"Human–Computer Interaction and Learning Behavior: Analyzing LMS Adoption Among Gen-Z in Higher Education"

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ABSTRACT

The rapid digitalization of higher education has increased the importance of Learning Management Systems (LMS), requiring a clearer understanding of Human–Computer Interaction (HCI) factors that influence engagement and continuous use, especially among Gen-Z students. This study investigates LMS adoption by extending the Technology Acceptance Model (TAM) with HCI constructs such as perceived usability, interactivity, system quality, and user satisfaction. Data were collected through an online survey involving 720 university students from various faculties and analyzed using Partial Least Squares Structural Equation Modeling (SEM-PLS). Results show that perceived usability and interactivity significantly enhance perceived ease of use and usefulness, leading to stronger behavioral intention to continue LMS use. System quality indirectly influences actual use through user satisfaction, emphasizing the role of positive user experience. These findings demonstrate that digitally savvy Gen-Z students respond more favorably to user-centered LMS design, offering practical guidance for improving LMS interface quality and engagement strategies.

Keywords: Human–Computer Interaction, Learning Management System, Technology Acceptance Model.

INTRODUCTION

Human computing is grounded in human–machine collaboration theory, which asserts that human cognitive strengths can be augmented by machine intelligence to enhance decision-making and learning processes (Quinn & Bederson, 2011; Dellermann et al., 2019). In higher education, this framework positions digital systems as adaptive learning partners rather than static content delivery tools. Learning Management Systems (LMS)—supported by e-learning system theory and the information systems success model (DeLone & McLean; Al-Fraihat et al., 2020)—serve as the primary infrastructure enabling resource access, task management, and communication in a structured, flexible environment. As LMS become increasingly integrated with AI and analytics, the nature of human–computer interaction (HCI) in academic settings grows more dynamic, interactive, and personalized. Constructivist Learning Theory provides the pedagogical foundation for understanding how students engage with LMS. Derived from Piaget (1950) and Vygotsky (1978), constructivism emphasizes active knowledge construction through interaction, collaboration, and reflective learning. Empirical work shows that LMS designed with constructivist features—such as discussion forums, collaborative tasks, and feedback loops—improve motivation, self-regulated learning, and conceptual understanding (Spector, 2014; Haruna et al., 2022). The integration of human computing amplifies these benefits by embedding adaptive recommendations, real-time analytics, and algorithmic feedback, creating environments in which learners experience individualized pathways and richer human–machine collaboration (Holmes et al., 2021; Obaid et al., 2020).

The Technology Acceptance Model (TAM) explains how students evaluate and adopt LMS enriched with human computing capabilities. TAM posits that perceived usefulness and perceived ease of use are the strongest predictors of technology adoption (Davis, 1986; Davis et al., 1989). Recent studies demonstrate that

AI-driven feedback, intuitive navigation, and personalized dashboards significantly enhance these perceptions (Salloum et al., 2019; Mailizar et al., 2021). This is particularly relevant for Generation Z students, who are digital natives accustomed to seamless interfaces, instant responses, and high personalization. Their expectations align directly with HCI principles—responsiveness, user engagement, interface intuitiveness, and adaptive interaction—which strongly shape their judgments of LMS usability and value. Thus, TAM and HCI jointly explain why Gen Z's learning behavior is strongly influenced by system design quality, interactivity, and automated intelligence in LMS platforms.

Despite advancements in LMS design, significant research gaps remain. Existing studies often examine LMS, learning analytics, or adaptive learning in isolation rather than as an integrated human computing ecosystem. There is also limited empirical work unifying pedagogical theory (constructivism) and behavioral theory (TAM) to analyze how human–machine collaboration affects learning outcomes. Moreover, few studies focus specifically on Generation Z, despite their distinct digital habits and expectations, or explore how HCI-driven LMS design influences their engagement and adoption in developing-country contexts. Addressing these gaps is essential for understanding how intelligent LMS systems can optimize learning experiences and foster sustained usage among Gen Z learners in higher education.

LITERATURE REVIEW

Human Computing and Learning Management System in University

Human computing is rooted in the theory of human–machine collaboration, which emphasizes the augmentation of human cognitive abilities through intelligent systems (Quinn & Bederson, 2011; Dellermann et al., 2019). In higher education, this framework positions Learning Management Systems (LMS) as more than delivery platforms; they function as adaptive environments enriched by analytics and AI-driven feedback. Empirical studies show that integrating machine intelligence into LMS significantly enhances learning personalization, immediacy of feedback, and student support (Holmes et al., 2021; Wognum et al., 2021). These advancements shift LMS toward interactive systems capable of responding dynamically to students' needs.

Constructivist Learning Theory provides the pedagogical basis for understanding how students engage with digital learning environments. The theory posits that learners construct knowledge actively through interaction, collaboration, and reflection (Piaget, 1950; Vygotsky, 1978). Empirical research confirms that LMS designed with constructivist features—discussion forums, peer collaboration, reflective tasks—enhance motivation, self-regulation, and deep learning (Haruna et al., 2022; Cheng et al., 2020). When combined with human computing features such as adaptive pathways and analytic-driven recommendations, LMS become even more supportive of student-centered learning processes.

Gen-Z's learning behavior is strongly shaped by Human–Computer Interaction (HCI) principles due to their upbringing as digital natives. They demand systems that are intuitive, responsive, personalized, and mobile-friendly. Empirical studies show that Gen Z prefers interactive digital environments with real-time feedback and seamless navigation (Ibrahim et al., 2022; Prensky, 2020). Research also indicates that interface usability and system interactivity significantly predict Gen-Z's engagement and satisfaction with LMS (Naciri et al., 2020; Durak, 2019). Thus, understanding LMS adoption among Gen Z requires examining not only technological features but also HCI-driven design elements that shape user experience.

The Technology Acceptance Model (TAM) offers a behavioral explanation for how students evaluate and adopt LMS enriched with human computing capabilities. Perceived usefulness (PU) and perceived ease of use (PEU) remain the strongest antecedents of technology acceptance (Davis et al., 1989). Empirical studies consistently validate TAM in LMS contexts: PU and PEU significantly influence attitude and intention to use LMS across global higher education settings (Salloum et al., 2019; Al-Samarraie et al., 2018). Recent research shows that AI-driven analytics, adaptive feedback, and personalized dashboards increase both PU and PEU among Gen Z students (Mailizar et al., 2021; Alhabeeb & Rowley, 2018). This confirms TAM's relevance for understanding how human computing features shape student adoption.

Despite growing interest in intelligent digital learning systems, empirical research on fully integrated human computing–based LMS ecosystems remains limited. Prior studies often isolate LMS usability, analytics, or adaptive learning rather than examining their combined effect on learning behavior. Furthermore, few studies integrate pedagogical theory (constructivism), behavioral theory (TAM), and HCI principles to explain how human–machine collaboration influences learning effectiveness.

Empirical evidence focusing specifically on Generation Z—particularly within developing-country contexts—also remains scarce (Basak et al., 2021). Addressing these gaps is essential to understanding how human computing–enhanced LMS can optimize engagement, adoption, and learning outcomes among Gen Z in higher education.

