https://doi.org/10.65166/g5h1et20

Asian Journal of Educational Leadership, Management and Pedagogy
Volume I, Issue 1, June 2026
https://journal.ijhba.com/index.php/ajelmp
https://slsipress.com

Conditional Acceptance of AI-Assisted Gamified Learning among Senior High School and Higher Education Students: The Roles of Learning Value, Engagement, and Responsible-Use Safeguards

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Abstract

Artificial intelligence-assisted gamified learning combines generative AI functions with game-based instructional elements to support explanation, practice, feedback, and student participation. However, student acceptance may depend not only on prior exposure but also on perceived educational value, engagement, and confidence in responsible-use safeguards. This study examined the factors associated with the acceptance of AI-assisted gamified learning among 136 students in the Philippines, comprising 91 higher education students and 45 senior high school students. A cross-sectional analytical survey design was used. Data were analyzed using descriptive statistics, Cronbach's alpha, Welch's independent-samples t tests, Pearson correlation, hierarchical multiple regression with HC3 robust standard errors, sensitivity analysis, and supplementary content analysis of open-ended responses. Students reported generally favorable perceptions of exposure, learning value, safeguards, and acceptability, while motivation and engagement were rated at a moderate level. Higher education students reported significantly greater acceptability than senior high school students. Acceptability was strongly associated with perceived learning value and motivation and engagement and was moderately associated with responsible-use safeguards. In the final regression model, learning value, motivation and engagement, and safeguards remained statistically significant factors associated with acceptability, whereas prior exposure did not. Open-ended responses emphasized concerns regarding overdependence, weakened critical thinking, competition, accuracy, privacy, teacher guidance, and unequal access. The findings indicate that student acceptance is conditional on pedagogical usefulness, meaningful engagement, teacher mediation, transparency, privacy protection, academic-integrity safeguards, and equitable access.

Keywords: *artificial intelligence; gamified learning; student acceptance; learning engagement; responsible AI; educational technology*

Article History: Received: May 15, 2026 Revised: June 2, 2026 Accepted: June 28, 2026

1. Introduction

Generative artificial intelligence has rapidly developed from a specialized computational technology into an accessible educational resource capable of producing explanations, examples, summaries, assessment items, feedback, translations, and multimodal learning materials. Its growing availability has created new possibilities for instructional design, particularly when combined with gamification, or the application of game-design elements in non-game contexts (Deterding et al., 2011). In educational settings, this combination may take the form of adaptive quizzes, personalized practice activities, AI-generated feedback, progress indicators, badges, challenges, and interactive learning tasks. These features can potentially make learning more responsive to individual needs while increasing participation, persistence, and learner engagement.

The integration of artificial intelligence and gamification, however, presents a more complex adoption problem than the use of either technology independently. Students are not merely evaluating a digital tool. They are assessing an instructional arrangement that may influence academic integrity, assessment practices, teacher authority, data privacy, access to educational resources, and the quality of learning itself. A system may appear innovative and engaging while still raising concerns regarding inaccurate information, excessive reliance on AI, superficial reward-seeking, surveillance, or unequal access. Consequently, acceptance of AI-assisted gamified learning cannot be presumed solely from students' familiarity with artificial intelligence or prior exposure to gamified activities.

Research on educational gamification has generally reported positive but varied effects. Gamified learning environments may improve motivation, participation, persistence, and selected cognitive outcomes, although these effects depend heavily on instructional design, context, and the specific game elements employed (Sailer & Homner, 2020). Points, badges, rankings, and competition can encourage participation, but they do not necessarily produce deep learning. When poorly aligned with instructional objectives, such mechanics may shift attention from understanding to reward accumulation, create unnecessary pressure, or discourage students who are less responsive to competition. Artificial intelligence may improve gamification by providing adaptive difficulty, immediate feedback, and personalized learning sequences. At the same time, it may amplify existing concerns when AI-generated content is inaccurate, opaque, biased, or insufficiently supervised.

Students' acceptance of educational technology is therefore central to successful implementation. The Technology Acceptance Model proposes that individuals are more likely to adopt technologies that they perceive as useful and manageable (Davis, 1989). The Unified Theory of Acceptance and Use of Technology further emphasizes performance expectancy, facilitating conditions, social influence, effort expectancy, hedonic motivation, and experience as determinants of adoption behavior (Venkatesh et al., 2003, 2012). Recent studies of generative artificial intelligence in education similarly indicate that perceived usefulness, performance expectancy, trust, attitude, and institutional support influence students' intention to use AI-enabled tools (Shahzad et al., 2024; Strzelecki, 2024).

Perceived learning value is particularly important because students are more likely to support instructional technologies that they believe can improve understanding, practice, retention, mastery, and academic performance. Studies have shown that students recognize the potential of generative AI for personalized explanations, brainstorming, writing assistance, research support, and productivity enhancement (Chan & Hu, 2023). Nevertheless, favorable perceptions often coexist with concerns regarding accuracy, authorship, academic misconduct, privacy, and dependence on automated systems. This coexistence suggests that acceptance may be conditional rather than unconditional. Students may value AI-assisted learning while simultaneously demanding clear boundaries, teacher oversight, and safeguards against misuse.

Motivation and engagement are equally relevant. Gamification is often introduced on the assumption that game elements naturally increase students' willingness to participate. However, engagement depends on whether activities are meaningful, appropriately challenging, and pedagogically aligned. Self-determination theory suggests that sustained motivation is more likely when learners experience competence, autonomy, and supportive relationships rather than external control alone (Deci & Ryan, 2000). AI-assisted gamification may support these needs through adaptive practice, individualized feedback, and visible progress. Conversely, it may weaken motivation if students perceive the activities as repetitive, manipulative, overly competitive, or disconnected from actual learning goals.

Responsible-use safeguards also form a crucial part of the adoption environment. Generative AI introduces concerns that traditional technology-acceptance models do not fully capture, including the protection of student data, transparency regarding AI use, academic-integrity rules, teacher mediation, and equitable access. UNESCO (2023) emphasizes that educational uses of generative AI should be human-centered, transparent, inclusive, and subject to appropriate oversight. Students may consider an AI-assisted learning system useful yet remain unwilling to support its classroom adoption if they believe that it compromises privacy, produces unreliable information, facilitates academic dishonesty, or favors learners with better devices, connectivity, or access to paid services.

These concerns are especially relevant in the Philippine educational setting, where institutions and students experience uneven levels of digital readiness, internet access, device availability, and affordability. Philippine higher education institutions are increasingly required to formulate policies that balance the instructional potential of generative AI with the risks associated with misuse, inequity, and weak institutional governance. Policy-oriented work has emphasized the need for curricular reform, AI literacy, and clear institutional guidance rather than prohibition alone (Vergara, 2024). Research involving Filipino students has likewise shown that perceptions of AI use vary across educational levels and that responsible integration remains necessary (Fabro et al., 2024).

Despite the expanding literature on generative AI and gamification, these areas are often examined separately. Existing studies commonly investigate acceptance of generative AI, use of AI-based learning tools, or the effects of gamification on motivation and achievement. Less attention has been given to students' acceptance of instructional approaches that deliberately combine AI and gamified learning. It also remains unclear whether prior exposure is sufficient to produce acceptance or whether students' support depends more strongly on perceived learning value, engagement, and confidence in institutional safeguards.

