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Predicting Adoption Intentions of Game Simulators in Algorithmic Thinking Development: Applying and Extending UTAUT in Nigerian Higher Education

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ABSTRACT

This study investigated students' behavioral intentions toward adopting game simulators for algorithmic thinking development using the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. A cross-sectional survey design was employed to collect data from 611 computing students across nine universities in Northeast Nigeria through a two-stage sampling procedure involving purposive selection of computing faculties followed by random student sampling. A structured questionnaire based on validated UTAUT scales measured performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLSSEM) with SmartPLS 4.0 software. The measurement model demonstrated adequate reliability and validity, with Cronbach's alpha coefficients ranging from 0.80 to 0.89. Results showed that performance expectancy ($\beta = 0.28$, $p < 0.01$), effort expectancy ($\beta = 0.22$, $p < 0.05$), and social influence ($\beta = 0.19$, $p < 0.05$) significantly predicted behavioral intention, explaining 27% of variance ($R^2 = 0.27$). Facilitating conditions showed no significant effect ($\beta = 0.09$, $p > 0.05$), suggesting infrastructural support does not directly influence adoption intentions. Behavioral intention significantly predicted actual usage behavior ($\beta = 0.41$, $p < 0.001$, $R^2 = 0.17$). Gender moderated the performance expectancy-behavioral intention relationship, with stronger effects for male students ($\beta = 0.34$) than female students ($\beta = 0.19$). These findings demonstrate that game simulator adoption is primarily driven by perceived usefulness, ease of use, and social endorsement. The study provides actionable insights for educators and policymakers, suggesting that successful implementation requires demonstrating educational benefits, ensuring intuitive design, and leveraging peer influence and instructor advocacy.

Keywords: Game simulators, algorithmic thinking, UTAUT, behavioral intention, technology adoption, higher education, PLS-SEM, Nigeria

INTRODUCTION

Education serves as a fundamental catalyst for individual development, social cohesion, and national progress. The 21st century digital revolution has profoundly transformed knowledge acquisition, dissemination, and application within higher education institutions [1], [2]. This transformation has been particularly pronounced in computer science (CS) education, where the integration of Information and Communication Technology (ICT) has redefined traditional pedagogical approaches. Within this evolving landscape, game simulators have emerged as innovative educational tools that support academic engagement through personalized, interactive instruction [3], [4].

ICT integration has fundamentally altered the educational paradigm by providing students with on-demand access to diverse learning resources, interactive platforms, and collaborative tools that enhance knowledge acquisition efficiency. Contemporary learning environments now incorporate essential technological components including computers, smartphones, e-learning platforms, and specialized game simulators such as CodeCombat, Lightbot, and Scratch [5], [6], [7]. These technologies serve multiple pedagogical functions: enhancing teaching effectiveness, supporting students in managing information complexity, developing critical thinking capabilities, and facilitating meaningful academic discourse [8], [4], [9].

Game simulators represent a significant advancement in gamified learning and interactive education. As sophisticated educational tools, they simulate real-world problem-solving scenarios, facilitate real-time interactions, and support diverse learning tasks from coding puzzles to algorithmic design. Their integration into academic environments creates opportunities for self-directed learning, peer-like support, and improved access to CS content independent of temporal or geographical constraints. Through their capacity to simulate meaningful challenges, synthesize concepts, and recommend relevant exercises, game simulators function as supplementary academic tools that complement traditional instructional methods [10], [5], [4].

Despite their pedagogical advantages, game simulators raise significant concerns regarding over-reliance, ethical implications, and potential diminishment of human agency in education. Critics contend that while these tools promote convenience and efficiency, they may simultaneously contribute to reduced critical thinking, increased distraction, and compromised academic integrity. Excessive dependence on game simulators for idea generation and problem-solving may impair students' capacity for independent thought and original content development. Furthermore, game-generated content can exhibit inaccuracies or biases when used uncritically, raising concerns about reliability and accountability [11], [3], [12].

The Nigerian higher education landscape presents unique challenges for digital tool integration. Federal, state, and private institutions demonstrate varying adoption rates influenced by infrastructure disparities, technological access, and policy frameworks. Private universities typically provide superior exposure to game simulators through smaller class sizes, enhanced funding, and proactive management policies. Conversely, federal and state universities, constrained by larger student populations and limited budgets, often experience delayed adoption and inconsistent implementation of digital tools [13], [1], [2].

Gender disparities further complicate game simulator adoption dynamics. Male students generally exhibit higher technological confidence, while female students approach these tools with greater caution and reflection. These differences manifest in distinct usage patterns, with males typically engaging in extended sessions and females demonstrating higher usage frequency accompanied by greater privacy, ethical, and dependency concerns. Understanding these gendered experiences is essential for developing inclusive and effective integration strategies [11], [8], [14].