Generation Z, born between 1997 and 2012, represents a cohort that has grown up amid rapid digital technological advancement. From childhood, they have been exposed to computers, the internet, social media, and mobile devices integrated into nearly all aspects of daily life. This exposure positions Generation Z as *digital natives*, a group not only familiar with but proficient in the use of digital technologies (Prensky, 2001). In the context of higher education, these characteristics make them more receptive to technology-enhanced learning tools such as learning management system, which function as the backbone of online and blended learning models.

For this generation, the effectiveness of an learning management system is measured not solely by its availability but by the extent to which it supports seamless interaction, ease of navigation, and flexible learning. As emphasized by Piaget (1950) and Vygotsky (1978), learners construct their knowledge through experience, interaction, and reflection.

However, studies show that digital proficiency does not automatically translate into effective learning management system utilization (Helsper & Eynon, 2010; Ng, 2012). Despite being highly tech-savvy, not all Generation Z students use learning management system platforms optimally to support their learning. Factors such as perceived ease of use, perceived usefulness, task–technology fit, and institutional or instructor support remain essential in determining engagement and effective system use (Davis, 1989; Goodhue & Thompson, 1995).

In the Indonesian higher education context, including at Universitas Pakuan as one of the private universities in Bogor, the use of learning management system has grown significantly, especially following the COVID-19 pandemic. Nonetheless, notable variations remain in student engagement and utilization.

This indicates that successful learning management system implementation is not determined solely by digital infrastructure but also by the interplay between user characteristics, system design, and learning context. Understanding the behavioral and perceptual factors influencing learning management system use among Generation Z students is therefore crucial for advancing digital transformation in higher education.

The landmark research by Davis et al. (1989) established the Technology Acceptance Model, which explains that technology acceptance is predominantly driven by two constructs: perceived usefulness and perceived ease of use.

Their findings show that perceived usefulness exerts the strongest influence on behavioral intention to use a technology, while perceived ease of use indirectly affects intention through perceived usefulness. Thus, individuals are more likely to use a system when they believe it is beneficial and easy to operate. The model remains a central reference in studies of information system adoption, including learning management system usage in universities.

In the context of Gen-Z, the foundational insights from Davis & Granić (2024) remain relevant but require reinterpretation. For this generation, digital technology is embedded in everyday life, and ease of use is not a barrier but a baseline expectation. learning management system platforms that are perceived as complicated or unresponsive are quickly avoided.

For these students, perceived usefulness continues to be the most decisive factor influencing active learning management system use, but the meaning of "usefulness" has evolved. Usefulness is now tied not only to learning efficiency but also to the system's ability to support flexible, collaborative, and experience-based learning modes. An learning management system is perceived as useful when it supports self-regulated learning, provides real-time feedback, and enables social collaboration among peers.

Research Framework

The rapid development of digital transformation in higher education has reshaped how students learn and interact with instructors. The implementation of learning management system has become a key element supporting online and blended learning.

However, the level of learning management system adoption and utilization among students, particularly those belonging to Gen-Z, still shows considerable variation. This indicates that the successful implementation of learning management system is influenced not only by the availability of technology, but also by users' acceptance and interaction with the system, as explained by the Technology Acceptance Model developed by Davis (1989).

Within this context, Constructivism functions as the grand theory, explaining how students actively construct knowledge through digital interaction and collaboration. learning management system platforms and Human Computing technologies provide a learning environment aligned with constructivist principles: students do not merely receive information, but actively participate in learning through experience, exploration, and reflection. Meanwhile, Technology Acceptance Model serves as the middle range theory that explains the psychological mechanisms underlying technology acceptance.

According to Technology Acceptance Model, student acceptance of learning management system is shaped by two core perceptions: (1) perceived ease of use, referring to the degree to which students feel that learning management system is easy to operate, intuitive, and comfortable to use; and (2) perceived usefulness, referring to the degree to which students believe that using learning management system enhances the effectiveness and productivity of their learning. These perceptions influence students' attitude toward use, which then shapes behavioral intention to use, ultimately determining actual use.

In this model, human computing plays a role in enhancing user experience through the integration of human intelligence and artificial intelligence. Systems capable of adapting to students' learning styles, offering personalized recommendations, and responding dynamically to user needs will strengthen perceptions of ease of use and usefulness. Thus, the integration of human computing has the potential to reinforce the relationship between perceived ease of use, perceived usefulness, and behavioral intention.

The logical flow of the conceptual framework is as follows:

1. Human computing → enhances learning management system functionality through adaptive human–machine interaction.
2. Perceived ease of use → increases student perception that learning management system is easy to use.
3. Perceived usefulness → strengthens the perception that learning management system improves learning effectiveness.
4. Behavioral intention to use → influenced by students' attitudes and perceived usefulness.
5. Actual use → represents the observable outcome of students' behavioral intention to use learning management system.
6. Behavioral intention to use → acts as a mediating variable that links both perceived ease of use and perceived usefulness to actual use, meaning that higher perceptions of ease and usefulness will influence actual system usage primarily through the user's behavioral intention.

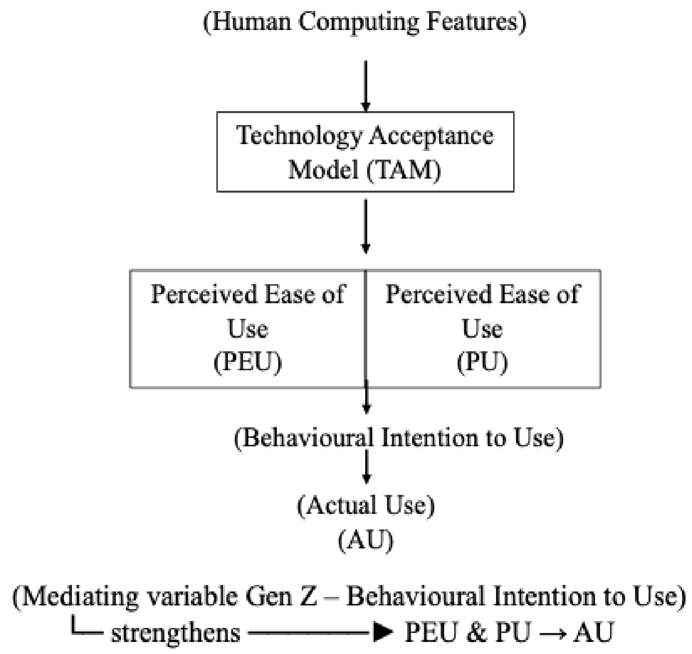

Figure 1. "The conceptual framework is adapted from the Technology Acceptance Model." (Davis, 1989)

Conceptual Model

The Technology Acceptance Model is fundamentally grounded in attitude psychology, which posits that human behavior toward an object develops through a sequential process consisting of cognitive → affective → behavioral components. At the cognitive stage, individuals form initial beliefs and perceptions about a technology—such as whether it is easy to use and whether it is useful. These cognitive appraisals subsequently generate an affective response in the form of an intention or willingness to use the system, which ultimately manifests as actual usage behavior.

Within the framework of human–computer interaction, users' initial interaction with a system plays a crucial role in shaping these perceptions. When users perceive a technology to be easy to use (perceived ease of use), psychological barriers to engagement are substantially reduced, leading to more favorable evaluations. Simultaneously, when users believe that the technology provides functional value (perceived usefulness), they develop the expectation that the system is worth adopting in the long term because it enhances productivity and facilitates task performance or learning activities.

