporting > $0 (willing to pay), n (%)	52 (43.0%)

Note. M = Mean; SD = Standard Deviation; n = frequency

3.2. Research Instrument

The research instrument included the consent information, qualifying criteria, key variables based on the Technology Acceptance Model (Likert scale), questions related to willingness to pay, and demographic information. After the respondents read the consent information and consented to participate, they needed to satisfy two criteria to qualify as valid participants: first, they needed to be 18 years or older, and second, they needed to be an undergraduate student at OSU at the time of the survey. Once they moved forward with the qualifying criteria, we provided them with a definition of what “generative AI” and “educational

purposes" meant in the case of this survey so that we could ensure they had a universal understanding of the meaning of these terminologies while completing the survey. Data were analyzed using partial least squares structural equation modeling (PLS-SEM), which is well-suited for predictive research models and handles complex mediation pathways effectively (Hair et al., 2019). The survey measures included in the PLS-SEM analysis are described below.

3.2.1. Perceived Ease of Use (PEU)

We measured perceived ease of use of GenAI tools on a 5-point Likert scale with six items. The items were informed from past studies (Falebita & Kok, 2024; Li, 2023; Shahzad et al., 2024; Sukirman et al., 2024). Some example items included, "I find it easy to get AI tools to do what I want them to do," and "Learning to use AI tools is not easy for me (reverse-coded)." Appendix A (Table A.1) provides the list of all items used to measure the variable. All reverse-coded items were recoded in the appropriate direction before data analysis. Instrument reliability was satisfied on the pilot test using Cronbach's alpha value (α = .94).

3.2.2. Perceived Usefulness (PU)

We instructed participants to rate their agreement or disagreement on eight items measuring the perceived usefulness of GenAI tools in education on a 5-point Likert scale. The items were informed from past studies (Falebita & Kok, 2024; Li, 2023; Shahzad et al., 2024; Sukirman et al., 2024). Example items included, "Using AI tools for my coursework enhances my productivity," and "AI tools do not make it easier for me to complete my academic work (reverse-coded)." Appendix A (Table A.2) provides the list of all items used to measure the variable. All reverse-coded items were recoded in the appropriate direction before data analysis. Instrument reliability was satisfied on the pilot test using Cronbach's alpha value (α = .94).

3.2.3. Behavioral Intention toward GenAI Use (BI)

We measured behavioral intention toward GenAI use in education using five items on a 5-point Likert scale. Similar to other Likert-scale variables in the survey, we asked participants to rate their level of agreement with GenAI intention-related statements on a scale from *1 = strongly disagree* to *5 = strongly agree.* The statements/items were informed from past research (Li, 2023), which included, "I intend to adopt (or continue to adopt) AI tools for my classes in the future," and "I would not use (or continue to use) AI tools if I were given the opportunity (reverse coded)." Appendix A (Table A.3) provides the list of all items used to measure the variable. All reverse-coded items were recoded in the appropriate direction before data analysis. Instrument reliability was satisfied on the pilot test using Cronbach's alpha value (α = .96).

3.2.4. Willingness to Pay for GenAI (WTP)

Participants were asked: "If AI tools were no longer free, how much would you be willing to pay per month to access all AI tools combined for academic purposes?" with instructions to enter "0" if unwilling to pay. Prior to this question, "AI tools" was defined in the survey as "Generative AI tools (AI tools that can create new content or paraphrasing AI tools)," and participants had already indicated which specific tools they used (e.g., ChatGPT, Grammarly, Copilot). The WTP question was intentionally framed generically to capture students' overall valuation of GenAI access for academic purposes rather than willingness to pay for any single tool, reflecting real-world scenarios where students often use multiple GenAI platforms simultaneously.

While multi-item scales are preferred for latent constructs in PLS-SEM, WTP represents a concrete economic decision with a clear, objective monetary value rather than an abstract psychological construct. Single-item measures of WTP are common and validated in economics,

marketing, and consumer behavior research when measuring concrete preferences (Bergkvist & Rossiter, 2007; Rossiter, 2002). As Bergkvist and Rossiter (2007) demonstrate, single-item measures can be appropriate when (1) the construct is concrete and unambiguous, (2) respondents have a clear understanding of what is being measured, and (3) the object of evaluation is singular. WTP for GenAI tools satisfies these criteria; students understand the concept of monthly subscription costs from their experience with streaming services, software subscriptions, and other digital platforms.

Furthermore, recent studies examining economic commitment to digital services and AI tools have successfully employed single-item monetary measures (Jo, 2024; Kuberska & Ruszczyk, 2025). The direct monetary format has been shown to reduce hypothetical bias and social desirability effects compared to Likert-scale measures of purchase intention (Breidert et al., 2006; Miller et al., 2011), while providing actionable price-point data for pricing decisions (Wertenbroch & Skiera, 2002).