The present study addresses this gap by examining the acceptance of AI-assisted gamified learning among senior high school and higher education students. It adopts a conditional-acceptance perspective in which support for classroom adoption is associated with four principal factors: prior exposure, perceived learning value, motivation and engagement, and responsible-use safeguards. The study does not measure objective improvements in academic achievement. Instead, it investigates students' perceptions of educational value and their willingness to support classroom implementation under conditions involving integrity, transparency, privacy, teacher guidance, and equitable access.

Objectives of the Study

This study aimed to examine the factors associated with students' acceptance of AI-assisted gamified learning among senior high school and higher education students. Specifically, it sought to:

1. determine the extent of students' exposure to generative AI, gamified learning activities, and combined AI-assisted gamified learning;
2. assess students' perceptions of learning value, motivation and engagement, responsible-use safeguards, and acceptability;
3. determine whether senior high school and higher education students differ significantly in their perceptions of the study constructs;
4. examine the relationships among exposure, perceived learning value, motivation and engagement, responsible-use safeguards, and acceptability;
5. identify the factors significantly associated with acceptability of classroom adoption; and
6. describe the principal concerns expressed by students regarding the classroom use of AI-assisted gamified learning.

2. Review of Related Literature

2.1 Artificial Intelligence-Assisted Learning and Perceived Learning Value

Artificial intelligence has expanded the range of digital tools available for instruction by enabling automated explanation, feedback, content generation, translation, summarization, assessment support, and adaptive practice. Earlier research on artificial intelligence in higher education identified intelligent tutoring, prediction, assessment, and personalization as among its principal applications. However, much of the early literature emphasized technological capability more than pedagogy and the role of educators in implementation (Zawacki-Richter et al., 2019). The emergence of generative AI has broadened access to these functions by allowing students to interact with conversational systems capable of producing immediate, customized responses.

Students' willingness to use generative AI is frequently associated with whether they perceive the technology as educationally useful. Chan and Hu (2023) found that students recognized benefits related to personalized learning support, writing assistance, brainstorming, and research, although these benefits were accompanied by concerns about reliability and ethical use. Romero-Rodríguez et al. (2023) similarly reported that students' perceived usefulness of ChatGPT was associated with its potential to support complex thinking and university-level learning activities. In technology-acceptance research, such perceptions correspond to performance-related beliefs, particularly the expectation that a technology will improve the quality or efficiency of academic work.

Recent studies further indicate that awareness or competence alone may not be sufficient to ensure sustained adoption. Shahzad et al. (2024) showed that perceived usefulness and trust were central to students' acceptance of ChatGPT, while Delcker et al. (2024) reported that students' AI competence was related to both intended and actual use of AI tools in learning. These findings suggest that experience with AI may facilitate adoption, but students are more likely to support its educational use when they perceive a clear contribution to comprehension, practice, feedback, and task completion. Comparable Philippine evidence shows that stakeholders perceive AI as more useful for engagement, content relevance, and learning analytics than for direct academic-performance improvement, while still identifying access, cost, bias, and privacy as implementation constraints (Rao et al., 2025).

The present study therefore uses the term perceived learning value rather than educational effectiveness. Learning value refers to students' judgments that AI-assisted gamified activities can help clarify lessons, support retention, improve practice, and contribute to mastery. Such perceptions are relevant to acceptance, but they do not constitute direct evidence that the technology improves academic achievement. Objective effectiveness would require experimental, longitudinal, or performance-based evaluation rather than cross-sectional self-report data.

2.2 Gamification, Motivation, and Learner Engagement

Gamification refers to the use of game-design elements in contexts that are not primarily games (Deterding et al., 2011). In education, commonly used elements include points, badges, progress indicators, challenges, levels, feedback, narratives, and leaderboards. These features are generally intended to make learning tasks more interactive and to encourage participation, persistence, and sustained attention.

The motivational rationale for gamification is consistent with self-determination theory, which proposes that motivation is strengthened when learners experience competence, autonomy, and relatedness (Deci & Ryan, 2000). Progress indicators and immediate feedback may support competence by making improvement visible. Learner choice and adaptive activities may contribute to autonomy, while collaborative tasks may promote relatedness. When these elements are appropriately designed, gamified activities can encourage students to remain engaged with difficult or repetitive learning tasks. Evidence from vocational education likewise suggests that internally oriented professional values are more supportive of learning motivation than externally oriented values, reinforcing the need to distinguish meaningful motivation from reward-driven participation (Yan, 2026).

Nevertheless, the effectiveness of gamification is not uniform. Dichev and Dicheva (2017) observed that enthusiasm for educational gamification has often exceeded the strength of the available evidence, particularly when game elements are implemented without sufficient attention to instructional objectives. Sailer and Homner's (2020) meta-analysis reported generally positive effects on cognitive, motivational, and behavioral outcomes, but also found that results varied across contexts, designs, and learner populations. These findings indicate that gamification should not be treated as inherently motivating.

Game mechanics may also produce unintended consequences. Excessive reliance on rewards can shift students' attention from understanding to point accumulation, while leaderboards and competition may create anxiety or discourage students who consistently perform below their peers. Novelty effects may initially increase participation but diminish over time. AI-assisted gamification may address some of these limitations by personalizing difficulty, generating adaptive practice, and providing immediate explanatory feedback. However, AI-generated activities may also weaken engagement when they are inaccurate, repetitive, opaque, or poorly aligned with learning outcomes. Motivation and engagement should therefore be assessed empirically rather than assumed to result automatically from the presence of AI or game elements. Adjacent research on Generation Z digital behavior further shows that intensive online exposure may remain predominantly passive, underscoring that frequency of use should not be equated with active or educational engagement (Dancel et al., 2026).

2.3 Responsible Use, Academic Integrity, and Institutional Safeguards

The educational use of generative AI raises governance concerns that extend beyond conventional measures of usefulness or ease of use. Students may perceive AI-assisted tools as beneficial while remaining uncertain about their reliability, fairness, privacy implications, and influence on academic integrity. Tlili et al. (2023) emphasized that systems such as ChatGPT present both educational opportunities and substantial risks, including misinformation, dependency, bias, and inappropriate use. These concerns are especially consequential when AI becomes embedded in classroom activities, assessment, or gamified performance systems.

UNESCO (2023) recommends a human-centered approach to generative AI in education that emphasizes transparency, data protection, inclusion, human oversight, and institutional capacity. Such safeguards are not merely administrative restrictions. They affect whether students perceive an AI-enabled instructional system as legitimate and trustworthy. Transparency allows students to understand when and how AI is being used, while privacy protections reduce concern over the collection and processing of personal data. Teacher oversight also remains necessary because AI-generated content may be inaccurate, incomplete, biased, or unsuitable for particular learning objectives. Practitioner evidence from another high-accountability domain similarly shows that AI is accepted most readily for assistive, lower-risk tasks and remains contingent on verification, policy institutionalization, and accountable human judgment (Bendal et al., 2026).