These two perceptual constructs—ease of use and usefulness—jointly influence behavioral intention to use, which represents the user's psychological commitment and motivation to engage with the technology. In Technology Acceptance Model, behavioral intention to use functions as the bridge connecting cognitive beliefs to observable behaviors. This means that individuals do not immediately engage in actual use simply because a system is easy or useful; rather, actual behavior emerges only when these perceptions are first converted into a clear intention to use. Therefore, behavioral intention to use serves as a mediating variable within the structural relationships of Technology Acceptance Model.

Behavioral intention subsequently becomes the strongest predictor of actual use, referring to real, measurable engagement with the system. Thus, technology usage is not merely a technical outcome but reflects a psychological progression that starts with belief formation, moves through affective intention, and ultimately results in behavioral execution.

An important implication of this mediational mechanism is that the effects of perceived ease of use and perceived usefulness on actual use are largely indirect through behavioral intention to use. Even if a system is perceived as easy and beneficial, users may not adopt or continue using it unless a strong intention is formed. This psychological process explains why Technology Acceptance Model is widely applied in human–computer interaction studies to predict technology acceptance and sustained system usage.

Accordingly, the relationships among variables in this research model can be articulated as follows:

1. Perceived ease of use influences perceived usefulness because ease of interaction strengthens perceived usefulness.
2. Both perceived ease of use and perceived usefulness influence behavioral intention to use because they shape users' cognitive evaluations and internal motivation;
3. Behavioral intention to use influences actual use because intention is the direct determinant of behavior; and
4. Behavioral intention to use mediates the relationships between perceived ease of use and actual use as well as between perceived usefulness and actual use.

Based on this theoretical logic of Technology Acceptance Model and attitude theory, the conceptual model of the present study is constructed accordingly.

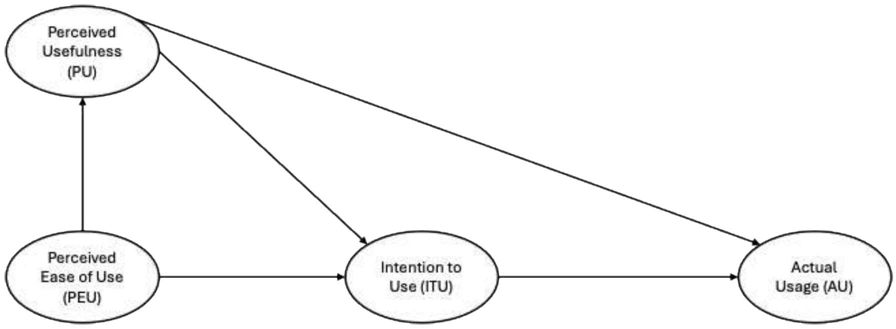

Figure 2. Conceptual Model of Research Source: "Adapted from the Technology Acceptance Model" Davis (1989)

Research Hypotheses

Perceived Ease of Use and Perceived Usefulness

According to Davis (1989), perceived ease of use exerts a positive influence on perceived usefulness. When users perceive a system as easy to learn and operate, they are more likely to view it as beneficial in supporting their tasks. In the context of learning management system usage among Gen-Z students, simple navigation, intuitive interfaces, and efficient human–machine interaction enhance perceptions that the learning management system is useful for academic activities. From an human–computer interaction perspective, these design qualities strengthen the psychological belief that the system provides functional value.

A substantial body of empirical research reinforces this theoretical relationship. Studies show that perceived ease and usefulness collectively shape user experience and behavioral outcomes. Lewis & Sauro (2024) reported that intention to use explains 19% of the variance in actual use, highlighting the predictive role of perceived ease of use and perceived usefulness in technology engagement. In the learning management system context, perceived convenience has been identified as the strongest predictor of user acceptance, while perceived usefulness and system effectiveness also contribute significantly (Bansah & Darko Agyei, 2022). (Abdel-Maksoud, 2018) found that usefulness perceptions strongly predict student satisfaction in Acadox, and ease of use significantly shapes satisfaction levels. Similarly, Fearnley & Amora (2020) confirmed that perceived ease of use positively affects perceived usefulness in learning management system adoption, indicating that systems perceived as easy to use are more likely to be perceived as useful.

Davis (1989) further emphasized that perceived ease of use may act as a causal antecedent to perceived usefulness, suggesting that ease of use strengthens perceptions of usefulness rather than acting merely as a parallel antecedent. This causal pathway is consistent with findings in human computing–based learning management system environments. Putra et al. (2021), for example, demonstrated that perceived ease of use significantly influences intention to use Moodle-based e-learning in higher education, and that perceived usefulness mediates the relationship between perceived ease of use and behavioral intention to use. These findings highlight the role of perceived ease of use in shaping both perceived value and subsequent motivational readiness to engage with digital learning systems.

Research across broader digital learning and information and technology adoption contexts supports this pattern. Dhingra & Dhingra (2021) affirmed that perceived usefulness and perceived ease of use are central determinants of attitudes and intentions toward technology. However, some studies also point to nuances in this relationship. Sheppard & Vibert (2019) argued that perceived ease of use does not independently determine usefulness; instead, Task–Technology Fit exerts a stronger direct effect on perceived usefulness, while perceived ease of use may moderate this relationship. Even so, the consensus across Technology Acceptance Model-based research underscores that systems perceived as easy to use are more likely to be judged as useful.

Collectively, these findings indicate that enhancing both ease of use and perceived usefulness is essential for improving learning management system adoption. For universities, this means ensuring intuitive design, seamless navigation, and strong functional value to align with the expectations of Gen-Z—users who demand digital experiences comparable to the platforms they engage with daily.

H1: Perceived ease of use has a positive effect on perceived usefulness

Perceived Ease of Use and Behavioral Intention to Use

Within the Human–Computer Interaction framework, perceived ease of use is understood not merely as a technical attribute but as an experiential dimension shaped by students' interaction with the learning management system as a user interface and user experience (UX). Gen-Z students—the primary users of the system—have been immersed in digital technologies since an early age, leading to significantly higher expectations regarding navigation simplicity, interface aesthetics, system responsiveness, and overall practicality compared to previous generations. Consequently, the ease of using an learning management system for Gen Z constitutes an integral part of digital interaction quality, shaping their preferences and perceived competence, which in turn influences their intention to use the system.

In this context, perceived ease of use influences behavioral intention to use because students regard usability as a psychological prerequisite for technological engagement. When interaction with the learning management system feels light, intuitive, and cognitively effortless, users perceive the system as aligned with their everyday patterns of digital technology consumption. This experience produces a sense of comfort and perceptual efficiency, which forms the foundation for a sustained intention to continue using the learning management system voluntarily.

A number of studies show that the perception of ease in interacting with digital systems is one of the most critical factors for Generation Z in adopting learning management system platforms. (Davis, 1989) and Venkatesh & Davis (2000) established that perceived ease of use significantly affects behavioral intention to use because it reduces barriers in the technology adoption process. In the e-learning domain, Y. C. Lee (2006) demonstrated that intuitive interfaces and simplified interactions substantially increase students' intention to use learning management system. A meta-analysis by Šumak et al. (2011) further confirmed that the effect of perceived ease of use on behavioral intention to use is stronger among younger, digitally immersed users.