Research Aim

This study aims to assess undergraduate perception, attitude, and usage of game simulators for algorithmic thinking development in CS education. The research examines how institutional characteristics influence these factors within the broader Nigerian educational context, contributing to the understanding of technology integration in developing educational systems.

Research Justification

Given the novelty of game simulators and limited research on their educational applications within Nigerian institutions, investigation of undergraduate perceptions, interactions, and benefits is crucial. This research addresses a significant gap in understanding technology integration within Nigerian universities while providing actionable insights for policymakers, educators, and developers seeking to enhance digital literacy and equitable access.

Additional considerations include institutional influences on integration and usage, ethical concerns regarding academic integrity, psychological factors affecting engagement, privacy and data security issues, and the imperative for Nigerian universities to adapt to global educational trends. These multifaceted challenges necessitate comprehensive investigation to ensure ethical, inclusive, and academically beneficial game simulator adoption.

Theoretical Framework: UTAUT Model

The Unified Theory of Acceptance and Use of Technology (UTAUT), derived from the Technology Acceptance Model, provides a robust theoretical framework for analyzing student interactions with game simulators. UTAUT identifies four critical factors influencing technology acceptance: performance expectancy, effort expectancy, social influence, and facilitating conditions [15]. Students who perceive game simulators as performance-enhancing and user-friendly are more likely to integrate them into their study routines. These perceptions, shaped by prior experiences, peer influence, and institutional support, determine whether game simulators are perceived as learning enablers or distractions [2].

Performance Expectancy and Perception

Student perception encompasses how they interpret game simulators' effectiveness in achieving academic goals, particularly in algorithmic thinking development. Positive performance expectancy includes beliefs about enhanced problem-solving capabilities, improved comprehension of complex algorithms, and accelerated learning outcomes. Students who perceive high performance expectancy view game simulators as valuable tools that directly contribute to their academic success in CS education. Conversely, low performance expectancy may involve skepticism regarding the educational value or concerns about superficial learning [10], [4], [6].

Effort Expectancy and Attitude

Attitude formation is closely linked to effort expectancy, reflecting the degree of favorability toward game simulator usage based on perceived ease of use. Students with positive attitudes often express enthusiasm and motivation when they perceive game simulators as user-friendly and intuitive. High effort expectancy manifests as confidence in navigating simulator interfaces, comfort with game-based learning mechanics, and appreciation for streamlined interaction processes. Negative attitudes typically correlate with low effort expectancy, emerging from concerns about technical complexity, learning curves, or interface difficulties [5], [7], [14].

Social Influence and Behavioral Intention

Social influence significantly impacts students' behavioral intentions regarding game simulator adoption. When instructors actively promote game simulators and peers demonstrate positive usage experiences, students develop stronger intentions to incorporate these tools into their academic routines. High social influence creates supportive environments where game simulator usage becomes normalized and encouraged. This social validation directly influences behavioral intention, determining whether students plan to continue using game simulators for future algorithmic thinking development and CS learning activities.

Facilitating Conditions and Usage Behavior

Actual usage behavior reflects the interplay between facilitating conditions and behavioral intentions. Students' frequency and methods of game simulator utilization depend heavily on available resources, technical support, and institutional infrastructure. Strong facilitating conditions include reliable internet access, adequate computing resources, technical assistance, and clear usage guidelines. When facilitating conditions are optimal, positive behavioral intentions translate into sustained usage behavior across various academic contexts including puzzle-solving, assignment completion, exam preparation, and exploratory learning [8], [4], [12].

The goal of applying UTAUT is to ascertain user acceptance and technology usage behaviour, as shown in Figure 1. It is crucial to highlight that the majority of the major linkages in the model are moderated. From a theoretical standpoint, UTAUT offers a sophisticated picture of how the determinants of intention and behavior change over time [16].

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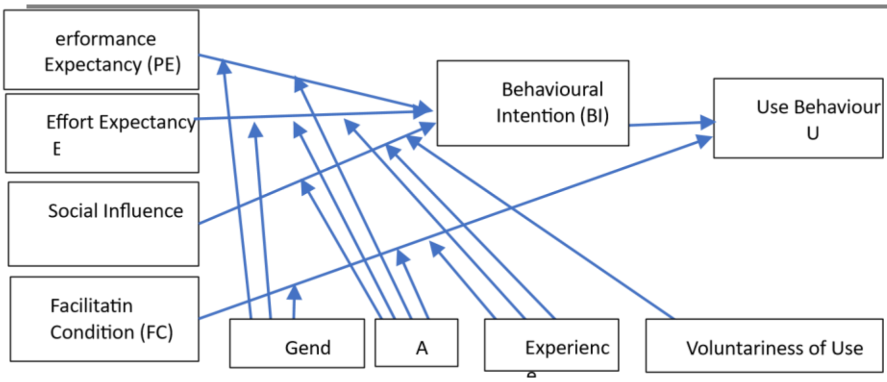