Academic integrity constitutes another central issue. Generative AI can support brainstorming, explanation, and formative practice, but it can also facilitate unauthorized assistance, misrepresentation of authorship, and submission of work that does not reflect the student's independent ability. Yusuf et al. (2024) found that support for generative AI in higher education coexisted with concerns about academic dishonesty and the need for ethical guidance. Clear rules regarding disclosure, permissible use, verification, and assessment are therefore essential to responsible implementation. Correlational evidence among Philippine senior high school students also indicates that dishonesty-related tendencies may be associated with underlying personality vulnerabilities, reinforcing the need for explicit preventive integrity structures rather than reliance on student self-regulation alone (Lolong et al., 2026).

Equitable access must also be considered. AI-assisted learning environments may depend on stable internet connectivity, appropriate devices, or paid subscriptions. Where access is unequal, students with greater financial and technological resources may receive more extensive support, feedback, or practice opportunities. Institutional safeguards should therefore include accessible alternatives, adequate infrastructure, and policies that prevent required learning activities from disadvantaging students with limited resources. In this sense, responsible use operates as a condition of acceptance because students may support AI-assisted gamification only when it is transparent, supervised, fair, and accessible.

2.4 Technology Acceptance and Conditional Adoption

The Technology Acceptance Model identifies perceived usefulness and perceived ease of use as primary determinants of individuals' intention to adopt technology (Davis, 1989). The Unified Theory of Acceptance and Use of Technology expanded this perspective by including performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). Its later extension incorporated hedonic motivation, habit, and additional contextual influences on technology use (Venkatesh et al., 2012).

Recent research on generative AI confirms the relevance of these acceptance factors. Strzelecki (2024) found that university students' acceptance of ChatGPT was associated with performance expectancy and other UTAUT-related variables. Shahzad et al. (2024) further demonstrated that trust and perceived usefulness contributed to awareness, acceptance, and adoption in higher education. These findings indicate that students do not adopt AI solely because it is available. Their willingness to use it depends on whether they expect meaningful academic benefits and whether the surrounding environment supports legitimate and reliable use. Adjacent evidence from higher education marketing likewise shows that extensive digital exposure and awareness do not translate automatically into stronger behavioral intention, as trust and engagement quality remain more consequential than exposure alone (Espelita et al., 2026).

The present study does not constitute a complete test of either TAM or UTAUT because the questionnaire did not measure all of their standard constructs, particularly perceived ease of use, effort expectancy, social influence, and habit. Instead, it applies a TAM-informed conditional-acceptance framework. Prior exposure represents familiarity and experience; perceived learning value reflects performance-related usefulness; motivation and engagement capture the affective and behavioral appeal of the instructional approach; and responsible-use safeguards represent governance-oriented facilitating conditions.

The outcome construct is acceptability of classroom adoption rather than actual continued use. This distinction is important because the study investigates whether students support institutional implementation under specified educational and ethical conditions. Acceptance is therefore conceptualized as conditional: students may endorse AI-assisted gamified learning when it contributes to learning, sustains engagement, preserves teacher guidance, protects data, supports academic integrity, and remains accessible.

2.5 Synthesis and Literature Gaps

The literature indicates that artificial intelligence and gamification can contribute to educational practice, but neither technology guarantees meaningful learning or sustained acceptance. Generative AI is valued for personalized support, explanation, feedback, and productivity, yet its use is accompanied by concerns regarding accuracy, dependence, academic integrity, privacy, and unequal access (Chan & Hu, 2023; Tlili et al., 2023; Yusuf et al., 2024). Gamification can improve motivation and participation, although its effects depend on instructional design, context, and the appropriateness of the game mechanics employed (Dichev & Dicheva, 2017; Sailer & Homner, 2020).

Technology-acceptance research further suggests that perceived usefulness, trust, and facilitating conditions are more influential than exposure alone in shaping adoption intentions (Davis, 1989; Shahzad et al., 2024; Strzelecki, 2024). However, most existing studies examine generative AI and gamification as separate educational innovations. Limited evidence is available on how students evaluate their combined use in classroom instruction. It is also unclear whether familiarity with AI and gamified activities independently contributes to acceptance after learning value, engagement, and governance safeguards are considered.

The Philippine context remains comparatively underexamined. Existing local research has identified differences in AI perceptions and utilization among students and has emphasized the need for responsible integration and AI literacy (Fabro et al., 2024; Vergara, 2024). At the institutional level, Philippine HEIs often frame digitalization primarily as continuity infrastructure rather than as a fully integrated pedagogical strategy, indicating that adoption depth depends on curricular and governance alignment (Atento, 2025). Related evidence from Philippine health professions education also positions academic leadership as a mediating function in balancing digital change, pedagogical quality, student well-being, and institutional viability (Bermido et al., 2025). Nevertheless, there is limited empirical evidence on student support for AI-assisted gamified learning across senior high school and higher education. The present study addresses this gap by examining whether acceptance is associated with exposure, perceived learning value, motivation and engagement, and responsible-use safeguards, while also identifying students' principal concerns regarding classroom implementation.

3. Methodology

3.1 Research Design

The study employed a cross-sectional analytical survey design with supplementary content analysis of responses to an open-ended question. The quantitative component described students' exposure to artificial intelligence and gamified learning, assessed their perceptions of learning value, motivation and engagement, responsible-use safeguards, and acceptability, and examined differences and relationships among these constructs. The open-ended component was used to identify recurring concerns regarding the classroom implementation of AI-assisted gamified learning.

The study was not treated as a full mixed-methods investigation because the qualitative data were derived from a single short-response item rather than from interviews, focus-group discussions, or an independently designed qualitative phase. The design enabled the identification of statistical associations but did not permit causal conclusions regarding the effects of AI-assisted gamified learning.

3.2 Participants and Sampling

The analytical dataset consisted of 136 student responses collected from February 5 to May 6, 2026. The participants included 91 higher education students, representing 66.9% of the sample, and 45 senior high school students, representing 33.1%. Their ages ranged from 16 to 25 years.

Of the respondents, 95 identified as female, 40 identified as male, and one did not indicate sex. The participants were enrolled in academic programs or strands that included business, accountancy, management accounting, entrepreneurship, hospitality management, Accountancy, Business and Management, and Humanities and Social Sciences. Because some program labels were inconsistently entered and several program groups contained only a small number of respondents, program-level inferential comparisons were not conducted.

The survey link was made available to eligible students. Because participation depended on voluntary response and no probability-based selection procedure was used, the sample was treated as a voluntary non-probability sample. The participating institution is not identified in the manuscript to reduce the possibility of indirectly identifying the student population from which the respondents were drawn.

3.3 Research Instrument

Data were collected using a researcher-developed online questionnaire administered through Google Forms. The instrument was constructed by the lead author through a review and synthesis of recurring constructs in the literature on artificial intelligence-assisted learning, educational gamification, technology acceptance, student engagement, and responsible AI use. The literature review guided the identification of five principal constructs: exposure and use, perceived learning value, motivation and engagement, responsible-use safeguards, and acceptability of classroom adoption.

A generative artificial intelligence tool, ChatGPT, was used during the preliminary development stage as a brainstorming aid in organizing the recurring concepts identified from the literature and proposing possible item formulations. The lead author reviewed, selected, revised, and finalized all questionnaire items and retained full responsibility for the instrument's conceptual alignment, wording, and appropriateness for the intended respondents. The instrument was not adopted directly from ChatGPT output or from a previously standardized questionnaire.