4. Data Analysis

The analysis followed the core logic of partial least squares structural equation modeling (PLS-SEM), beginning with a careful assessment of how well each construct was measured and then moving to the relationships linking them. We first examined the measurement model to confirm that the constructs were both reliable and clearly differentiated. After establishing this foundation, we tested the structural pathways connecting perceived ease of use, perceived usefulness, behavioral intention, and willingness to pay. PLS-SEM provided the right tool for this work because it handles predictive models and intricate mediation patterns with ease, even with a limited sample size (Hair et al., 2019).

4.1. Measurement Model

All latent variables were modeled reflectively. The measurement model was examined for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity, following established PLS-SEM guidelines (Chin, 1998; Fornell & Larcker, 1981; Hair et al., 2019, 2021).

4.1.1. Indicator Reliability

Indicator reliability was evaluated by inspecting the standardized factor loadings. Loadings of 0.70 or higher are typically considered acceptable, although values above 0.60 can be retained in early-stage or exploratory research when other reliability metrics are satisfactory (Chin, 1998; Hair et al., 2019). Indicator reliability for the item i is given by:

$$IR_i = \lambda_i^2$$

where $\lambda_i$is the standardized loading of the item.

4.1.2. Internal Consistency Reliability

Internal consistency was assessed using Cronbach's alpha and composite reliability. Values of at least 0.70 indicate acceptable reliability for research purposes (Carmines & Zeller, 1979; Cronbach, 1951; Hair et al., 2019; Nunnally & Bernstein, 1994).

Cronbach's alpha is defined as:

$$\alpha = \left[\frac{k}{(k-1)}\right]\left[1 - \left(\frac{\sum_{i=1}^{k} {\sigma_i}^2}{{\sigma_t}^2}\right)\right]$$

where k is the number of items, σ_i^2 is the variance of the item i, and σ_t^2 is the variance of the total score.

Composite reliability (CR), which is considered more appropriate for PLS-SEM, is computed as follows (Chin, 1998; Hair et al., 2019).

$$CR = \frac{\left(\sum_{i=1}^{k} \lambda_i\right)^2}{\left[\left(\sum_{i=1}^{k} \lambda_i\right)^2 + \sum_{i=1}^{k}(1 - \lambda_i{}^2)\right]}$$

4.1.3. Convergent Validity

Convergent validity was evaluated using the Average Variance Extracted (AVE), which captures the proportion of variance in the indicators explained by the latent construct (Fornell & Larcker, 1981; Hair et al., 2019):

$$AVE = \frac{\sum_{i=1}^{k} \lambda_i{}^2}{k}$$

An AVE of 0.50 or higher indicates that the construct explains more than half of the variance of its indicators, which is typically taken as evidence of convergent validity (Hair et al., 2019).

4.1.4. Discriminant Validity

Discriminant validity was examined using the Fornell-Larcker criterion, cross loadings, and the heterotrait-monotrait (HTMT) ratio of correlations.

First, the Fornell-Larcker criterion requires that the square root of the AVE for each construct exceeds its correlations with other constructs (Fornell & Larcker, 1981):

$\sqrt{AVE_j} > r_{jk}$ for all constructs $j \neq k$.

Second, cross-loadings were examined to confirm that each item loaded higher on its own construct than on any other construct, indicating that the indicators represent their intended latent variables (Chin, 1998; Hair et al., 2021). Third, the HTMT ratio was used as a more stringent test of discriminant validity (Henseler et al., 2015). HTMT is defined as the ratio of construct correlations to within-construct correlations. Values below 0.90 (or 0.85 under more conservative criteria) are typically interpreted as evidence of adequate discriminant validity (Hair et al., 2021; Henseler et al., 2015).

4.2. Structural Model

After establishing sound measurement properties, the structural model was evaluated to test the direct and indirect effects specified by the Technology Acceptance Model and its extension to willingness to pay. The model examined the relationships among perceived ease of use (PEU), perceived usefulness (PU), behavioral intention (BI), and willingness to pay (WTP). Path estimates were obtained using a nonparametric bootstrap procedure with 5,000 resamples, which provides robust standard errors and confidence intervals for PLS-SEM (Chin, 1998; Hair et al., 2019).