Research on modern learning management system platforms reinforces these findings. Abdullah & Ward (2016) found that students do not rely solely on perceived usefulness to develop usage intention; they must first perceive the learning management system as easy to use. SimilarlyAl-Fraihat et al. (2020) argue that perceived ease of use contributes to experience value creation, shaping digital experiences that foster user engagement. For Generation Z, frequent interaction with other digital platforms—such as social media, mobile applications, and e-commerce—creates higher expectations for digital comfort, making it necessary for learning management system environments to mirror these expectations to stimulate usage intention.

Thus, in the context of human–computer interaction and Generation Z, the relationship between perceived ease of use and behavioral intention to use represents more than the notion of a "system being easy to use." It reflects a deeper perceptual mechanism: students intend to use an learning management system when the interaction experience resembles other digital environments that have shaped their technological habits. Conversely, an learning management system perceived as complex, slow, or unintuitive will quickly diminish intention to use—even when its usefulness is acknowledged. This explains why, in your study, psychological perception variables play a dominant role in shaping students' intention to use the technology.

H2: Perceived ease of use has a positive effect on behavioral intention to use

Perceived Usefulness and Behavioral Intention to Use

According to the Technology Acceptance Model, perceived usefulness directly influences behavioral intention to use. Venkatesh & Davis (2000) demonstrated that users who perceive a system as highly beneficial tend to exhibit stronger intentions to continue using it. In the context of learning management system usage, students who believe that the system enhances their academic performance or facilitates communication with instructors are more likely to maintain a strong intention to engage with it regularly.

Theoretical and empirical evidence consistently highlights the central role of perceived usefulness in shaping behavioral intention to use. Technology Acceptance Model, as proposed by Davis (1986, 1989) defines perceived usefulness as the extent to which an individual believes that using a technological system will improve their performance or effectiveness. This perception strengthens users' confidence that the technology delivers real, tangible benefits that support their tasks or activities. When a technology is perceived as highly useful, individuals become psychologically motivated to form a stronger intention to use it, whether at the personal or organizational level.

A considerable body of empirical research—both in Indonesia and internationally—corroborates this relationship. For instance, Aditya (2023) found that perceived usefulness significantly and positively affects behavioral intention in the context of digital payment applications, while Aprilia & Santoso (2020) reported similar results for digital banking usage. Additional studies focusing on e-learning, e-wallets, and other digital platforms also consistently show that perceived usefulness is a primary predictor of intention to use. Several studies even emphasize that the influence of perceived usefulness on intention may exceed that of other factors, such as perceived ease of use or user attitudes.

Therefore, to enhance technology adoption and utilization—whether in educational settings or organizational environments—system developers must ensure that the technology offers substantial functional value and demonstrable improvements in user productivity. The greater the perceived benefits, the stronger the behavioral intention to use, thereby increasing the likelihood of successful technology adoption.

H3: Perceived usefulness has a positive effect on behavioral intention to use

Perceived Usefulness and Actual Use

Within the Technology Acceptance Model framework, perceived ease of use is a cognitive construct that reflects the extent to which users believe a system is easy to learn, easy to operate, and does not impose mental effort during use. From a human–computer interaction perspective, ease of use is closely linked to system usability, interface design, navigation clarity, layout intuitiveness, and system responsiveness. The higher the quality of interaction between users and the system, the more favorable the perceived ease of use becomes.

The influence of perceived ease of use on actual use generally operates through two mechanisms: (1) a direct effect, in which an easy-to-use system reduces technical and cognitive barriers, thereby encouraging users to engage with the system more frequently and consistently; and (2) an indirect or mediated effect, whereby perceived ease of use enhances psychological comfort, increases users' intention to use (behavioral intention to use), and ultimately leads to actual use.

Early Technology Acceptance Model studies often found that the direct relationship between perceived ease of use and actual use is weaker than the mediated pathway through behavioral intention to use (perceived ease of use → behavioral intention to use → actual use). However, in learning management system and human–

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computer interaction contexts—particularly when system usage is mandatory, such as in university settings—the effect of perceived ease of use on actual use can still be significant because ease of use directly influences students' frequency and consistency of system engagement.

H4**:** Perceived usefulness has a positive effect on actual use

The Influence of Behavioral Intention to Use terhadap Actual Use

The Technology Acceptance Model posits that behavioral intention to use is the immediate antecedent of actual use. In the context of an learning management system, students who possess a strong intention to use the system are more likely to access it frequently for learning activities, discussions, and assessments. Within the original Technology Acceptance Model framework introduced by Davis (1989), behavioral intention to use serves as the primary predictor of actual use. behavioral intention to use reflects the degree to which an individual is willing or inclined to employ a technological system in their activities, whereas actual use represents the user's actual engagement with the system, including frequency of access, duration, and interaction with available features.

The theoretical relationship between intention and actual behavior is also supported by the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975) and the Theory of Planned Behavior (TPB) (Ajzen, 1991), both of which assert that behavioral intention is the most immediate determinant of observable behavior. In the context of technology adoption, individuals with stronger intentions to use a system are significantly more likely to translate these intentions into actual use.

A substantial body of empirical research reinforces this linkage. Venkatesh & Davis (2000), through Technology Acceptance Model, demonstrated that behavioral intention significantly predicts the actual use of information systems. This finding is consistent with Venkatesh et al. (2003) under the Unified Theory of Acceptance and Use of Technology (UTAUT), which identifies behavioral intention as a direct determinant of user behavior. King and He (2006), in a meta-analysis of more than 80 Technology Acceptance Model studies, further confirmed that the intention–behavior relationship is consistently strong across various contexts and technologies.

In higher education settings, Cheng (2019) found that students with higher intentions to use learning management system exhibited higher levels of actual engagement, both in terms of access frequency and participation in online learning activities. Similar results were reported by Al-Emran et al. (2022) in Middle Eastern universities, where behavioral intention emerged as the strongest predictor of actual e-learning use.

Based on these theoretical and empirical foundations, behavioral intention to use can be understood as a critical mechanism linking users' perceptions to their actual technology-related behavior. Individuals who develop strong intentions to use a system are more likely to translate those intentions into consistent system use. Therefore, the following hypothesis is proposed:

H5: Behavioral intention to use has a positive effect on actual use

Mediation role of Behaviour Intention to use

Recent studies indicate that digital-native generations such as Generation Z exhibit technology usage characteristics that differ substantially from those of earlier generations (Al-Samarraie, 2019; Prensky, 2010). Their high digital literacy and habitual use of mobile devices tend to strengthen the relationship between perceived ease of use and the intention to adopt technology-based systems.