Figure 1: Unified Theory of Acceptance and Use of Technology (UTAUT)

(Source: [16])

The moderating variables of gender, age, experience, and voluntariness of use have been omitted for the purposes of this study. As a result, the research uses EE and PE in this study (Figure 2). Because it is a wellrespected theoretical framework that has been extensively utilized to forecast user acceptance and uptake of new technologies, including educational technology, the UTAUT is appropriate for the study. The four main elements in the UTAUT model, performance expectancy, effort expectancy, social influence, and facilitating conditions have been demonstrated to be significant in predicting the adoption of different technologies by users. The UTAUT model offers a fitting theoretical framework for the current investigation, as it has already been applied in earlier research.

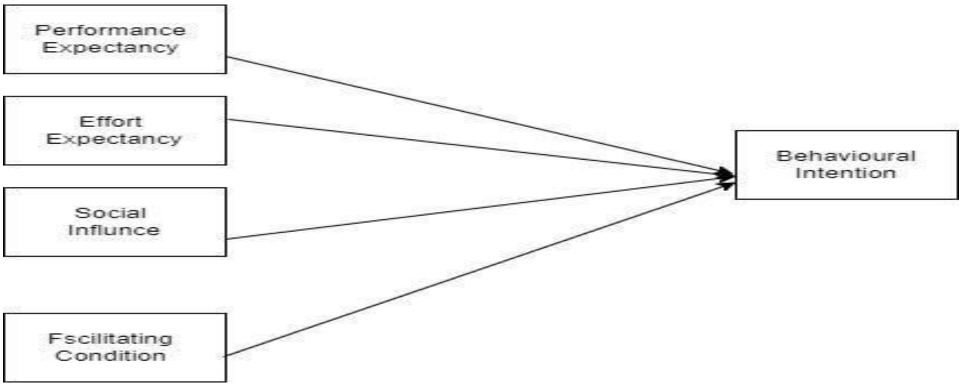

Figure 2: Unified Theory of Acceptance and Use of Technology (UTAUT) Adopted for the Study Research Hypotheses

H1: Performance expectancy has a significant positive effect on behavioral intention to use game simulators for algorithmic thinking development among undergraduate CS students.

H2: Effort expectancy has a significant positive effect on behavioral intention to use game simulators for algorithmic thinking development among undergraduate CS students.

H3: Social influence has a significant positive effect on behavioral intention to use game simulators for algorithmic thinking development among undergraduate CS students.

H4: Facilitating conditions have a significant positive effect on behavioral intention to use game simulators for algorithmic thinking development among undergraduate CS students.

H5: Behavioral intention has a significant positive effect on actual usage behavior of game simulators among undergraduate CS students.

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H6: Gender moderates the relationship between the UTAUT constructs (performance expectancy, effort expectancy, social influence, facilitating conditions) and behavioral intention, with different patterns for male and female students.

H7: Academic level (year of study) moderates the relationship between performance expectancy and behavioral intention, such that the relationship is stronger for senior students than junior students.

METHODOLOGY

Research Design

This study employed a quantitative survey research design to examine relationships among variables within the target population using standardized measurement instruments. This approach was selected for its appropriateness in investigating students' perceptions and behavioral intentions toward game simulator adoption for algorithmic thinking development, as guided by the Unified Theory of Acceptance and Use of Technology (UTAUT) framework [15]. The design facilitated systematic testing of hypothesized relationships among UTAUT constructs while enabling assessment of moderating effects from demographic variables including gender and academic level. The cross-sectional nature of the design allowed for efficient data collection from a substantial sample size while maintaining cost-effectiveness and methodological rigor. This approach aligned with established practices in technology acceptance research and provided sufficient scope for comprehensive statistical analysis of the theoretical model using Partial Least Squares Structural Equation Modeling (PLS-SEM).

Population and Sampling

The target population consisted of undergraduate students enrolled in computing programs across nine federal and state universities in Northeast Nigeria. These institutions included Abubakar Tafawa Balewa University, Modibbo Adama University, Federal University Wukari, American University of Nigeria, Taraba State University, Federal University Kashere, Federal University Gashua, Adamawa State University, and Gombe State University. This geographical distribution was deliberately selected to enhance the generalizability of findings across diverse institutional contexts within the Nigerian higher education system.