The core structural equations can be written as:

$$PU = \beta_1 PEU + \epsilon_1$$

$$BI = \beta_2 PU + \epsilon_2$$

$$WTP = \beta_3 BI + \epsilon_3$$

Indirect effects were assessed to capture mediation processes:

$$IE_{PEU \rightarrow BI} = \beta_1 \times \beta_2$$

$$IE_{PU \rightarrow WTP} = \beta_2 \times \beta_3$$

$$IE_{Serial} = \beta_1 \times \beta_2 \times \beta_3$$

4.2.1. Explained Variance (R^2)

The explanatory power of the model for each endogenous construct was assessed using the coefficient of determination, R^2:

$$R_j^2 = 1 - \left(\frac{\sigma_{ej}^2}{\sigma_{yj}^2}\right)$$

where $\sigma_{e_j}^2$ is the error variance, and $\sigma_{y_j}^2$ is the total variance of the endogenous construct j. In behavioral research, R^2 values around 0.25, 0.50, and 0.75 are sometimes interpreted as weak, moderate, and substantial, respectively (Hair et al., 2019).

4.2.2. Effect Sizes (f^2)

To assess the contribution of each predictor to an endogenous construct, Cohen's f^2 effect size was calculated (Cohen, 2013; Hair et al., 2019):

$$f^2 = \frac{\left(R^2_{\{included\}} - R^2_{\{excluded\}}\right)}{\left(1 - R^2_{\{included\}}\right)}$$

Values of 0.02, 0.15, and 0.35 are commonly interpreted as small, medium, and large effects, respectively (Cohen, 2013).

4.2.3. Predictive Relevance (Q^2)

Predictive relevance was evaluated using the Stone-Geisser Q^2statistic obtained via blindfolding (Geisser, 1975; Hair et al., 2019; Stone, 1974). The statistics are defined as:

$$Q^2 = 1 - \frac{SSE}{SSO}$$

where SSE is the sum of squared prediction errors, and SSO is the sum of squared observations. Positive Q^2 values indicate that the model has predictive relevance for the corresponding endogenous constructs.

4.2.4. Overall Model Fit

Finally, overall model fit was examined using the standardized root mean square residual (SRMR), which assesses the discrepancy between the observed and model-implied correlation matrices (Henseler et al., 2014). SRMR values below 0.08 are generally interpreted as indicative of acceptable fit in PLS-SEM applications (Hair et al., 2019; Henseler et al., 2014).

5. Results

5.1. Measurement Model Assessment

Evaluating the measurement model is an essential step in PLS-SEM because it determines whether the constructs are measured in a reliable and valid manner before

interpreting the structural paths (Hair et al., 2019, 2021). The measurement model assessment for this study included indicator reliability, internal consistency, convergent validity, and discriminant validity (Table 2).

5.1.1. Indicator Reliability and Internal Consistency

Factor loadings for perceived ease of use, perceived usefulness, and behavioral intention ranged from 0.657 to 0.808, 0.631 to 0.833, and 0.660 to 0.909, respectively. These values fell within acceptable ranges and indicated that the items contribute meaningfully to their respective constructs (Chin, 1998; Hair et al., 2019).

Perceived ease of use achieved a Cronbach's alpha of 0.883 and a composite reliability of 0.881. Perceived usefulness had a Cronbach's alpha of 0.847 and a composite reliability of 0.848. Behavioral intention showed the strongest reliability, with both Cronbach's alpha and composite reliability at 0.917. These results indicate that items within each construct are highly consistent, satisfying the standard benchmarks (Cronbach, 1951; Hair et al., 2019; Nunnally & Bernstein, 1994). In addition, perceived ease of use and behavioral intention had an AVE of 0.554 and 0.691 respectively indicating that they met the established threshold of 0.50 to confirm convergent validity (Fornell & Larcker, 1981; Hair et al., 2019). However, perceived usefulness had a value lower than the threshold, which increased to 0.530 after three items were dropped.

Table 2
Measurement Model Assessment

Latent Variable	Item	Factor Loading	Cronbach's Alpha	Composite Reliability (ρ_c)	Average Variance Extracted (AVE)	(ρa)
Perceived Ease of Use (PEU)	PEU1	0.789	0.883	0.881	0.554	0.885
	PEU2	0.808				
	PEU3	0.659				
	PEU4	0.737				
	PEU5	0.657				
	PEU6	0.800				

Perceived Usefulness (PU)	PU1	0.631	0.847	0.848	0.530	0.856
	PU2	0.638				
	PU3	0.722				
	PU4	0.833				
	PU5	0.792				
Behavioral Intention (BI)	BI1	0.884	0.917	0.917	0.691	0.925
	BI2	0.839				
	BI3	0.909				
	BI4	0.842				
	BI5	0.660				

5.1.2. Discriminant Validity

Discriminant validity ensures that each construct is empirically distinct from the others. It was examined using cross-loadings, the Fornell-Larcker criterion, and the HTMT ratio.

Cross Loadings

Cross-loadings were examined to assess indicator-level discriminant validity. As shown in Table 3, all perceived ease of use items loaded more strongly on PEU (loadings from 0.732 to 0.855) than on perceived usefulness, behavioral intention, or willingness to pay. Similarly, all perceived usefulness items loaded highest on PU (loadings from 0.727 to 0.851). The behavioral intention items also showed the strongest loadings on BI (0.789 to 0.925), well above their loadings on other constructs. Willingness to Pay, measured as a single item, also showed the highest loading on its own construct. These patterns confirmed that each item aligned most strongly with its intended construct and provided initial evidence of discriminant validity at the indicator level (Chin, 1998; Hair et al., 2021).