The questionnaire contained 32 variables organized into demographic, exposure, perceptual, acceptance, and open-ended components. The first section obtained information on educational level, academic program or strand, age, sex, and self-rated academic standing. The exposure section contained three five-point agreement items assessing respondents' prior use of generative AI for schoolwork, experience with gamified learning activities or applications, and experience with activities combining AI and gamification. Two additional questions measured the reported frequency of AI use and participation in classroom gamification.

The succeeding sections contained five items each measuring perceived learning value, motivation and engagement, responsible-use safeguards, and acceptability and support for classroom adoption. Agreement items were rated using a five-point scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The two behavioral frequency questions were rated from 1 (Never) to 5 (Very Often). The final question invited respondents to identify their principal concern regarding the classroom use of AI-assisted gamified learning.

The perceived learning value items assessed whether AI-assisted gamification could clarify lessons, support retention, improve performance in graded tasks, facilitate practice toward mastery, and improve perceived learning outcomes. Motivation and engagement items addressed interest in class participation, sustained attention, persistence, motivation from feedback, and engagement with schoolwork. The responsible-use safeguards scale measured the importance of academic-integrity rules, transparency concerning AI use, protection of student data, teacher guidance, and equitable access. The acceptability scale assessed willingness to use the approach, support for its integration into additional subjects and regular teaching, conditional support when safeguards were present, and its overall acceptability as an instructional innovation.

Internal consistency was examined using Cronbach's alpha. Reliability coefficients were .789 for exposure, .926 for perceived learning value, .908 for motivation and engagement, .920 for responsible-use safeguards, and .911 for acceptability. These coefficients indicated acceptable to excellent internal consistency within the present sample.

The instrument did not undergo formal expert validation, pilot testing, exploratory factor analysis, or confirmatory factor analysis before administration. Accordingly, the reliability coefficients are interpreted as evidence of internal consistency in the present sample and not as proof of complete psychometric validity. The measures are therefore treated as researcher-developed exploratory scales.

3.4 Data-Gathering Procedure

The study protocol and survey instrument were reviewed and approved by the institutional ethics board of the participating educational institution before data collection began. After approval, the questionnaire was administered electronically through Google Forms.

The introductory portion of the form presented the purpose of the study, the voluntary nature of participation, the intended use of the responses, and the respondents' right to decline or discontinue participation without penalty. Respondents proceeded with the questionnaire only after indicating informed consent.

For senior high school respondents younger than 18 years, parental or guardian consent was obtained before survey participation. The minor respondents were also informed of the study and voluntarily assented to participate.

The form did not collect names, student numbers, email addresses, or other direct personal identifiers. The researchers therefore could not link individual answers to identifiable students. Completed responses were downloaded for screening and statistical analysis and were reported only in aggregated form.

3.5 Data Screening and Scale Construction

All 136 submitted responses were retained in the primary analysis. No exact duplicate records were identified, and no missing responses were found among the 23 agreement items. One respondent did not provide information on sex; consequently, regression models that included sex were based on 135 cases.

Composite scores were calculated as the arithmetic mean of the items assigned to each construct: exposure (Items 6-8), perceived learning value (Items 11-15), motivation and engagement (Items 16-20), responsible-use safeguards (Items 21-25), and acceptability and adoption support (Items 26-30). The two behavioral frequency items were analyzed separately and were not incorporated into the exposure composite. Their exclusion preserved the conceptual consistency of the exposure scale and avoided reducing its internal reliability.

Thirteen respondents selected the same response category across all 23 agreement items. Such uniform response patterns may indicate either a genuine consistent position or low-effort responding. These cases were not automatically deleted because uniformity alone did not establish that the responses were invalid. Instead, a sensitivity analysis was conducted by re-estimating the final regression model after excluding the 13 cases.

A second robustness analysis addressed possible wording overlap between the responsible-use safeguards scale and Item 29 of the acceptability scale, which explicitly conditioned support on the presence of safeguards. The acceptability score was recalculated without Item 29, and the regression model was re-estimated using the resulting four-item scale.

3.6 Data Analysis

Frequencies and percentages were used to summarize the respondents' educational level, sex, academic standing, AI-use frequency, and exposure to gamified activities. Means and standard deviations were calculated for individual questionnaire items and composite-scale scores. Cronbach's alpha was used to assess the internal consistency of the multi-item scales.

Welch's independent-samples t test was used to compare senior high school and higher education students because the two groups differed in size and did not necessarily meet the assumption of equal variances. Cohen's d was reported to indicate the magnitude of group differences. Mann-Whitney U tests were additionally used as nonparametric sensitivity checks for the educational-level comparisons.

Pearson product-moment correlations were calculated to examine the bivariate relationships among exposure, perceived learning value, motivation and engagement, responsible-use safeguards, and acceptability.

Hierarchical ordinary least-squares regression was used to determine the factors statistically associated with acceptability. Educational level and sex were entered in the first model. Exposure was added in the second model. Perceived learning value, motivation and engagement, and responsible-use safeguards were entered in the final model. Educational level was coded as 1 for higher education and 0 for senior high school, while sex was coded as 1 for female and 0 for male.

HC3 heteroskedasticity-robust standard errors were used because the composite measures were bounded and the residual distributions did not fully satisfy normality assumptions. Variance inflation factors were examined to assess multicollinearity. Statistical significance was evaluated at an alpha level of .05. Exact probability values were reported except when $p < .001$.

Responses to the open-ended question were reviewed and grouped into recurring concern categories. Statements indicating no concern, such as "none" or "N/A," were excluded from thematic counting. A response could be assigned to more than one category when it contained multiple concerns. Accordingly, the reported qualitative frequencies represented coded mentions rather than mutually exclusive numbers of respondents.

3.7 Ethical Considerations

The research protocol and survey instrument were approved by the institutional ethics board of the participating educational institution before the commencement of the study. The ethics board did not issue a protocol number. The institution is described generically in the manuscript to protect the anonymity of the participating student population.

Participation was voluntary, and informed consent information was provided in the introductory section of the Google Forms questionnaire. Respondents were informed of the study's purpose, procedures, intended use of the data, and their right to decline or discontinue participation without penalty.

Parental or guardian consent was obtained for senior high school respondents younger than 18 years. The minor respondents also provided voluntary assent before completing the questionnaire.

No names, institutional identification numbers, email addresses, or other direct identifiers were collected. Individual respondents could not be identified by the researchers. The responses were treated confidentially, accessed only for research purposes, and presented in aggregate form.

4. Results and Discussion

4.1 Respondent Characteristics and Reported Use

The study included 136 respondents, of whom 91 (66.9%) were higher education students and 45 (33.1%) were senior high school students. Their ages ranged from 16 to 25 years. Ninety-five respondents (69.9%) identified as female, 40 (29.4%) identified as male, and one respondent did not indicate sex. Most respondents described their academic standing as average (84.6%), while 11.0% reported high academic standing and 4.4% reported low academic standing.

Generative AI was more frequently used than gamified classroom activities. Sixty-five respondents (47.8%) reported using AI often or very often, while 61 (44.9%) used it sometimes. Only 10 respondents (7.4%) reported never or rarely using AI. By contrast, only 25 respondents (18.4%) reported participating in gamified activities often or very often. Most experienced gamified learning sometimes (50.7%), while 30.9% reported never or rarely encountering it.