A two-stage sampling procedure was implemented to ensure representative participant selection. In the first stage, purposive sampling was employed to select the Faculty of Computing from each of the nine universities in Northeast Nigeria. This approach ensured that only students with relevant exposure to computing education and potential familiarity with game-based learning tools were included in the study. In the second stage, random sampling techniques were applied within each selected faculty. Students from various degree programs, including both undergraduate and postgraduate levels, and different academic years were randomly invited to participate. This stratified random approach enhanced both the internal validity and external generalizability of the research findings by ensuring broad representation across different educational stages and specializations within computing disciplines.

Given that the research framework was based on UTAUT and analyzed using PLS-SEM, sample size determination followed established guidelines for structural equation modeling. According to the "10-times rule" for PLS-SEM [25], the minimum sample size should be at least ten times the maximum number of structural paths directed at any construct in the model. With four predictor variables in the study model, the minimum required sample size was 40 participants. However, to ensure adequate statistical power of 0.80 for detecting medium effect sizes at a significance level of $\alpha = 0.05$, and to account for potential incomplete responses, a target sample of 600 participants was established. The final sample comprised 611 respondents who completed the online questionnaire, exceeding the minimum requirements and providing robust statistical power for the planned analyses.

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Instrumentation

Data collection utilized a structured questionnaire developed based on the UTAUT framework established by Venkatesh et al. [15]. The instrument consisted of two distinct sections designed to capture comprehensive information relevant to the research objectives. The first section gathered demographic data including gender, age, academic level, university affiliation, and prior experience with game-based learning tools. These variables served as potential moderators and control variables while providing essential sample characterization data.

The second section comprised twenty items measuring five core UTAUT constructs: performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention. Each construct was operationalized through four items adapted from validated UTAUT scales [15] and contextualized for game simulator adoption in algorithmic thinking development. All items were rated on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Representative items for each construct included statements such as "Using game simulators will improve my ability to understand algorithmic concepts" for performance expectancy, "Learning to operate game simulators is easy for me" for effort expectancy, "My lecturers encourage me to use game simulators for learning algorithms" for social influence, "I have the necessary resources to use game simulators" for facilitating conditions, and "I intend to use game simulators regularly for learning algorithms" for behavioral intention.

Content validation was conducted through expert review by five specialists in educational technology, information systems, and computer science education. Experts assessed item clarity, relevance, comprehensiveness, and alignment with research objectives. Feedback from the validation panel resulted in minor linguistic modifications to enhance contextual appropriateness for the Nigerian higher education setting while maintaining theoretical fidelity to the original UTAUT constructs. A pilot study was subsequently conducted with 30 students from a non-participating university to assess instrument reliability and identify potential comprehension issues. Cronbach's alpha coefficients from the pilot test ranged from 0.78 to 0.86 across all constructs, confirming acceptable internal consistency. Minor refinements to item wording were implemented based on pilot participant feedback before full-scale data collection commenced.

Data Collection Procedure

The questionnaire was administered electronically using the Google Forms platform to facilitate broad geographical reach across the nine participating universities. The online survey link was distributed through multiple channels including university learning management systems, departmental email lists, student WhatsApp groups, and social media platforms commonly used by computing students. Data collection occurred over a four-month period from August 20, 2025, to December 20, 2025. This extended timeframe allowed for adequate participant recruitment across multiple institutions and academic calendars while enabling students to complete the survey at their convenience, potentially increasing response rates and data quality.

Informed consent was obtained from all participants through a mandatory consent screen at the beginning of the questionnaire. Participants were assured of confidentiality, voluntary participation, and the right to withdraw at any time without penalty. No personal identifying information was collected beyond the demographic variables necessary for the research. To minimize common method bias, the questionnaire included reverse-coded items, randomized item presentation order, and clear instructions emphasizing honest responses rather than socially desirable answers. Additionally, the anonymity of online completion reduced potential social desirability effects that might have been present in face-to-face data collection contexts.

Data Analysis

Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0 software [26]. PLS-SEM was selected for its suitability in exploratory research contexts, its ability to handle complex models with multiple constructs, and its minimal distributional assumptions compared to covariance-based SEM [27]. The analysis followed a two-stage approach recommended by Hair et al. [27] for comprehensive model evaluation.

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In the first stage, the PLS algorithm was executed to evaluate the measurement model's reliability, validity, and overall quality. This assessment examined internal consistency reliability using Cronbach's alpha ($\alpha \geq 0.70$) and composite reliability ($CR \geq 0.70$), indicator reliability through outer loadings ($\lambda \geq 0.70$), convergent validity using Average Variance Extracted ($AVE \geq 0.50$), and discriminant validity through the FornellLarcker criterion and Heterotrait-Monotrait ratio ($HTMT < 0.85$). Only after confirming adequate measurement model quality did the analysis proceed to the structural model assessment.