Table 3
Cross Loadings

Item	PEU	PU	BI	WTP
PEU1	.739	.497	.533	.339
PEU2	.802	.511	.498	.217
PEU3	.732	.416	.514	.165
PEU4	.796	.464	.507	.239
PEU5	.835	.414	.519	.288

PEU6	.855	.504	.582	.351
PU1	.414	.766	.490	.253
PU2	.382	.727	.537	.341
PU3	.505	.768	.563	.297
PU4	.524	.851	.666	.315
PU5	.522	.827	.614	.296
BI1	.596	.691	.925	.384
BI2	.578	.631	.856	.405
BI3	.617	.693	.875	.424
BI4	.571	.635	.882	.403
BI5	.499	.489	.789	.331
WTP	.338	.379	.451	1.000

Fornell-Larcker Criterion

Discriminant validity was further assessed using the Fornell and Larcker criterion, which compares the square root of each construct's AVE with its correlations with other constructs. As shown in Table 4, the square root of the AVE for perceived ease of use (0.74) exceeded its correlations with perceived usefulness (0.59), behavioral intention (0.66), and willingness to pay (0.34). The square root of the AVE for perceived usefulness (0.73) was greater than its correlations with perceived ease of use (0.59), behavioral intention (0.73), and willingness to pay (0.38). Behavioral intention also met this requirement, with a square root of AVE of 0.83 that exceeded its correlations with perceived ease of use (0.66), perceived usefulness (0.73), and willingness to pay (0.45). Willingness to pay, measured as a single item, had a value of 1.00, which naturally exceeded its correlations with all other constructs. Taken together, the results satisfied the Fornell-Larcker criterion, indicating that each construct was empirically distinct and captured unique variance relative to the other constructs (Fornell & Larcker, 1981).

Table 4

Comparisons of Correlations Between Latent Variables and Square Root of AVE (Fornell–Larcker Criterion for Discriminant Validity)

Construct	PEU	PU	BI	WTP
PEU	0.74			
PU	0.59	0.73		

BI	0.66	0.73	0.83	
WTP	0.34	0.38	0.45	1.00

HTMT Ratio

Discriminant validity was also assessed using the heterotrait–monotrait ratio of correlations (HTMT). HTMT is considered a more sensitive and reliable measure for detecting discriminant validity issues compared to traditional criteria (Henseler et al., 2015). The HTMT value between PEU and PU was 0.680, between PEU and BI was 0.735, and between PU and BI was 0.817 (Table 5). All values were well below 0.90 and also below the more conservative threshold of 0.85 for two of the three construct pairs. These results provide strong evidence that the constructs were empirically distinct.

Table 5
HTMT Ratio

Construct	PEU	PU	BI
PEU	1.000		
PU	0.680	1.000	
BI	0.735	0.817	1.000

The combined results indicated that the measurement model was stable and reliable. Each construct was measured clearly by its indicators, the reliability benchmarks were met, and the validity criteria were met. These findings showed that the measures were suitable and allowed us to proceed with the evaluation of the structural model.

5.2. Structural Model

5.2.1. Direct Effects (H1 to H3)

Table 6 shows the bootstrapped structural path estimates. All three direct effects were significant and in the expected direction.

H1: The results support this hypothesis. The path from perceived ease of use to perceived usefulness was positive and significant ($\beta = .61$, $t = 10.70$, $p < .01$). This indicates that students who found generative AI tools easier to use were more likely to view them as useful for their academic work.

H2: This relationship was also supported. The path coefficient from perceived usefulness to behavioral intention was strong and significant ($\beta = .73$, $t = 13.40$, $p < .01$), suggesting that perceived usefulness played a central role in shaping students' intentions to continue or expand their use of GenAI tools.

H3: The findings confirmed this hypothesis as well. The path from behavioral intention to willingness to pay was positive and significant ($\beta = .45$, $t = 6.98$, $p < .01$). This indicates that students with higher intentions to use generative AI tools were also more willing to invest financially in them.

These findings provide strong evidence that the technology acceptance model (TAM) explains not only students' intentions to use generative AI tools, but also their willingness to pay for them.

Table 6

Bootstrapped Structural Path Estimates from the PLS-SEM Model

Path relation	Estimate	Std. Error	t-value	p-value	95% CI (Lower)	95% CI (Upper)
PEU to PU	0.607	0.057	10.700	< 0.01	0.494	0.710
PU to BI	0.734	0.055	13.400	< 0.01	0.617	0.827
BI to WTP	0.453	0.065	6.980	< 0.01	0.320	0.572

5.2.2. Indirect Effects (H4 to H6)

The study also examined whether perceived usefulness and behavioral intention act as mediators in the relationships proposed in the TAM. Table 7 presents the bootstrapped indirect effects, all of which were significant.