These results indicate that generative AI had already become relatively familiar in the respondents' academic routines, whereas gamification remained less consistently integrated into classroom instruction. This difference is relevant because exposure to AI did not necessarily imply equivalent experience with combined AI-assisted gamified learning.

4.2 Perceptions of AI-Assisted Gamified Learning

Table 1. *Descriptive Statistics and Internal Consistency of the Study Constructs*

Construct	M	SD	Cronbach's alpha	Descriptive interpretation
Exposure and use	3.61	0.77	.789	Favorable
Perceived learning value	3.72	0.66	.926	Favorable
Motivation and engagement	3.45	0.61	.908	Moderate
Responsible-use safeguards	3.96	0.69	.920	Favorable
Acceptability and adoption support	3.65	0.66	.911	Favorable

Note. Scores ranged from 1 to 5. The descriptive labels are interpretive aids and not empirically validated cutoffs.

Responsible-use safeguards obtained the highest composite mean ($M = 3.96$, $SD = 0.69$), indicating that the respondents placed substantial importance on the conditions governing classroom implementation. Perceived learning value followed with a mean of 3.72, while acceptability and adoption support obtained a mean of 3.65. Exposure and use were also generally favorable ($M = 3.61$).

Motivation and engagement received the lowest composite mean ($M = 3.45$, $SD = 0.61$). The result suggests that the respondents were not uniformly convinced that AI-assisted gamification would automatically increase interest, sustained attention, or active participation. Although they generally recognized its potential educational value, they appeared more cautious about its capacity to produce lasting engagement.

At the item level, protection of student data received the highest rating (M = 4.07), followed by equitable access (M = 3.99), transparency regarding AI use (M = 3.97), and active teacher guidance (M = 3.93). These findings show that students' strongest agreement concerned responsible implementation rather than the novelty or motivational appeal of the technology.

Among the learning-value items, support for practice until mastery received the highest mean (M = 3.80). The lowest-rated motivation items concerned increased interest in classroom participation and feedback motivating continued learning, both of which obtained means of 3.38. These results reinforce the distinction between perceiving a system as useful and experiencing it as intrinsically engaging.

All scales demonstrated acceptable to excellent internal consistency. The exposure scale obtained an alpha coefficient of .789, while the four five-item scales produced coefficients ranging from .908 to .926. These estimates support the internal coherence of the measures in the present sample, although they do not establish full construct validity.

4.3 Differences Between Higher Education and Senior High School Students

Welch's independent-samples t tests were used to examine whether higher education and senior high school students differed in their perceptions of AI-assisted gamified learning.

Table 2. *Differences Between Higher Education and Senior High School Students*

Construct	HE M	SHS M	t	Df	p	Cohen's d
Exposure and use	3.74	3.34	2.57	63.71	.013	0.53
Perceived learning value	3.81	3.52	2.28	74.86	.026	0.44
Motivation and engagement	3.55	3.25	2.61	77.67	.011	0.50
Responsible-use safeguards	4.05	3.76	2.24	70.91	.028	0.44
Acceptability and adoption support	3.79	3.37	3.52	77.89	< .001	0.67

Note. HE = higher education (n = 91); SHS = senior high school (n = 45). Positive effect sizes indicate higher scores among higher education students.

Higher education students reported significantly higher scores on all five constructs. The largest difference concerned acceptability and adoption support, for which higher education students obtained a mean of 3.79 compared with 3.37 among senior high school students, $t(77.89) = 3.52$, $p < .001$, $d = 0.67$. The effect size was moderate to relatively large.

Differences in exposure and motivation and engagement produced moderate effect sizes, while differences in perceived learning value and responsible-use safeguards were small to moderate. The findings suggest that higher education students were more familiar with AI-assisted learning and more favorable toward its classroom adoption.

The nonparametric Mann-Whitney sensitivity tests produced the same substantive conclusions. No significant sex difference was observed for acceptability, $p = .663$. Educational level, rather than sex, therefore appeared more relevant to the initial differences in acceptance.

4.4 Relationships Among the Study Constructs

Pearson correlations were calculated to determine the associations among exposure, perceived learning value, motivation and engagement, responsible-use safeguards, and acceptability.

Table 3. *Correlations Among Exposure, Learning Value, Engagement, Safeguards, and Acceptability*

Construct	1	2	3	4	5
1. Exposure and use	-				
2. Perceived learning value	.546***	-			
3. Motivation and engagement	.390***	.731***	-		
4. Responsible-use safeguards	.350***	.451***	.407***	-	
5. Acceptability	.444***	.716***	.693***	.552***	-

*Note. N = 136. Lower triangle shown. *** p < .001.*

All study constructs were positively and significantly correlated. Acceptability was most strongly associated with perceived learning value, $r = .716$, $p < .001$, and motivation and engagement, $r = .693$, $p < .001$. These results indicate that students who perceived stronger educational benefits and greater engagement were more likely to support classroom adoption.

Responsible-use safeguards were moderately associated with acceptability, $r = .552$, $p < .001$. Exposure also showed a positive relationship with acceptability, although the association was weaker, $r = .444$, $p < .001$.

Perceived learning value and motivation and engagement were strongly correlated, $r = .731$, $p < .001$. Despite this relatively high association, variance inflation factors in the regression analysis ranged from 1.10 to 2.68, indicating that multicollinearity did not reach a problematic level.

4.5 Factors Associated with Acceptability

Hierarchical multiple regression was used to determine whether exposure, perceived learning value, motivation and engagement, and responsible-use safeguards were independently associated with acceptability after educational level and sex were considered.

Table 4. *Hierarchical Regression Predicting Acceptability of AI-Assisted Gamified Learning*

Model	Predictor	B	HC3 SE	beta	t	p
1	Higher education	0.428	0.122	.306	3.50	< .001
	Female	-0.069	0.130	-.048	-0.53	.595
2	Higher education	0.288	0.103	.206	2.80	.005
	Female	0.019	0.121	.013	0.15	.877
	Exposure and use	0.337	0.102	.395	3.29	< .001
3	Higher education	0.151	0.082	.108	1.85	.064
	Female	-0.111	0.075	-.077	-1.47	.141
	Exposure and use	0.006	0.061	.007	0.09	.927
	Perceived learning value	0.344	0.106	.346	3.24	.001
	Motivation and engagement	0.333	0.106	.309	3.14	.002
	Responsible-use safeguards	0.248	0.069	.256	3.61	< .001

Note. N = 135 because one respondent did not indicate sex. Model 1 $R^2 = .095$. Model 2 $R^2 = .237$. Model 3 $R^2 = .643$; adjusted $R^2 = .626$. Higher education = 1; senior high school = 0. Female = 1; male = 0.

In Model 1, higher education status was significantly associated with greater acceptability, while sex was not significant. The demographic variables explained 9.5% of the variance in acceptability.

The inclusion of exposure in Model 2 increased the proportion of explained variance to 23.7%. At this stage, both educational level and exposure were statistically significant. This result indicates that greater familiarity with AI and gamified learning was associated with stronger acceptance before students' evaluative perceptions were considered.

The final model explained 64.3% of the variance in acceptability. Perceived learning value emerged as the strongest independent factor, beta = .346, $p = .001$, followed by motivation and engagement, beta = .309, $p = .002$, and responsible-use safeguards, beta = .256, $p < .001$.