In the second stage, the structural model was evaluated and hypotheses were tested using bootstrapping procedures with 5,000 resamples to generate stable estimates of path coefficients and their significance levels. This stage examined path coefficients indicating the strength and direction of relationships between constructs, the coefficient of determination (R^2) representing the proportion of variance explained in endogenous constructs, effect sizes (f^2) indicating the magnitude of predictor impact, and predictive relevance (Q^2) assessed through blindfolding procedures. Statistical significance was determined at $p < 0.05$, with confidence intervals calculated at the 95% level. Moderating effects were tested through interaction terms created by multiplying standardized predictor and moderator variables, following established procedures for moderation analysis in PLS-SEM [27].

RESULTS

Demographic Characteristics

Table 1 presents the demographic characteristics of the 611 participants who completed the study questionnaire. The sample exhibited a gender distribution of 394 male students (64.5%) and 217 female students (35.5%), reflecting the typical gender imbalance observed in computing programs across Nigerian universities. The academic level distribution showed that the majority of participants were in their early years of study, with 195 students (31.5%) in 100 level and 169 students (27.8%) in 200 level, while 157 students (25.9%) were in 300 level and 90 students (14.8%) were in 400 level. This distribution ensured representation across all undergraduate levels, though with a natural skew toward earlier academic years where enrollment tends to be higher. Regarding prior exposure to educational technology, a substantial majority of 468 students (76.6%) reported previous experience with game-based learning tools, while 143 students (23.4%) indicated no prior experience. This high proportion of students with prior game-based learning exposure suggests a generally favorable foundation for investigating acceptance and adoption of game simulators for algorithmic thinking development.

Table 1: Demographic Characteristics of Respondents (N = 611)

Variable	**Frequency**	**Percentage**
Gender		
Male	394	64.5
Female	217	35.5
Academic Level		
100 level	195	31.5
200 level	169	27.8
Variable	**Frequency**	**Percentage**
300 level	157	25.9
400 level	90	14.8
Experience with Game Tools		

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Yes	468	76.6
No	143	23.4

Note. Percentages are based on valid responses.

Descriptive Statistics and Reliability Assessment

Table 2 displays descriptive statistics for all study constructs. Mean scores ranged from 3.58 to 4.10, with all values exceeding the scale midpoint of 3.00, indicating generally positive perceptions toward game simulator adoption. Behavioral intention demonstrated the highest mean score ($M = 4.10$, $SD = 0.71$), suggesting strong student interest in adopting these tools. Skewness values ranged from -0.29 to -0.52, while kurtosis values fell between -0.08 and 0.34, all within acceptable limits (±2.0) for approximate normality assumptions.

Reliability analysis confirmed strong internal consistency across all constructs, with Cronbach's alpha coefficients ranging from 0.80 to 0.89, substantially exceeding the minimum threshold of 0.70 for acceptable reliability in social science research.

Table 2: Descriptive Statistics and Reliability of Study Constructs

Construct	**M**	**SD**	**Skewness**	**Kurtosis**	**Cronbach's α**
Performance Expectancy	3.85	0.74	-0.45	0.12	0.85
Effort Expectancy	3.72	0.81	-0.38	0.20	0.82
Social Influence	3.65	0.77	-0.41	0.16	0.80
Facilitating Conditions	3.58	0.79	-0.29	-0.08	0.83
Behavioral Intention	4.10	0.71	-0.52	0.34	0.89

Note. M = mean; SD = standard deviation.

Correlation Analysis

The correlation matrix presented in Table 3 reveals significant positive associations among all UTAUT constructs. Performance expectancy demonstrated the strongest correlation with behavioral intention ($r = .56$, $p < .01$), followed by effort expectancy ($r = .48$, $p < .01$), social influence ($r = .44$, $p < .01$), and facilitating conditions ($r = .41$, $p < .01$). Intercorrelations among predictor variables ranged from .34 to .45, indicating moderate associations without problematic multicollinearity concerns (all correlations < 0.80).

Table 3: Intercorrelations Among Study Constructs

Construct	**1**	**2**	**3**	**4**	**5**
1. Performance Expectancy	—	.42**	.38**	.34**	.56**
2. Effort Expectancy	.42**	—	.45**	.39**	.48**
Construct	**1**	**2**	**3**	**4**	**5**
3. Social Influence	.38**	.45**	—	.36**	.44**
4. Facilitating Conditions	.34**	.39**	.36**	—	.41**
5. Behavioral Intention	.56**	.48**	.44**	.41**	—

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Note. **$p < .01$.