H4: The results supported this mediation. The indirect effect from perceived ease of use through perceived usefulness to behavioral intention was significant ($\beta = 0.45$, $t = 7.09$, $p < 0.01$). This indicates that perceived ease of use increased students' intentions to adopt generative AI tools partly because it enhances their perceptions of usefulness.

H5: This hypothesis was also supported. The indirect path from perceived usefulness to willingness to pay through behavioral intention was significant ($\beta = 0.33$, $t = 6.08$, $p < 0.01$). This means that perceived usefulness influenced students' willingness to pay by shaping their intention to use (or continue using) generative AI tools.

H6: The findings confirmed this hypothesis as well. The serial indirect effect from perceived ease of use through perceived usefulness to behavioral intention, and from behavioral intention to willingness to pay, was significant ($\beta = 0.20$, $t = 4.87$, $p < 0.01$). This suggests that ease of use contributes to students' willingness to pay primarily when it enhances usefulness perceptions and strengthens behavioral intentions.

Overall, the mediation results indicate that perceived ease of use did not directly influence willingness to pay. Instead, its effect operated through perceived usefulness and behavioral intention, demonstrating the TAM's central role in shaping students' financial commitment to generative AI tools.

Table 7

Bootstrapped Indirect Effects via Perceived Usefulness and Behavioral Intention in the PLS-SEM Model

Path relation	Estimate	Std. Error	t-value	p-value	95% CI (Lower)	95% CI (Upper)
PEU to PU to BI	0.447	0.063	7.090	< 0.01	0.318	0.565
PU to BI to WTP	0.333	0.055	6.080	< 0.01	0.222	0.437
PEU to PU to BI to WTP	0.203	0.042	4.870	< 0.01	0.123	0.287

5.2.3. Model Fit, Explained Variance, and Predictive Relevance

Table 8 reports the model's explanatory power (R^2), effect sizes (f^2), and predictive relevance (Q^2) for the endogenous constructs. The results show that the model explained a meaningful proportion of variance in all three key outcomes. Perceived ease of use accounted for 35.2 percent of the variance in perceived usefulness ($R^2 = 0.352$), which indicates a moderate level of explanatory power. Perceived usefulness was a strong predictor of behavioral intention, explaining 53.4 percent of its variance ($R^2 = 0.534$). Behavioral intention, in turn, explained 20.4 percent of the variance in willingness to pay for generative AI tools ($R^2 = 0.204$). The effect sizes, interpreted based on Cohen's (2013) guidelines, demonstrated the strength of these relationships. Perceived ease of use had a large effect on perceived usefulness ($f^2 = 0.542$). Perceived usefulness demonstrated a very large effect on behavioral intention ($f^2 = 1.140$). Behavioral intention had a medium effect on willingness to pay ($f^2 = 0.256$).

The predictive relevance values (Q^2) for perceived usefulness (0.328), behavioral intention (0.515), and willingness to pay (0.180) were all greater than zero, indicating that the model has meaningful predictive power for all endogenous constructs. This follows the criterion suggested by Geisser (1975) and Stone (1974), which states that positive Q^2 values reflect acceptable predictive accuracy in PLS-SEM.

The overall model fit, measured using SRMR, was 0.062. This falls below the recommended threshold of 0.08, suggesting that the model demonstrates a good level of fit for PLS-SEM applications (Henseler et al., 2015). Together, the R^2, f^2, Q^2, and SRMR values show that the model performs well in explaining and predicting students' behavioral intention and willingness to pay for generative AI tools.

Table 8

R^2, f^2, and Q^2 Values for Endogenous Constructs and Their Predictors

Construct	Predictor	f^2	R^2	R^2_{adj}	Q^2	SRMR
PU	PEU	0.542	0.352	0.346	0.328	0.062
BI	PU	1.140	0.534	0.530	0.515	
WTP	BI	0.256	0.204	0.197	0.180	