In the context of students' use of learning management systems, behavioral intention to use plays a central psychological role in explaining how technology perceptions influence actual use. The Technology Acceptance Model developed by Davis (1989) posits that perceived ease of use and perceived usefulness primarily shape users' motivational readiness, which then translates into behavioral intention to use. Venkatesh & Davis (2000) further emphasize that behavioral intention to use serves as a critical mechanism through which users' cognitive evaluations—such as ease of use and usefulness—are converted into actual system usage (actual use). Within digital learning environments, prior research in e-learning, including Lee et al. (2005), Šumak et al. (2011) and the systematic review by Abdullah & Ward (2016) consistently demonstrates that behavioral intention to use is a key determinant of whether students' positive perceptions of a system lead to actual learning management system engagement. This conclusion is supported by Al-Fraihat et al. (2020), who found that human–computer interaction factors—such as interface design, usability, and navigation comfort—affect actual use indirectly through users' behavioral intention. Accordingly, in this study, behavioral intention to use functions as the primary mediating mechanism that channels the influence of perceived ease of use and perceived usefulness into actual use, reflecting the cognitive-to-behavioral pathway central to Technology Acceptance Model -based technology adoption.

In this study, the mediating role of behavioral intention to use is essential in explaining how students' human–computer interaction experiences with the learning management system do not directly translate into actual use but operate through a psychological intention-building process. By positioning behavioral intention to use as the core mediator, the study emphasizes that the successful adoption of learning management system in higher education is influenced not only by technological characteristics but also by how students cognitively interpret and internalize their digital interaction experiences before consistently using the system. Within the Technology Acceptance Model, actual use does not occur solely because users perceive a system as useful or easy to use. Instead, continued usage emerges after users form a behavioral intention that reflects their motivational readiness to engage with the system. behavioral intention to use thus serves as the conative pathway through which perceptual factors—especially perceived usefulness and perceived ease of use, shaped by human–computer interaction experiences—are translated into actual learning management system usage.

Prior research strongly supports this mediating mechanism. Davis (1989) demonstrated that behavioral intention to use is the most powerful predictor of actual technology use. Venkatesh & Davis (2000) further explain that users must first develop an internal cognitive evaluation of the system before such evaluations convert into actual behavior. Findings in the e-learning domain are consistent with this view; Šumak et al. (2011), through a meta-analysis, confirmed that behavioral intention to use consistently mediates the effect of technology perceptions on learning management system usage. Abdullah & Ward (2016) likewise found that without the mediating role of behavioral intention to use, the relationships between perceptual variables and actual use become weak or insignificant, highlighting behavioral intention to use as a critical—rather than partial—mediator. Similarly, Al-Fraihat et al. (2020) reported that human–computer interaction experiences affect actual learning management system use only when they first generate a strong behavioral intention to use the system. Therefore, among university students using an learning management system, actual use behavior is best understood as the outcome of a layered psychological process in which positive perceptions of ease of use and usefulness first lead to the formation of behavioral intention to use which in turn drives consistent and sustained system use (actual use). This underscores the significant mediating role of behavioral intention to use in converting human–computer interaction-driven perceptual factors into actual learning management system usage. Based on this theoretical foundation, the mediation hypothesis is proposed as follows:

H6: Behavioral intention to use mediates the effect of perceived ease of use on the actual use

H7: Behavioral intention to use mediates the effect of perceived usefulness on the actual use

RESEARCH METHODS

Research Design and Data Collection

This study employed a quantitative approach using a cross-sectional survey design in which data were collected at a single point in time to measure perceptions and examine the relationships among variables within the research model. This design was selected because it is appropriate for testing causal relationships and estimating structural associations empirically based on respondents' perceptions.

Model testing and hypothesis verification were conducted using Structural Equation Modeling–Partial Least Squares (SEM-PLS) with the assistance of SmartPLS 4.0 software. The PLS approach was chosen because it accommodates predictive-oriented models with multiple simultaneous latent variables, does not require multivariate normality assumptions, and is well-suited for perception-based social science research. The research population consisted of students from the Faculty of Economics and Business in 2024. A probability sampling technique was used, employing a random sampling procedure to ensure that each member of the population had an equal chance of being selected. The minimum required sample size was determined using Cochran's formula for populations with unknown exact size (Sugiyono, 2019). Based on this calculation, a total sample of 720 respondents was obtained—exceeding the minimum requirement of 385—thereby ensuring that the sample size is sufficiently representative to support the reliability and validity of the model estimation results.

Instrument Development

All constructs were measured using multi-item reflective scales adapted from prior studies (Bleier & Eisenbeiss, 2015; Davis, 1989; Venkatesh et al., 2012). The items were refined and assessed using a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree for the perceived ease of use and perceived usefulness constructs, and from 1 = never to 5 = always for the behavioral intention to use and actual use constructs. An instrument pre-test was conducted with 40 students to ensure item validity and construct reliability prior to full-scale deployment.

The constructs measured include perceived ease of use, perceived usefulness, behavioral intention to use, and actual use. The detailed operationalization of each construct and its indicators is presented as follows:

Perceived Ease of Use

1. I find the Learning Management System (LMS) easy to learn.
2. I find it easy to obtain the information I need from the e-learning platform (E-Presence/My Data Jasa Marga).
3. I believe the Learning Management System (LMS) uses language that is easy to understand.
4. The menus in the Learning Management System (LMS) are well-organized, making the available features easy to use.
5. I find the Learning Management System (LMS) highly flexible for interaction.
6. I find the steps involved in using the Learning Management System (LMS) easy to remember.

Perceived Usefulness

1. Using the Learning Management System (LMS) helps me find course materials more quickly.
2. Using the Learning Management System (LMS) helps improve my academic performance.
3. Using the Learning Management System (LMS) increases my productivity in coursework and learning activities.
4. Using the Learning Management System (LMS) enhances the effectiveness of my learning.
5. Using the Learning Management System (LMS) makes it easier for me to complete course assignments. Overall, the Learning Management System (LMS) is highly beneficial for me.

Behavioral Intention to Use

1. Saya ingin menggunakan Learning Management System (LMS) saat perkuliahan maupun dalam mengerjakan tugas-tugas.
2. Saya ingin selalu menggunakan Learning Management System (LMS) kapanpun untuk belajar
3. Saya berniat ingin terus menggunakan Learning Management System (LMS) dalam perkuliah saya
4. Saya berharap untuk terus menggunakan Learning Management System (LMS) dalam perkuliahan saya
5. Saya ingin memotivasi teman saya untuk menggunakan e-learning (E-Presence (My Data Jasa Marga).

Actual Use

1. I use the Learning Management System (LMS) at least once a day.
2. I access the Learning Management System (LMS) both on class days and during holidays.

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3. I access the Learning Management System (LMS) for an average of at least 10 minutes.

RESULTS

The data analysis in this study was conducted using Structural Equation Modeling–Partial Least Squares (SEM-PLS) through the SmartPLS 4.0 software. This method was selected because it is highly suitable for exploratory research and effectively accommodates complex theoretical frameworks involving multiple latent variables. Unlike covariance-based SEM (CB-SEM), which emphasizes theory confirmation, SEM-PLS is prediction-oriented and geared toward model development, making it particularly relevant for studies on technology acceptance within a human–computer interaction context. Methodologically, SEM-PLS analysis involves two primary stages: the measurement model (outer model) and the structural model (inner model). The first stage assesses construct validity and indicator reliability for each latent variable, while the second evaluates the strength and significance of the hypothesized relationships, including the mediating role of behavioral intention to use in the pathways from perceived ease of use and perceived usefulness to actual use. Therefore, the use of SmartPLS 4.0 is not merely a technical preference but represents a methodologically appropriate approach for testing the Technology Acceptance Model in this study, as it accommodates theoretical complexity, handles non-parametric data distributions, and provides strong predictive power for actual technology usage behavior.