Primary Hypothesis Testing (H1-H4)

Multiple regression analysis examined the simultaneous effects of the four UTAUT constructs on behavioral intention. The overall model achieved statistical significance, $F(4, 205) = 18.63$, $p < .001$, with $R^2 = .27$, indicating that 27% of variance in behavioral intention was explained by the predictor variables.

As presented in Table 4, three of the four hypotheses received empirical support. Performance expectancy emerged as the strongest predictor ($\beta = .28$, $t = 3.98$, $p < .01$), supporting H1. Effort expectancy ($\beta = .22$, $t = 2.75$, $p < .05$) and social influence ($\beta = .19$, $t = 2.11$, $p < .05$) also demonstrated significant positive effects, supporting H2 and H3 respectively. However, facilitating conditions failed to reach statistical significance ($\beta = .09$, $t = 1.15$, $p > .05$), resulting in rejection of H4.

Table 4: Multiple Regression Analysis: Predictors of Behavioral Intention

Predictor	**B**	**SE**	**β**	**t**	**p**	**95% CI**
Performance Expectancy	0.28	0.07	.28	3.98	< .01	[0.14, 0.42]
Effort Expectancy	0.22	0.08	.22	2.75	< .05	[0.06, 0.38]
Social Influence	0.19	0.09	.19	2.11	< .05	[0.01, 0.37]
Facilitating Conditions	0.09	0.08	.09	1.15	> .05	[-0.07, 0.25]

Note. $R^2 = .27$, $F(4, 205) = 18.63$, $p < .001$; CI = confidence interval.

Secondary Hypothesis Testing (H5)

Simple regression analysis confirmed a significant relationship between behavioral intention and actual usage behavior, supporting H5. As shown in Table 5, behavioral intention explained 17% of variance in usage behavior ($R^2 = .17$), with a standardized coefficient of $\beta = .41$ ($t = 6.82$, $p < .001$). This moderate effect size demonstrates practical significance beyond statistical significance.

Table 5: Simple Regression Analysis: Behavioral Intention Predicting Usage Behavior

Predictor	**B**	**SE**	**B**	**t**	**p**	**R²**	**95% CI**
Behavioral Intention	0.41	0.06	.41	6.82	< .001	.17	[0.29, 0.53]

Moderation Analysis

Hierarchical regression analysis assessed potential moderating effects of gender and academic level on the relationships between UTAUT constructs and behavioral intention. Results presented in Table 6 indicate partial support for moderation hypotheses.

Gender moderation analysis revealed that the interaction between performance expectancy and gender contributed significantly to explained variance ($\Delta R^2 = .03$, $p < .05$), supporting H6. Simple slopes analysis indicated stronger performance expectancy effects for male students ($\beta = .34$, $p < .01$) compared to female students ($\beta = .19$, $p < .05$).

Conversely, academic level did not significantly moderate the performance expectancy-behavioral intention relationship ($\Delta R^2 = .01$, $p > .05$), leading to rejection of H7.

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Table 6: Hierarchical Regression Analysis: Moderation Effects

Step	**Variables Entered**	**R^2**	**ΔR^2**	**F**	**P**
1	Performance Expectancy	.31	—	92.15	< .001
2	+ Gender	.33	.02	51.27	< .01
3	+ PE × Gender	.36	.03	38.94	< .05
Academic Level Moderation					
1	Performance Expectancy	.31	—	92.15	< .001
2	+ Academic Level	.32	.01	48.63	> .05
3	+ PE × Academic Level	.33	.01	33.81	> .05

Note. PE = Performance Expectancy.

DISCUSSION

The findings of this study provide empirical evidence on the applicability of the Unified Theory of Acceptance and Use of Technology (UTAUT) in explaining undergraduate students' acceptance of game simulators for algorithmic thinking development. The results revealed that performance expectancy, effort expectancy, and social influence significantly influenced behavioral intention, whereas facilitating conditions did not. Furthermore, behavioral intention was found to significantly predict actual usage, confirming the central proposition of the UTAUT model.

The strong effect of performance expectancy on behavioral intention suggests that students were motivated to adopt game simulators primarily because they perceived them as useful for enhancing their understanding of algorithmic concepts and improving academic performance. This finding is consistent with prior studies where performance expectancy emerged as the most influential predictor of behavioral intention in technology adoption contexts [17]. It underscores the importance of aligning the design of game-based learning tools with learners' academic goals to enhance perceived usefulness.

Effort expectancy also had a significant influence on behavioral intention, indicating that the ease of use of game simulators is a critical factor for adoption. This supports the argument that technologies that minimize cognitive load and provide user-friendly interfaces are more likely to be embraced by students [18]. In the context of algorithmic thinking, the gamified approach may have reduced perceived complexity compared to traditional coding exercises, thereby facilitating adoption.