6. Discussion

We found a substantial gap between students' GenAI usage patterns and their willingness to pay for these tools. While most of the students participating in the survey reported using at least one GenAI tool, slightly less than half had willingness to pay if free access became unavailable. This disconnect reveals a critical dependency on free-tier offerings that distinguishes GenAI adoption from traditional educational technology. They also had a low mean WTP per month to access GenAI tools for academic purposes. Students' valuations fall way below the cumulative cost of premium versions of common GenAI tools. For context, a student using ChatGPT Plus ($20/month), Grammarly Premium ($12/month), and GitHub Copilot ($10/month) (Grammarly, 2026; Microsoft, 2026; OpenAI, 2026) would face $42/month in subscription costs, yet our participants' mean WTP was only $5.71, revealing a huge gap between current pricing and stated willingness to pay. This suggests that while students perceive value in GenAI tools, they expect either (a) continued access to free versions, (b) institutional subscriptions that eliminate individual costs, or (c) substantially lower pricing than current commercial rates (Mäntymäki et al., 2020). The finding that more than half of the participants reported zero willingness to pay highlights the critical role of free-tier offerings in maintaining accessibility, particularly for students facing financial constraints. For universities considering institutional subscriptions, these WTP estimates suggest that students perceive moderate value in these tools, but direct cost remains a notable barrier for the majority of them.

The structural model offers a clear demonstration of how the technology acceptance model continues to provide explanatory power in contemporary AI-supported learning environments. The relationships observed among perceived ease of use, perceived usefulness, behavioral intention, and willingness to pay indicate that the foundational logic of the model remains relevant even as the technological context evolves. The strong pathway from perceived ease of use to perceived usefulness aligns with early conceptualizations of technology acceptance (Davis, 1986, 1989) and confirms that students' initial encounters with a system still shape their judgment of its academic value. When interaction with a generative AI tool feels easy, simple, and unintimidating, students are better positioned to identify how it can enhance their work, a pattern also reported in examinations of technology supported learning (Dahri et al., 2024; Lee et al., 2003). As GenAI tools are constantly evolving, relevant improvements should be made on a continuous basis to ensure that students continue to feel at ease using GenAI tools, which helps maintain their perceived usefulness of the tools. Future research should hence explore the ways to enhance the user interface of the tools. However, from an economic standpoint, students may find GenAI tools useful because they are easy to try with no payment barrier. This frictionless entry point allows usefulness perceptions to form through direct experience rather than marketing claims. Yet this same ease creates a psychological anchoring effect which leads students to calibrate their value assessments based on free access, making paid alternatives feel expensive by comparison (Tversky & Kahneman, 1974; Mäntymäki et al., 2020).

The effect of perceived usefulness on behavioral intention was the most pronounced relationship in the model. This result is consistent with decades of research showing that perceived usefulness remains the dominant predictor of behavioral intention across several technologies, platforms, and systems (Venkatesh & Davis, 2000; Venkatesh et al., 2003). Recent

studies focused specifically on generative AI, including ChatGPT, report similar findings, noting that students' plans to integrate these tools stem primarily from their belief that the tools can improve performance, understanding, or productivity (Brandhofer et al., 2025; Ittefaq et al., 2025). The present study reinforces this central insight. Students commit to using generative AI when they perceive that it substantively supports their academic goals, rather than merely offering novelty or convenience. However, what distinguishes GenAI from prior educational technologies is the nature of the usefulness being perceived. Unlike learning management systems that organize content or tutoring systems that provide targeted feedback, GenAI tools offer generative support as they create new explanations, personalized examples, and adaptive responses that static resources cannot match (Kasneci et al., 2023). When using GenAI tools in education seems appropriate and students can benefit greatly, colleges and universities can launch programs that help students understand how these tools enhance their learning. For example, workshops incorporating hands-on experiences, asking a GenAI tool to break down complex course content into simpler ideas, generate personalized study schedules, or convert an article into a podcast, may help students understand the usefulness of GenAI tools in education. However, from a practical standpoint, as the appropriateness of using GenAI in education may differ by cases, colleges and universities may benefit more in the long-term by launching programs that educate students about potential challenges, and best practices of using these tools in education rather than focusing on only positive use cases (Michel-Villarreal et al., 2023).

The positive association between behavioral intention and willingness to pay represents an important extension of AI in education research. While prior work has examined the determinants of intentions to use AI-mediated systems (Conrad & Nuebel, 2025; Miranda & Chamorro-Mera, 2025), very few studies have connected these intentions to economic behaviors.

The present results indicate that intention serves as a meaningful predictor of willingness to pay, echoing patterns observed in digital service adoption where sustained engagement and perceived ongoing benefits shape subscription decisions (Babiker et al., 2024; Noor et al., 2022). Students in this study were more willing to pay when they already planned to rely on generative AI for academic work. This suggests that financial commitment is influenced not only by perceptions of value but also by a student's envisioned long-term relationship with the tool. However, this finding reveals a timing problem in GenAI monetization. Willingness to pay emerges only after students develop sustained reliance, and they must first integrate the tool into their academic workflow, experience repeated success, and envision continued dependence. This sequential development means that paywalls imposed early (before intention solidifies) will fail, while those imposed after dependency forms may succeed but raise ethical concerns about "bait and switch" dynamics. For universities, this timing dynamic suggests that institutional subscriptions should be negotiated before students develop individual payment expectations.