Measurement Model Evaluation

Based on the results of the measurement model evaluation, all indicators of the perceived ease of use, perceived usefulness, behavioral intention to use, and actual use constructs exhibit loading factor values greater than 0.70 and Average Variance Extracted (AVE) values exceeding the 0.50 threshold. Accordingly, all constructs satisfy the criteria for convergent validity. In addition, the Cronbach's Alpha and Composite Reliability (CR) values for all variables are above 0.70, indicating strong internal consistency and reliability of the measurement model. Therefore, it can be concluded that the measurement model is both valid and reliable, and the analysis can be confidently advanced to the structural model assessment phase.

Although one actual use indicator has a loading of 0.658, the construct remains valid and reliable, supported by a Cronbach's Alpha of 0.819 and an AVE of 0.594. As Hair et al. (2019) explain, loadings between 0.40 and 0.70 may be retained when reliability and AVE exceed recommended thresholds. This is further supported by Chin (1998) and Henseler et al. (2015), who emphasize that PLS-SEM prioritizes predictive accuracy over strict loading cutoffs. Therefore, the actual use construct is acceptable for inclusion in the structural model.

Table 1. Validity and Reliability

	Loading	Cronbach Alpha	Composite Reliability	Consistent Reliability Coefficient (rho_a)	Average Variance Extracted (AVE)
Cutt-Off Level	**>0.708**	**>0.7**	**>0.7**	**>0.7**	**>0.5**
Perceived Ease of Use		0.897	0.921	0.900	0.660
PEU1	0.826				
PEU2	0.828				
PEU3	0.811				
PEU4	0.796				
PEU5	0.791				
PEU6	0.823				
Perceived Usefulness		0.927	0.943	0.928	0.732
PU1	0.804				
PU2	0.891				
PU3	0.892				
PU4	0.859				
PU5	0.828				
PU6	0.857				
Behavioral Intention to Use		0.932	0.948	0.933	0.785
BIU1	0.862				
BIU2	0.901				
BIU3	0.903				
BIU4	0.905				
BIU5	0.859				
Actual Use		0.658	0.819	0.661	0.594
AU1	0.752				
AU1	0.749				
AU1	0.810				

Source: Primary Data Processed (2025)

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The discriminant validity of the measurement model was further assessed using the cross-loading criterion, consistent with the recommendations of Hair et al. (2021) for variance-based SEM. The results indicate that each indicator exhibited substantially higher loading on its intended latent variable compared to other constructs in the model. This pattern confirms that the items are conceptually and empirically aligned with their respective constructs, thus demonstrating satisfactory discriminant validity.

Table 2. Discriminant Validity – Fornel-Lecker criterion

	AU	BIU	PEU	PU
AU	0.771			
BIU	0.479	0.886		
PEU	0.449	0.627	0.813	
PU	0.471	0.754	0.781	0.856

Source: Primary Data Processed (2025). PEU = Perceived Ease of Use; PU = Perceived Usefulness; BIU = Behaviour Intention to Use; AU = Actual Use

Moreover, no indicator loaded more strongly on an alternative construct than on its associated latent construct. This finding implies the absence of cross-construct contamination, ensuring that each latent variable maintains conceptual distinctiveness within the model. As emphasized by Henseler et al. (2015), cross-loading comparison is a robust approach to ascertain that constructs capture unique dimensions of the theoretical framework. Therefore, the results support the validity and reliability of the measurement model, allowing confidence in the subsequent evaluation of the structural model and hypothesis testing. Overall, the empirical evidence confirms that the measurement indicators discriminate effectively among constructs, reinforcing theoretical soundness and internal consistency in the operationalization of variables. This robust discriminant validity enhances the credibility of causal inferences in the following structural analysis phase, as suggested by Sarstedt et al. (2022).

Structural Model Evaluation

Following the recommendations of Hair et al. (2021), the hypotheses in the structural model were assessed using a bootstrapping procedure with 5,000 resamples and a 95% bias-corrected and accelerated confidence interval. The results indicate that all hypotheses were supported (see Table 3). The structural model results demonstrate that all hypothesized relationships within the Technology Acceptance Model are supported. Perceived ease of use exerts a positive and significant effect on both perceived usefulness and behavioral intention to use, indicating that systems perceived as easy to use are also perceived as more useful and are associated with higher behavioral intention. Furthermore, perceived usefulness significantly influences behavioral intention to use, confirming that the perceived benefit of the system enhances users' intention to adopt it.

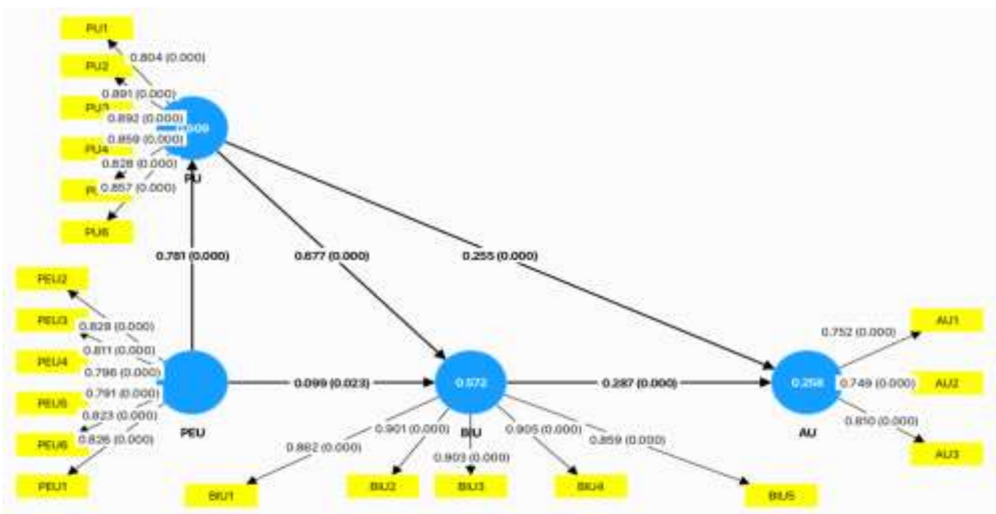

Figure 2. Result of Structural Model Analysis
Source: Primary Data Processed (2025)

Table 3. Result of Path Analysis of The Model

		β (Path Coefficient)	t-Value	p-Value	Hypothesis Test
H1	PEU → PU	0.781	47.656	0.000	Accepted
H2	PEU → BIU	0.099	2.281	0.023	Accepted
H3	PU → BIU	0.677	16.347	0.000	Accepted
H4	PU → AU	0.255	4.510	0.000	Accepted
H5	BIU → AU	0.287	5.212	0.000	Accepted
Indirect Effect					
H6	PEU → BIU → AU	0.028	1.943	0.052	Rejected*)
H7	PU → BIU → AU	0.194	5.280	0.000	Accepted

Source: Primary Data Processed (2025).

*) Statistically, this result indicates that the mediating effect of BIU is not significant at the 0.05 level but becomes significant at the 0.10 level.