Exposure became negligible after the three perceptual constructs were included, beta = .007, $p = .927$. Educational level was also reduced to marginal statistical significance, beta = .108, $p = .064$. These findings suggest that higher education students' stronger acceptance was largely accounted for by their more favorable judgments of learning value, engagement, and responsible implementation.

Overall, perceived learning value, motivation and engagement, and responsible-use safeguards were independently associated with acceptability. Exposure was associated with acceptability at the bivariate level but did not remain significant after adjustment. The direct educational-level difference was significant, although its contribution diminished after the perceptual variables were considered.

Robustness Analyses

The sensitivity analysis excluding the 13 respondents who gave uniform answers across all agreement items produced the same substantive pattern. Perceived learning value remained significant, beta = .343, $p < .001$; motivation and engagement remained significant, beta = .314, $p = .001$; and safeguards remained significant, beta = .245, $p < .001$. Exposure remained nonsignificant, beta = .041, $p = .589$.

The four-item acceptability scale, which excluded the item explicitly referring to the presence of safeguards, retained high internal consistency, alpha = .898. In the corresponding regression model, perceived learning value, beta = .360, $p = .001$; motivation and engagement, beta = .339, $p < .001$; and safeguards, beta = .193, $p = .010$, remained statistically significant.

The safeguards result therefore cannot be explained solely by wording overlap between the predictor and the acceptability outcome.

4.6 Concerns Regarding Classroom Implementation

Forty-three responses contained at least one discernible concern. Because a response could contain multiple concerns, the counts in Table 5 represent coded mentions rather than mutually exclusive respondents.

Table 5. *Recurring Concerns Regarding AI-Assisted Gamified Learning*

Concern	Coded mentions	Summary of responses
Overdependence and reduced independent or critical thinking	18	Reliance on AI, diminished thinking, weaker independent work, and possible long-term dependency
Responsible use, moderation, and academic misuse	8	Need for controlled use, monitoring, integrity rules, and prevention of abuse
Teacher guidance and preservation of the human role	6	Teacher competence, supervision, human intervention, and concern about diminishing the teacher's role
Alignment with curriculum, assessment, and learning objectives	6	Possible mismatch with examinations, lessons, grading practices, or expected outcomes
Distraction, reward focus, and unhealthy competition	5	Attention shifting toward points, rankings, or winning rather than understanding
Access and technical constraints	5	Paid features, internet connectivity, advertisements, device limitations, and system restrictions
Accuracy and reliability	3	Incorrect outputs and difficulty evaluating AI-generated information
Privacy and data protection	2	Risk of data breaches and inadequate protection of student information

The most frequently expressed concern was overdependence on AI and the possible weakening of independent or critical thinking. Respondents worried that excessive reliance on automated assistance could reduce students' willingness or ability to solve problems without technological support.

Several responses did not reject AI-assisted gamification outright but called for moderation, academic-integrity rules, and active monitoring. Teacher guidance was repeatedly identified as necessary to verify content, mediate use, and preserve the human role in instruction.

Some respondents also questioned whether game-based mechanics might redirect attention toward rewards, rankings, or competition rather than learning. Concerns regarding paid access, connectivity, accuracy, and privacy further demonstrate that acceptance depends on the conditions of implementation.

4.7 Discussion

The central finding of the study is that students' acceptance of AI-assisted gamified learning was more strongly associated with perceived learning value, motivation and engagement, and responsible-use safeguards than with prior exposure. Although exposure was positively correlated with acceptability and contributed significantly in the intermediate regression model, its effect disappeared once students' evaluative perceptions were included. Familiarity may therefore enable students to form judgments about the technology, but familiarity alone does not ensure support for institutional adoption.

This result is consistent with technology-acceptance research emphasizing perceived usefulness and performance expectancy as proximal influences on adoption. Davis (1989) proposed that individuals are more likely to accept a technology when they believe it will improve performance. Similarly, Shahzad et al. (2024) and Strzelecki (2024) identified perceived usefulness, trust, and performance-related expectations as important factors in students' adoption of generative AI. The present findings extend this perspective by showing that exposure to AI or gamification becomes comparatively unimportant when students do not perceive a clear learning benefit.

Perceived learning value was the strongest independent factor associated with acceptability. Students were more willing to support classroom use when they believed that AI-assisted gamification could clarify lessons, improve practice, support mastery, and contribute to academic performance. This pattern is consistent with findings that students value AI for personalized explanation, brainstorming, research assistance, and learning support (Chan & Hu, 2023). It also confirms the importance of distinguishing between technological novelty and pedagogical utility. Institutions should therefore introduce AI-assisted gamification only when its functions are explicitly aligned with defined learning outcomes.

Motivation and engagement also independently contributed to acceptability, but their descriptive ratings were lower than those of the other constructs. This result reflects the mixed evidence in the gamification literature. Sailer and Homner (2020) reported generally positive motivational and behavioral effects, while Dichev and Dicheva (2017) cautioned that the evidence remains dependent on design and context. The respondents' concerns regarding rankings, competition, and reward-seeking indicate that game elements may not always produce meaningful engagement.

The findings suggest that gamification should emphasize mastery, explanatory feedback, learner choice, revision, and visible progress rather than competition alone. This approach is consistent with self-determination theory, which holds that sustained motivation depends on competence, autonomy, and relatedness rather than purely external rewards (Deci & Ryan, 2000). AI can support these needs through adaptive practice and individualized feedback, but only when the system remains understandable, educationally relevant, and under human supervision.

Responsible-use safeguards obtained the highest mean and remained significant in both the primary and robustness models. This finding indicates that privacy, transparency, academic integrity, teacher guidance, and equitable access are not peripheral administrative concerns. They form part of the mechanism through which students evaluate whether the innovation is legitimate and acceptable.

The result is consistent with UNESCO's (2023) human-centered framework, which emphasizes data protection, transparency, inclusion, and human oversight. It also aligns with multicultural evidence showing that student interest in generative AI coexists with concerns regarding ethical use and academic dishonesty (Yusuf et al., 2024). Clear governance may therefore facilitate adoption rather than merely restrict it. Students may be more willing to use AI-assisted tools when they understand how the technology operates, what forms of use are permitted, and how their data and academic rights are protected.

Equitable access was among the highest-rated individual safeguards. This concern is particularly relevant in the Philippine educational context, where students differ in device ownership, internet stability, subscription access, and institutional support. Required activities should not depend on paid platforms or continuous broadband unless equivalent access and alternatives are provided. Otherwise, the technology may widen rather than reduce educational inequality.

Higher education students reported more favorable perceptions than senior high school students across all constructs. However, educational level was no longer conventionally significant in the final regression model. The result suggests that the difference was not simply an inherent preference associated with educational stage. Instead, higher education students may have had more opportunities to experience useful and well-supported applications of AI.

Senior high school students may become similarly accepting when implementation is developmentally appropriate, clearly connected to learning, and supported by teacher mediation and safeguards. This is especially important because younger students may require stronger guidance regarding verification, disclosure, privacy, and independent reasoning.

The open-ended responses reinforce the conditional-acceptance interpretation. Students did not generally express absolute opposition to AI-assisted gamification. Their concerns focused on the possibility of overdependence, reduced critical thinking, academic misuse, weak teacher supervision, inaccurate information, unequal access, and excessive competition. Acceptance was therefore contingent on how the technology would be designed, governed, and incorporated into instruction.