The mediation results capture the deeper structure of the decision-making process underlying the willingness to pay for GenAI tools. Perceived ease of use did not directly influence willingness to pay. Instead, its effect operated through usefulness and then through intention. This sequential pattern aligns with long-standing interpretations of the model, which describe perceived ease of use as a facilitating belief that helps students evaluate usefulness, while usefulness functions as the primary driver of intention (Lee et al., 2003; Venkatesh & Davis, 2000). The extension observed here demonstrates that willingness to pay emerges only after students experience a chain of positive assessments. They must first feel comfortable using the tool, then perceive clear academic advantages, and finally develop a commitment to continued use. This progression offers a coherent explanation for why interface design and

usability improvements alone are unlikely to increase subscription rates unless they translate into perceived academic value. In other words, even when students find it easy to use GenAI tools, it is unlikely to increase their intention to use and, in turn, WTP, unless it influences perceived usefulness. Similarly, merely perceiving GenAI as useful in education does not result in higher WTP unless that perceived usefulness translates into higher behavioral intention to use GenAI. We can relate this idea to Jo (2024), who described user satisfaction as an important component affecting WTP and a mediator between perceived usefulness and WTP toward GenAI. To achieve a more comprehensive understanding of economic behaviors toward GenAI in relation to user perceptions, future studies should examine how behavioral intention and user satisfaction interact to predict economic outcomes related to GenAI.

These findings demand specific changes in how researchers, educators, and tool developers approach GenAI in higher education. For researchers, future studies must move beyond adoption intentions to examine actual payment behavior, longitudinal changes in WTP as tool capabilities improve, and whether institutional subsidies alter students' value perceptions. Research should also investigate heterogeneity in WTP across student populations, particularly how financial constraints, disciplinary norms, and prior AI experience shape economic decisions. For educators and administrators, the findings suggest three strategic imperatives. First, universities should negotiate institutional licenses before individual student dependencies form, as our timing analysis suggests that post-adoption negotiation becomes both more expensive and more politically fraught. Second, institutions must develop clear guidelines about when GenAI use is pedagogically appropriate, as promoting tools without such frameworks risks both academic integrity violations and inequitable access. Third, universities should invest in AI literacy programs that help students understand not only how to use GenAI tools, but when use is

appropriate, how to verify outputs, and what risks opacity and generativity introduce. For tool developers and providers, our findings signal that current pricing models are misaligned with student economic realities. Developers must recognize that students' low WTP reflects not just price sensitivity but also concerns about reliability (due to algorithmic opacity), uncertainty about future need, and the expectation that educational infrastructure should be institutionally provided rather than individually purchased.

The model's explanatory power demonstrates that technology acceptance constructs remain relevant in modern generative AI environments, while also revealing GenAI-specific dynamics. The variance explained in perceived usefulness and behavioral intention mirrors findings from earlier studies using learning management systems, mobile learning platforms, and AI-supported tutoring (Wang & Fan, 2025; Zawacki-Richter et al., 2019). However, the lower variance in willingness to pay is both expected and instructive. Financial decisions are shaped by additional factors such as income constraints, opportunity costs, and access to free versions of the same tools (Babiker et al., 2024), factors that are particularly salient in the GenAI context due to dual-tier ecosystems. Even so, behavioral intention accounted for a meaningful share of this variation, underscoring its importance as a bridge between psychological constructs and economic behavior. This research extends the use of TAM to economic outcomes (WTP) for GenAI use in education, providing evidence on the model's relevance in this underexplored setting. The extension is not merely empirical, adding another technological context to TAM's portfolio, but theoretical, demonstrating that the model's sequential logic applies even when the outcome shifts from adoption to payment, and when the technology introduces generativity, opacity, and economic choice points absent in prior educational technologies.

The rapid evolution of GenAI capabilities complicates these dynamics further. Students' WTP reflects their current experience with tools that occasionally hallucinate, provide generic responses, and require careful verification. As accuracy improves, personalization deepens, and integration tightens, perceived usefulness and therefore WTP may increase. However, this improvement trajectory also raises the stakes for access equity. If next-generation capabilities remain behind paywalls while current free tiers stagnate, the educational advantage gap will widen. Also, premium capabilities may offer qualitatively different educational experiences, not merely faster or more convenient versions of free features, but fundamentally enhanced learning support that free tiers cannot match. Research must track how WTP evolves alongside capability improvements, whether institutional interventions successfully maintain equitable access, how algorithmic opacity affects long-term trust and value perceptions, and whether students' economic behaviors differ when tools become pedagogically required versus optional. The technology acceptance framework provides a foundation for understanding adoption dynamics, but the unique characteristics of GenAI, such as generative output, algorithmic opacity, dual-tier ecosystems, and rapid evolution, require theoretical extensions and policy interventions that traditional TAM applications did not anticipate. Factors such as trust, privacy, and ethical concerns are becoming increasingly prominent in discussions of AI adoption (Ali et al., 2025; Barakat et al., 2025), and future models may benefit from integrating these constructs alongside the traditional TAM pathways. Our findings suggest that without deliberate institutional action to address pricing misalignment and access barriers, GenAI adoption in higher education risks replicating and amplifying existing inequalities rather than democratizing access to powerful learning support.