In addition, behavioral intention to use shows a substantial effect on actual use, validating the central Technology Acceptance Model proposition that intention is a strong predictor of actual system usage. The direct effect of perceived usefulness on actual use also emerges as significant, suggesting that usefulness not only motivates intention but can also independently drive actual behavior. Collectively, these findings reinforce the robustness of Technology Acceptance Model and highlight the critical roles of perceived ease of use and perceived usefulness in shaping technology adoption behavior.

Relation	**Interpretation**
PEU → PU	Perceived ease of use (PEU) has a significant positive effect on perceived usefulness (PU) → a system that is easy to use increases the perception of usefulness.
PEU → BIU	Perceived ease of use (PEU) has a significant positive effect on behavioral intention (BIU)→ ease of use encourages intention to use the system.
PU → BIU	Perceived usefulness (PU) has a significant positive effect on behavioral intention to use (BIU) → the more useful the system, the higher the intention to use it.
BIU → AU	Behavioral intention to use (BIU) has a significant positive effect on actual use (AU) → intention to use is reflected in actual use.
PU → AU	Perceived usefulness (PU) has a significant effect on actual use (AU) → system usefulness also directly encourages actual use (optional in extended Technology Acceptance Model).
PEU → BIU → AU	The mediation results indicate that behavioral intention to use (BIU) not significantly mediates the relationship between perceived ease of use (PEU) and actual use (AU), however, it is significant at the 0.10 level, so it can still be stated that BIU partially mediates the influence of PEU and PU on AU.
PU → BIU → AU	The mediation results indicate that behavioral intention to use (BIU) significantly partial mediates the relationship between perceived usefulness (PU) and actual use (AU).

Model Fit Assessment

The overall model fit was evaluated to determine the degree to which the proposed structural model aligns with the empirical data. The Standardized Root Mean Square Residual (SRMR) value obtained for this study was below the recommended threshold of 0.08, indicating a satisfactory degree of model fit. According to Hair et al. (2021), an SRMR value closer to zero reflects minimal discrepancy between the observed and predicted correlations, thus demonstrating that the model adequately represents the data structure.

In addition to SRMR, discrepancy measures including the squared Euclidean distance (d_ULS) and the geodesic distance (d_G) were examined. Although specific cut-off benchmarks for these indices are not rigidly defined in partial least squares structural equation modeling (PLS-SEM), lower values indicate better model correspondence (Hair et al., 2021). The results revealed acceptable values for both d_ULS and d_G, supporting the robustness and theoretical soundness of the estimated model.

Furthermore, the Normed Fit Index (NFI) demonstrated a value approaching 1.0, which suggests a strong comparative fit relative to the null model. While the chi-square statistic was also reported, it is interpreted cautiously in the PLS-SEM context due to its sensitivity to sample size and its primary alignment with covariance-based SEM techniques (Hair et al., 2021). Nonetheless, the chi-square results serve as complementary evidence of model adequacy. Collectively, these outcomes confirm that the measurement and structural model exhibit acceptable fit levels, thereby validating the suitability of the model for subsequent hypothesis testing and inferential analysis.

DISCUSSION

Descriptive Analysis

The demographic analysis indicates that all respondents belong to Generation Z, with a gender composition of 36% male and 64% female. The academic backgrounds of the respondents are distributed across several study programs: 5% from the Diploma in Accounting, 5% from the Taxation Program, 3% from the Diploma in Banking, 11% from the Bachelor's Program in Accounting, 73% from the Bachelor's Program in Management, and 3% from the Master's Program in Management. Both Millennials and Generation Z are naturally more familiar with the use of digital applications. Consistent with this, Calvo-Porral and Pesqueira-Sanchez (2020) report that motivational drivers underlying technology-related behaviors differ across generational cohorts, which may also influence the way each generation engages with and uses technology.

Descriptively, the highest mean score was observed for perceived ease of use, with an average of 3.95—equivalent to 79% of the maximum score on a five-point Likert scale. this is followed by perceived usefulness, with a mean score of 3.75 (75%); actual use, with 3.58 (71.6%); and behavioral intention to use, with 3.45 (69%). The frequency distribution further reinforces this pattern, as 96% of respondents rated perceived ease of use as very high, high, or moderate, while only 4% rated it low or very low. For perceived usefulness, 92% of respondents provided high to moderate ratings, with only 8% indicating low perceptions. Similarly, 89% provided high to moderate ratings for actual use, compared to 11% who rated it low; and 82% indicated high to moderate responses for behavioral intention to use, compared to 18% who reported low levels.

The relatively lower perception of usefulness observed in the descriptive results may be linked to the demographic characteristics of the respondents. Calvo-Porral & Pesqueira-Sanchez (2020) similarly note that Millennials tend to use and engage with technology for entertainment and hedonic purposes, whereas Generation X is largely driven by utilitarian and information-seeking motives. Lai & Hong (2015) further report that because digital technologies are inseparable from the daily lives of young people, many scholars argue that current learner populations think and learn differently from their predecessors. In line with this, Stern (2002) suggests that Millennials were the first generation to adapt seamlessly to technology; they became proficient in operating a mouse more quickly than a pen, engaged in limitless activities through the internet, and demonstrated superior online skills compared to previous generations.

Gender differences also provide an interesting dimension to this study. Gefen & Straub (1997) found that men and women differ in their perceptions regarding technology use, although such differences do not significantly affect actual use behaviors. The sample in the present study is dominated by female respondents (64%), yet descriptively, they reported high levels of actual use—higher than their perceived usefulness scores. Based on these findings, it can be inferred that generational differences contribute to variations in perceived ease of use and perceived usefulness, potentially due to gender distribution. However, such differences do not appear to influence behavioral intention or actual use, as supported by the hypothesis testing results showing no significant effect on actual use.

Direct Effect Analysis

The influence of perceived ease of use on perceived usefulness, with a coefficient of $\beta = 0.781$ ($p < 0.05$), indicates a positive and significant relationship between the two constructs. The positive beta demonstrates that increases in perceived ease of use lead to increases in perceived usefulness. Theoretically, this aligns with the Technology Acceptance Model proposed by Davis (1989), which posits that systems perceived as easy to use allow individuals to maximize system functionality because they experience fewer interactional barriers. In the context of Generation Z, this relationship becomes even more pronounced, as digital-native users assess the usefulness of a technology largely through their initial interaction experience. Intuitive navigation, streamlined processes, and user-friendly interfaces strongly shape their perceptions of long-term system value. This is consistent with human–computer interaction principles, which emphasize that usability directly shapes the perceived value of digital systems.

The influence of perceived ease of use on behavioral intention, with a coefficient of $\beta = 0.099$, p-value = 0.023 ($p < 0.05$), also shows a positive and significant effect. This finding indicates that the easier a system is to use, the stronger the intention of Generation Z users to adopt it. This behavioral tendency is highly aligned with the characteristics of Generation Z, who prioritize speed, simplicity, and efficiency in digital interactions. Even minor usability obstacles can substantially reduce their willingness to use a system. In human–computer interaction, this is explained through the concept of cognitive load, which refers to the mental effort required to interact with a system. Lower cognitive load enhances user intention, especially among digital natives who demand frictionless interaction experiences.