Limitations

The findings should be interpreted in light of several limitations. The sample was relatively small, voluntary, non-probability based, and concentrated in selected academic programs; consequently, the results cannot be generalized to all Philippine students. The cross-sectional, self-report design identifies associations but does not establish causal effects or objective improvements in achievement, retention, or mastery. Collecting all quantitative measures through one questionnaire may also have increased common-method influence. Although the scales demonstrated strong internal consistency, the researcher-developed instrument had not undergone formal expert validation, pilot testing, or factor-analytic validation before administration. The safeguarding and acceptability constructs had partial conceptual proximity, although the reduced-scale robustness analysis preserved the main result. Finally, the qualitative component was limited to one brief open-ended item and cannot provide the depth available from interviews or focus groups.

Overall, the findings do not support a familiarity-only account of adoption. Exposure may initiate interest or reduce uncertainty, but acceptance depends more substantially on whether students perceive the technology as useful, engaging, transparent, supervised, and equitable. Educational institutions should therefore prioritize pedagogical design and responsible governance rather than treating technological availability as evidence of successful implementation.

5. Conclusions, Recommendations, and Implications

5.1 Conclusions

The study examined students' acceptance of AI-assisted gamified learning in relation to prior exposure, perceived learning value, motivation and engagement, and responsible-use safeguards.

Students had generally favorable exposure to generative artificial intelligence and AI-assisted learning, although their experience with gamified classroom activities was less frequent. AI use had already become relatively common among the respondents, but combined AI-assisted gamification had not yet reached the same level of routine classroom integration.

Students generally perceived AI-assisted gamified learning as educationally valuable and acceptable. They believed that it could support lesson clarification, practice, mastery, and academic performance. However, motivation and engagement received only a moderate rating, indicating that students did not automatically regard gamification as inherently interesting or sustaining. The presence of game elements alone therefore does not guarantee meaningful participation.

Responsible-use safeguards were given the highest importance among the study constructs. Students placed particular emphasis on data privacy, equitable access, transparency regarding AI use, academic-integrity rules, and active teacher guidance. Governance conditions therefore form an integral part of students' evaluation of educational technology.

Higher education students reported significantly more favorable perceptions than senior high school students across exposure, learning value, motivation and engagement, safeguards, and acceptability. However, the effect of educational level was substantially reduced after the perceptual variables were included in the regression model. The difference between the two groups was therefore largely associated with how useful, engaging, and responsibly implemented they perceived the technology to be.

Acceptability was positively related to all four antecedent constructs. Its strongest relationships were with perceived learning value and motivation and engagement, followed by responsible-use safeguards. Exposure was also associated with acceptability at the bivariate level, but the relationship was comparatively weaker.

Perceived learning value, motivation and engagement, and responsible-use safeguards remained statistically significant factors associated with acceptability in the final regression model. Prior exposure did not remain significant after these variables were considered. Familiarity with AI or gamification alone was therefore insufficient to account for students' support for classroom implementation.

The open-ended responses confirmed that acceptance was conditional. The principal concerns involved overdependence on AI, weakened critical thinking, academic misuse, diminished teacher involvement, misalignment with learning objectives, excessive competition, unequal access, inaccurate outputs, and privacy risks. AI-assisted gamified learning is therefore more likely to be accepted when it is pedagogically purposeful, developmentally appropriate, teacher-mediated, transparent, privacy-protective, academically responsible, and accessible to all students.

5.2 Recommendations

1. Educational institutions should adopt AI-assisted gamified learning gradually and through structured pilot implementation rather than through immediate large-scale deployment. Pilot programs should be evaluated in terms of learning alignment, student participation, accessibility, data protection, and unintended effects before expansion.
2. Teachers should begin with clearly defined learning outcomes and use AI or game mechanics only when these features contribute directly to explanation, practice, feedback, mastery, or assessment for learning. Technological novelty should not serve as the primary basis for adoption.
3. Gamification design should prioritize mastery, progress, learner choice, revision, and meaningful feedback. Excessive dependence on points, badges, leaderboards, or competitive ranking should be avoided, particularly when these features influence grades or create pressure among students. Collaborative and noncompetitive mechanics may be used where they better support inclusion and engagement.
4. Institutions should establish written guidelines governing the acceptable use of generative AI in instruction and assessment. These policies should specify permitted and prohibited uses, disclosure requirements, standards for source verification, responsibilities for checking AI-generated content, and consequences for academic misuse.
5. Teacher mediation should remain central to implementation. Teachers should verify AI-generated materials, contextualize outputs, explain limitations, monitor student use, and retain authority over instructional and assessment decisions. Professional development should include AI literacy, prompt evaluation, misinformation detection, privacy awareness, and ethical classroom integration.

6. Students should receive explicit instruction on responsible AI use. This should include verification of outputs, recognition of hallucinations and bias, proper attribution or disclosure, protection of personal information, preservation of independent reasoning, and appropriate limits on automated assistance.
7. Institutions should provide equitable access to required technologies. AI-assisted activities should not depend exclusively on paid subscriptions, high-end devices, or uninterrupted broadband unless equivalent institutional support is available. Computer laboratories, licensed platforms, low-bandwidth alternatives, and non-AI options should be provided where necessary.
8. For senior high school implementation, stronger developmental safeguards should be applied. These should include closer teacher supervision, age-appropriate explanations of AI limitations, parental communication where appropriate, and activities designed to strengthen rather than replace independent thinking.
9. Future studies should examine actual learning outcomes rather than relying solely on perceived value and acceptance. Experimental or quasi-experimental designs may compare AI-assisted gamified instruction with conventional instruction, gamification without AI, and AI-supported learning without gamification.
10. Further instrument development is recommended. The researcher-developed scales should undergo expert review, pilot testing, cognitive interviewing, exploratory factor analysis, confirmatory factor analysis, and measurement-invariance testing across educational levels.
11. Longitudinal research should determine whether acceptance and engagement persist after the novelty of AI-assisted gamification declines. Additional studies may also examine the moderating roles of AI literacy, teacher support, trust, digital access, academic discipline, socioeconomic conditions, and prior gaming experience.

5.3 Implications of the Study

Educational Implications. The findings indicate that effective implementation should be guided by pedagogy rather than technology. AI-assisted gamification is more likely to gain student support when it visibly contributes to learning and when game mechanics strengthen rather than distract from mastery. Educational design should therefore integrate AI and gamification as instructional supports, not as substitutes for sound teaching.

Institutional Implications. Responsible-use safeguards function as conditions of acceptance. Institutional policies concerning privacy, transparency, academic integrity, teacher oversight, and access may influence students' willingness to support adoption. Governance is therefore not merely a compliance requirement but part of the educational implementation process.

Leadership and Management Implications. School leaders should treat AI-assisted gamified learning as an organizational change initiative requiring policy development, staff preparation, infrastructure, ethical oversight, student orientation, and ongoing evaluation. Successful adoption depends on coordinated institutional leadership rather than isolated classroom experimentation.

Equity Implications. The high importance assigned to equitable access indicates that AI-assisted education may reproduce existing inequalities when access depends on subscriptions, devices, or stable connectivity. Institutions must ensure that innovation does not create different levels of learning opportunity for students with different technological resources.