7. Conclusion

This study demonstrates the mechanism through which students' perceptions of generative AI translate to genuine investment. Adoption is already high, yet willingness to pay is selective and deeply tied to students' academic experience with these tools. We find that perceived ease of use, perceived usefulness, behavioral intention to use (or continue using), and willingness to pay predict each other in sequence. We also find that the PU mediates the relationship between PEU and BI, BI mediates the relationship between PU and WTP, and PU and BI mediate the relationship between PEU and WTP. It means that students do not pay for generative AI simply because it is easy to use. They pay when it proves its usefulness, resulting in an intention to use. Hence, the structural model findings show a clear, logical, and theory-consistent progression in how students evaluate these technologies. Simple-to-use tools lay the foundation for perceived academic value. When students recognize that value, they develop stronger intentions to rely on the tool, and those intentions become the basis for financial commitment. This chain of reasoning underscores that willingness to pay is not a superficial judgment. It is a conclusion reached after repeated interactions, academic benefits, and a sense that the tool has become part of their regular learning process.

The technology acceptance model (Davis, 1989) remains a relevant and robust framework in this setting. Even as generative AI introduces new capabilities, students' decision-making follows the same core principles that have guided technology use for decades. What changes is the weight of the outcome. The decision to subscribe introduces an economic dimension that makes perceptions of usefulness even more consequential.

For educators and AI developers, the implication is direct. Students subscribe to paid access when they develop or continue their intention to use GenAI tools for academic purposes,

which can be achieved when a tool reliably improves accuracy, deepens understanding, or meaningfully enhances their workflow. Investments in improving the users' interface, quality, personalization, and academic relevance will matter more for developing an intent to use GenAI in education rather than directly influencing WTP. If institutions want students to adopt paid AI tools to support their learning, the tools must clearly outperform their free alternatives in ways that students can recognize in their everyday coursework. Academic institutions should emphasize the ethical considerations of using GenAI for academic purposes and guide students to ensure responsible use (Russell Group, 2023). Even when students find GenAI tools easy to use and useful for academic work, the emphasis on responsible use helps them figure out when to (not) use these tools (Michel-Villarreal et al., 2023). This trade-off between use intention and responsible/ethical use then acts as the basis of their decision-making on whether they want to use the paid version. Generative AI is becoming a permanent feature of the learning environment. As its role expands, understanding not only whether students accept these tools but also when they deem them worth paying for becomes essential. This study shows that students reward technologies that demonstrate genuine value, promoting their willingness to use them. GenAI tools that earn their trust, improve their academic outcomes, and integrate seamlessly into their study routines are the ones positioned to shape the future of learning.

8. Limitations and Future Research

Several limitations warrant consideration. First, the convenience sample of 121 undergraduates from a single U.S. institution limits generalizability, and the cross-sectional design precludes causal inference. Future research should use larger, probability based samples across multiple institutions and incorporate longitudinal or experimental designs to establish

causal mechanisms. Second, measuring stated rather than actual willingness to pay introduces hypothetical and social desirability bias; studies examining real subscription decisions would provide more accurate demand estimates. Third, broad definitions of "generative AI" and "educational purposes" may obscure heterogeneity across specific tools, disciplines, and use cases. Future research should examine whether these relationships work differently for different GenAI tools (e.g., ChatGPT, Grammarly, Microsoft Copilot, etc.) or for specific educational purposes (e.g., brainstorming, completing assignments, summarizing notes, etc.). Fourth, findings may not generalize to graduate students, faculty, or institutions with different AI readiness, cultural attitudes, or resource constraints. This research was conducted in the context of the United States, a leading country in its readiness to adopt and govern AI platforms (Nettel et al., 2024). Relationships identified in this research may differ in a different context, and hence, future research may benefit by examining economic behaviors related to GenAI in a resource-constrained economy or universities with minimal AI-related initiatives. Fifth, awareness of research participation may have influenced responses despite survey anonymity. Despite these limitations, this study provides foundational evidence linking technology acceptance to willingness to pay for GenAI and identifies critical adoption-payment tensions. Future research should examine how payment willingness evolves with GenAI capabilities, psychological mechanisms underlying the usage-payment gap, institutional intervention effectiveness, relationships between payment and learning outcomes, and equity implications as GenAI transitions from an optional tool to an essential infrastructure.

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