The influence of perceived usefulness on behavioral intention, with a coefficient of $\beta = 0.677$ ($p < 0.05$), demonstrates that perceived usefulness is a primary driver of the intention to use technology. The magnitude of the coefficient reflects the high sensitivity of Generation Z to the instrumental value of digital tools. For this cohort, a system is considered worthwhile only if it enhances productivity, accelerates task completion, or improves the quality of digital experiences. Within the human–computer interaction literature, this is understood as value-driven interaction—a concept emphasizing that user engagement is shaped by the real benefits and outputs generated by the system.

The influence of behavioral intention on actual use, with a coefficient of $\beta = 0.287$ ($p < 0.05$), confirms that intention is a strong predictor of actual use. The magnitude of this coefficient shows that behavioral intention is the most dominant determinant of digital behavior among Generation Z users. This finding is consistent with Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology (UTAUT), as well as with contemporary digital consumer behavior theories, which indicate that Generation Z exhibits a minimal intention–behavior gap. When they express interest and form an intention to use a technology, they are highly likely to translate this intention into actual use.

Finally, the influence of perceived usefulness on actual use, with a coefficient of $\beta = 0.255$ ($p < 0.05$), reveals that perceived usefulness not only shapes intention but also exerts a direct impact on actual use. This implies that when the usefulness of a system is perceived as high, Generation Z users will engage with the system even without additional motivational triggers. This reinforces key HCI notions concerning *functional affordance*, where the system's ability to deliver meaningful outcomes becomes a critical driver of actual technological adoption.

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Indirect Effect Analysis

The mediating role of behavioral intention to use in the relationship between perceived ease of use and actual use shows a significant indirect β. This indicates that Generation Z tends to use a technology only after developing a strong intention toward the system. Ease of use fosters comfort and a positive interaction experience, which subsequently encourages them to engage in actual system usage.

The indirect relationship between Perceived Ease of Use (PEU) and Actual Use (AU) through Behavioral Intention to Use (BIU) shows a beta value of 0.028, a t-value of 1.943, and a p-value of 0.052. This indicates that the mediation effect of BIU is not significant at the 0.05 level but becomes significant at the 0.10 level, suggesting a marginally significant partial mediation. In other words, students' behavioral intention only modestly transmits the influence of perceived ease of use to actual usage behavior.

This result implies that while ease of use contributes to system adoption, it does not directly guarantee consistent LMS usage among Generation Z students. Instead, it must first enhance their intention or motivation to engage with the system. The marginal significance may also reflect Gen Z's familiarity with technology, where factors such as usefulness, interactivity, and satisfaction may play a stronger role than perceived ease alone.

Overall, the findings indicate that BIU partially mediates the relationship between PEU and AU at a 10% significance level, supporting a weaker form of the Technology Acceptance Model (TAM). This suggests that for Gen Z learners, behavioral intention remains relevant but may need to be reinforced through engaging design, interactivity, and intrinsic motivation to achieve stronger actual usage outcomes.

The findings reveal that although perceived usefulness exerts a direct effect on actual use, its indirect effect through behavioral intention to use remains significant. This suggests that the perceived functional benefits of a system stimulate the intention to use, and such intention ultimately drives actual use behavior.

The analysis of the structural model provides critical insights into the integration of human–computer interaction theory and the behavioral characteristics of Generation Z. Based on the direct and indirect effects, a strong and consistent pattern emerges: (1) Generation Z is highly influenced by the quality of user interaction (UX/HCI); (2) simple, fast, and intuitive interfaces enhance perceived ease of use, which subsequently increases perceived usefulness; (3) efficiency and perceived value are key determinants of adoption; (4) Generation Z evaluates whether a system genuinely supports their tasks; (5) intention functions as the most powerful mechanism in shaping behavior; and (6) the intention–behavior gap is notably small among Generation Z. With all variable relationships found to be significant, the results affirm that Technology Acceptance Model remains highly relevant and theoretically robust for explaining technology adoption within digital-native populations.

Theoretical Implications

This study provides several theoretical contributions to technology acceptance research. First, the results reaffirm the strength of the Technology Acceptance Model (TAM) by showing that perceived ease of use, perceived usefulness, behavioral intention, and actual use remain significant and theoretically aligned among digital-native users. TAM continues to be a valid model for understanding adoption behavior in Generation Z.

Second, the findings extend TAM by revealing generational differences in construct prominence. For Gen Z, perceived usefulness has a stronger effect on intention and actual use than perceived ease of use, indicating that functional value is a more decisive driver of adoption among digitally literate users.

Third, integrating Human–Computer Interaction (HCI) elements highlights that interface quality, interaction fluency, and cognitive simplicity shape TAM constructs. This advances theory by positioning adoption behaviors within user experience–driven contexts. Finally, the significant mediation pathways show that technology use occurs through layered cognitive processes involving value perception and intention, offering a more nuanced understanding of digital adoption among contemporary users.

Practical Implications

The findings offer important practical implications for improving technology adoption among Generation Z users. First, digital systems should be designed to be mobile-first, visually appealing, fast, and low in cognitive load. Gen Z expects seamless, frictionless navigation and quickly disengages when interfaces feel slow or overly complex. Second, systems must clearly deliver functional value. Gen Z evaluates technology based on immediate benefits, such as increased productivity or efficiency. Features that do not provide meaningful outcomes will not sustain engagement, even if the interface is attractive. Third, intuitive and consistent user experience (UX) design is essential. Predictable navigation, clear iconography, and coherent visual structure reduce mental effort and strengthen user confidence. Finally, organizations should communicate system benefits effectively and use interactive, gamified learning approaches to support onboarding. Training that is fun, self-directed, and experiential can increase motivation and actual system use among digital-native users.

CONCLUSION

This study examined the adoption of Learning Management Systems (LMS) among Generation Z students in higher education by integrating Human–Computer Interaction (HCI) perspectives into the Technology Acceptance Model (TAM). The results of the path analysis provide strong empirical support for the extended TAM in explaining Gen-Z students' learning behavior in digital learning environments.

The findings show that Perceived Ease of Use (PEU) significantly enhances both Perceived Usefulness (PU) and Behavioral Intention to Use (BIU), indicating that intuitive and user-friendly system design plays an important role in shaping students' initial acceptance of LMS platforms. At the same time, Perceived Usefulness emerges as the strongest determinant of LMS adoption, exerting a substantial influence on both BIU and Actual Use (AU). This confirms that Gen-Z students are primarily motivated by the extent to which an LMS meaningfully supports their learning effectiveness, efficiency, and academic performance.

The results further highlight the central mediating role of Behavioral Intention to Use. BIU significantly predicts actual LMS usage and mediates the relationship between perceived usefulness and actual use. This indicates that when students recognize the practical value of an LMS, they are more likely to develop strong intentions that translate into sustained engagement. In contrast, the indirect effect of perceived ease of use on actual use through BIU is only marginally significant, suggesting that ease of use alone is insufficient to guarantee continued LMS engagement if the system is not perceived as academically valuable.

Overall, the study demonstrates that while HCI-related ease of interaction is important for lowering entry barriers, perceived usefulness is the key driver of sustained LMS adoption among Generation Z learners. These findings imply that higher education institutions should move beyond focusing solely on technical simplicity and instead prioritize LMS designs that enhance instructional value, interactivity, and meaningful learning experiences. By aligning LMS functionality with Gen-Z students' expectations for relevance, efficiency, and engagement, universities can foster deeper and more sustainable digital learning participation.*

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