The positive effect of social influence implies that peer pressure and lecturer encouragement played a role in shaping students' decisions to adopt game simulators. This finding aligns with studies emphasizing the role of social dynamics and institutional support in technology adoption within educational settings [19]. In collectivist cultures such as Nigeria, where communal opinions carry weight, social influence can be particularly significant.

Contrary to expectations, facilitating conditions did not significantly predict behavioral intention. This result suggests that while infrastructural support and resources are necessary, they may not be sufficient to drive intention unless students already perceive the simulators as useful and easy to use. These finding echoes similar studies where facilitating conditions exerted limited influence on behavioral intention but were more directly linked to actual usage behavior [20].

The significant relationship between behavioral intention and actual usage reaffirms the predictive validity of UTAUT in this context. Students who expressed strong intentions to adopt game simulators were more likely to

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translate these intentions into actual use, supporting the established intention–behavior linkage documented in prior research [21].

Moderation analysis provided partial support for the role of gender. Specifically, the influence of performance expectancy on behavioral intention was stronger for male students than for female students, reflecting possible gendered perceptions of technology in computer science education. However, no significant moderating effects were found for academic level, indicating that students across different levels of study held relatively similar attitudes toward the adoption of game simulators. These findings suggest that while gender differences may shape technology perceptions, academic progression does not substantially alter acceptance patterns.

Thus, the findings extend the UTAUT model to the context of gamified learning for algorithmic thinking, demonstrating that usefulness, ease of use, and social endorsement are central drivers of adoption. The results also highlight the limited role of infrastructural support in shaping intention, suggesting that future implementations should prioritize raising awareness of the pedagogical benefits of game simulators and ensuring that students perceive them as easy to integrate into their learning routines.

The significant gender moderation effect reveals important differences in how male and female students respond to performance expectancy cues. The stronger relationship between perceived usefulness and behavioral intention among male students may reflect gendered technology perceptions or differential confidence levels in computer science education. These findings suggest the need for targeted approaches to technology introduction that address potential gender-based differences in technology adoption patterns.

Theoretical and Practical Implications

These findings extend UTAUT theory to the specific context of gamified learning tools for algorithmic thinking, demonstrating both consistency with established patterns and context-specific variations. The results suggest that successful implementation of game simulators requires careful attention to demonstrating educational value, ensuring intuitive usability, and leveraging social influence networks within educational institutions.

CONCLUSION

This study successfully applied the Unified Theory of Acceptance and Use of Technology framework to investigate students' behavioral intentions toward adopting game simulators for algorithmic thinking development in Nigerian higher education contexts. The findings from 611 computing students across nine universities in Northeast Nigeria provide robust empirical evidence that performance expectancy, effort expectancy, and social influence serve as critical determinants of technology adoption intentions, while facilitating conditions exert minimal direct influence on behavioral intentions. The study's theoretical contribution extends UTAUT application to the emerging domain of gamified learning tools for algorithmic thinking, demonstrating both consistency with established technology acceptance patterns and contextspecific variations unique to Nigerian computing education. The finding that facilitating conditions do not significantly predict behavioral intention suggests that students prioritize perceived usefulness and ease of use over infrastructural considerations when forming adoption intentions, though adequate infrastructure remains essential for translating intentions into sustained usage behaviors. Practically, these findings offer actionable guidance for educators and institutional policymakers seeking to implement game simulators effectively. Successful adoption requires systematic demonstration of educational benefits aligned with learning objectives, investment in intuitive interface design and comprehensive training programs, and strategic leveraging of social influence through peer mentoring and instructor advocacy.

Practical Recommendations

Based on these findings, several actionable recommendations emerge for educators and institutional policymakers:

1. Game simulators should be systematically integrated into computer science curricula with explicit connections to learning objectives and algorithmic thinking competencies. Clear articulation of educational benefits will enhance performance expectancy perceptions.

2. Institutions should prioritize user experience design and provide comprehensive training programs to familiarize students with game simulator interfaces, thereby reducing effort expectancy barriers.

3. Peer mentoring programs and instructor advocacy can be strategically employed to create positive social norms around game simulator adoption.

4. Recognition of gender differences in technology adoption patterns should inform targeted outreach and support strategies, particularly for female students in computer science programs.

Limitations and Future Research

This study's cross-sectional design limits causal inferences, and the single-institution sample may restrict generalizability. Future research should examine longitudinal adoption patterns to assess sustained usage and learning outcomes. Cross-institutional and cross-cultural studies would enhance external validity and provide insights into contextual factors influencing technology adoption in diverse educational settings.