Theoretical Implications. The results support a conditional-acceptance perspective. Exposure was associated with acceptability but lost significance after perceived learning value, motivation and engagement, and safeguards were introduced. This suggests that familiarity is a distal condition, whereas pedagogical value, affective engagement, and governance legitimacy are more immediate correlates of acceptance. The study also suggests that responsible-use safeguards may operate as governance-oriented facilitating conditions within technology-acceptance frameworks.

Methodological Implications. The study demonstrates the value of combining descriptive, comparative, correlational, multivariable, robustness, and open-ended analyses when examining educational-technology acceptance. The sensitivity tests strengthened the interpretation by showing that the central findings remained stable after uniform-response cases and a potentially overlapping acceptability item were addressed. However, the researcher-developed instrument remains exploratory, and subsequent research should strengthen the measurement model across institutions and student populations.

Declarations

Ethics Approval and Consent to Participate

The study protocol and survey instrument were approved by the institutional ethics board of the participating educational institution before data collection. No protocol number was issued. The institution is not named to protect the anonymity of the participating student population. Participation was voluntary, and informed consent was obtained electronically before respondents completed the online questionnaire. For senior high school respondents younger than 18 years, parental or guardian consent and student assent were obtained before participation. No direct personal identifiers were collected, and all responses were analyzed and reported in aggregate form.

Data Availability

The de-identified dataset may be made available by the corresponding author subject to institutional approval and applicable consent and privacy restrictions.

Declaration of Generative AI Use

ChatGPT was used during the preliminary development of the researcher-designed questionnaire to assist in organizing literature-derived concepts and generating possible item formulations. The authors independently reviewed, revised, selected, and approved the final items and assume full responsibility for the instrument and the manuscript. ChatGPT was not listed as an author.

6. References

Atento, R. G. (2025). Exploring E-Learning for Sustainable Development: Integrating SDGs in Management Education at Philippine Higher Education Institutions. *International Journal of Health & Business Analytics*, *1*(1). https://doi.org/10.65166/2qcjx561

Bendal, A., Sabasa, S. A., Espelita, C. A. M. H., & Atento, R. G. O. (2026). Artificial intelligence as disruptive technology in accounting: A qualitative study of practitioner perceptions on automation, judgment, and decision support. *Journal of Enterprise Strategy & Management Innovation*, *1*(1). https://doi.org/10.65166/0sdayg70

Bermido, C. M., Quinto, L. F., & Atento, R. G. O. (2025). A qualitative thematic review of contemporary challenges affecting health professions education: Implications for higher education leadership. *International Journal of Health and Business Analytics*, *1*(2). https://doi.org/10.65166/yfm5w791

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, *20*, Article 43. https://doi.org/10.1186/s41239-023-00411-8

Dancel, M. R., España, G. B., Asnar, D. A., Batol, C. Y., & Atento, R. G. (2026). Introversion and passive social media engagement among generation Z college students: A descriptive-correlational study. *International Journal of Behavioral and Social Analytics*, *1*(1). https://doi.org/10.65166/d56jma06

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340. https://doi.org/10.2307/249008

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, *11*(4), 227-268. https://doi.org/10.1207/S15327965PLI1104_01

Delcker, J., Heil, J., Ifenthaler, D., Seufert, S., & Spirgi, L. (2024). First-year students' AI-competence as a predictor for intended and de facto use of AI-tools for supporting learning processes in higher education. *International Journal of Educational Technology in Higher Education*, *21*, Article 18. https://doi.org/10.1186/s41239-024-00452-7

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness: Defining "gamification." In *Proceedings of the 15th International Academic MindTrek Conference: Envisioning future media environments* (pp. 9-15). Association for Computing Machinery. https://doi.org/10.1145/2181037.2181040

Dichev, C., & Dicheva, D. (2017). Gamifying education: What is known, what is believed and what remains uncertain: A critical review. *International Journal of Educational Technology in Higher Education*, *14*, Article 9. https://doi.org/10.1186/s41239-017-0042-5

Espelita, C. A. M. H., Atento, A. G. B., & Atento, R. G. O. (2026). Social media marketing and enrollment intent among college-bound learners: Evidence from a private higher education institution in Region IV-A, Philippines. *Journal of Enterprise Strategy & Management Innovation*, *1*(1). https://doi.org/10.65166/bcn4pt87

Fabro, R. B. B., Rivera, J. C., Sambrano, L. C., Dinoy, L. J. M., Alcozer, N. G., & Agustin, M. C. (2024). Perceptions and extent of utilization of generative artificial intelligence (AI) among Filipino students. *International Journal of Education and Research*, *12*(7), 107-126.

Lolong, J. R. V., Aparejado, A. S. S., Carino, S. Y. M., Valderama, M. L., & Atento, R. G. (2026). Dark triad personality traits and academic dishonesty-related tendencies among senior high school students: A correlational study. *International Journal of Behavioral and Social Analytics*, *1*(1). https://doi.org/10.65166/2xe1ga71

Rao, L., Tian, Y., & Atento, R. G. O. (2025). Adoption and perceived effectiveness of AI in education: Personalization, outcomes, and equity. *International Journal of Health & Business Analytics*, *1*(1). https://doi.org/10.65166/qgq89291

Romero-Rodríguez, J.-M., Ramírez-Montoya, M.-S., Buenestado-Fernández, M., & Lara-Lara, F. (2023). Use of ChatGPT at university as a tool for complex thinking: Students' perceived usefulness. *Journal of New Approaches in Educational Research*, *12*(2), 323-339. https://doi.org/10.7821/naer.2023.7.1458

Sailer, M., & Homner, L. (2020). The gamification of learning: A meta-analysis. *Educational Psychology Review*, *32*, 77-112. https://doi.org/10.1007/s10648-019-09498-w

Shahzad, M. F., Xu, S., & Javed, I. (2024). ChatGPT awareness, acceptance, and adoption in higher education: The role of trust as a cornerstone. *International Journal of Educational Technology in Higher Education*, *21*, Article 46. https://doi.org/10.1186/s41239-024-00478-x

Strzelecki, A. (2024). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. *Innovative Higher Education*, *49*(2), 223-245. https://doi.org/10.1007/s10755-023-09686-1

Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments*, *10*, Article 15. https://doi.org/10.1186/s40561-023-00237-x

UNESCO. (2023). *Guidance for generative AI in education and research*.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157-178. https://doi.org/10.2307/41410412

Vergara, J. P. C. (2024). *Navigating the generative artificial intelligence era: Charting the course for curricular reform in higher education in the Philippines*. University of the Philippines Center for Integrative and Development Studies.

Yan, H. (2026). Craftsmanship spirit, professional values, and learning motivation among Chinese higher vocational college students. *International Journal of Behavioral and Social Analytics*, *1*(1). https://doi.org/10.65166/wvm4ge89

Yusuf, A., Pervin, N., & Román-González, M. (2024). Generative AI and the future of higher education: A threat to academic integrity or reformation? Evidence from multicultural perspectives. *International Journal of Educational Technology in Higher Education*, *21*, Article 21. https://doi.org/10.1186/s41239-024-00453-6

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education-Where are the educators? *International Journal of Educational Technology in Higher Education*, *16*, Article 39. https://doi.org/10.1186/s41239-019-0171-0