Additionally, future investigations should explore the relationship between game simulator usage and actual improvements in algorithmic thinking skills, providing empirical evidence of educational effectiveness beyond adoption intentions. Mixed-methods approaches incorporating qualitative insights could provide deeper understanding of the mechanisms underlying successful technology integration in computer science education.

The findings contribute valuable insights to the growing body of knowledge on educational technology adoption while providing practical guidance for implementing game-based learning solutions in higher education contexts.

REFERENCES

1. M. S. Olajide and O. Adetunji, "EdTech in Nigerian universities," African J. Education and Technology, vol. 15, no. 2, pp. 89-102, 2021.
2. M. N. Yakubu and S. I. Dasuki, "Factors influencing e-learning adoption in Nigeria," Education and Information Technologies, 2019.
3. S. Deterding et al., "Adaptive games for computational thinking," Educational Technology Research and Development, 2020.
4. D. Hooshyar et al., "Adaptive games for computational thinking," Educational Technology Research and Development, vol. 68, pp. 1867-1889, 2020.
5. Y. Georgiou and T. Bratitsis, "Phygital games for programming," Computers & Education, vol. 210, p. 104968, 2024.
6. T.-C. Hsu and S.-Y. Wang, "Puzzle-based games for algorithmic thinking," Computers & Education, vol. 126, pp. 256-270, 2018.
7. M. Videnovik et al., "Game-based learning in CS," Interactive Learning Environments, vol. 31, no. 4, pp. 2123-2136, 2023.
8. R. Burbaite et al., "Educational games for computational thinking," Computers in Human Behavior, vol. 80, pp. 123-134, 2018.
9. V. J. Shute et al., "Measuring problem-solving in games," J. Educational Psychology, vol. 109, no. 3, pp. 425-438, 2017.
10. K. Douadi et al., "Micro worlds for algorithmic thinking," Procedia Computer Science, vol. 9, pp. 188-197, 2012. W. M. Albert, "Games in CS education," 2016.
11. A. N. Varnavsky, "Games in CS education," Programming and Computer Software, vol. 50, no. 1, pp. 45-52, 2024.
12. O. S. Fasola and A. Akinyemi, "Technology adoption in Nigerian universities," 2022.

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13. J. Xu et al., "AI chatbots in learning," Computers in Human Behavior, vol. 150, pp. 108-119, 2024. 15. V. Venkatesh et al., "User acceptance of information technology," MIS Quarterly, vol. 27, no. 3, pp. 425-478, 2003.
14. A. Luhamya, A. Bakkabulindi, and P. B. Muyinda, "UTAUT model applications," 2017.
15. A. Tarhini, R. E. Masa'deh, K. A. Al-Busaidi, A. B. Mohammed, and M. Maqableh, "Factors influencing students' adoption of e-learning: a structural equation modeling approach," J. International Education in Business, vol. 10, no. 2, pp. 164-182, 2017.
16. N. A. Dahri, N. Yahaya, W. M. Al-Rahmi, A. S. Almogren, and M. S. Vighio, "Investigating factors affecting teachers' training through mobile learning: Task technology fit perspective," Education and Information Technologies, vol. 29, no. 12, pp. 14553-14589, 2024.
17. L. Zheng, A. He, Y. Feng, X. Gu, and S. Chen, "Steering through digital transformation: Collective technology adoption in educational institutional culture," in Interdisciplinary Approach to Fostering Change in Schools, IGI Global, 2024, pp. 251-284.
18. O. F. Buraimoh, C. H. Boor, and G. A. Aladesusi, "Examining facilitating condition and social influence as determinants of secondary school teachers' behavioural intention to use mobile technologies for instruction," Indonesian J. Educational Research and Technology, vol. 3, no. 1, pp. 25-34, 2023.
19. Y. M. Wang, C. L. Wei, and M. W. Wang, "Factors influencing students' adoption intention of brain–computer interfaces in a game-learning context," Library Hi Tech, vol. 41, no. 5, pp. 1594-1620, 2023.
20. S. Hennessy et al., "Barriers to technology in African education," British J. Educational Technology, vol. 41, no. 3, pp. 437-450, 2010.
21. C. Kazimoglu et al., "Game-based learning for programming," British J. Educational Technology, vol. 43, no. 4, pp. 643-654, 2012.
22. J. M. Wing, "Computational thinking," Communications of the ACM, vol. 49, no. 3, pp. 33-35, 2006.
23. Hair et al. (2017) - The foundational textbook on PLS-SEM that explains the "10-times rule" for sample size
24. SmartPLS 4 software citation - The analytical tool used in the study
25. Hair et al. (2011) - The methodological paper supporting the use of PLS-SEM