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TEACHERS' ADOPTION OF GAMIFICATION AND SIMULATION-BASED LEARNING IN SCIENCE EDUCATION: AN EXTENDED UTAUT2 MODEL

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Abstract

The rapid advancement of digital technologies has intensified interest in innovative educational approaches such as gamification and simulation-based learning (GSBL) in science education. Despite their documented pedagogical benefits, teachers' adoption of these approaches remains limited. This study examines the determinants of in-service science teachers' intention to use GSBL through the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). A cross-sectional survey design was employed with a sample of 800 in-service science teachers who participated in a structured professional development program. Structural equation modeling (SEM) was used to test the proposed research model and hypotheses. The results indicate that performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit significantly predict teachers' behavioral intention to adopt GSBL. The findings contribute to the literature by validating UTAUT2 in the context of science education and by offering practical implications for policymakers, teacher educators, and school administrators seeking to promote technology-enhanced pedagogies.

Keywords: gamification, simulation-based learning, UTAUT2, science education, teacher adoption, technology acceptance

Introduction

The rapid digital transformation of education has intensified long-standing pedagogical challenges in science education, a domain characterized by abstract concepts (e.g., atomic structures and energy transfer), invisible phenomena (e.g., molecular interactions), and potentially hazardous experimental processes (Nkadimeng & Ankiewicz, 2022). These characteristics often limit students' opportunities for direct experimentation and conceptual modeling in real classroom settings. In response, contemporary science education frameworks, including inquiry-based learning (IBL) and the 5E educational model, emphasize active exploration, hypothesis generation, experimentation, and evidence-based reasoning as central components of meaningful science learning (Morris, 2025). However, despite their pedagogical promise, such approaches are frequently constrained by practical limitations related to time, safety, material resources, and students' prior knowledge (Limbere et al., 2022).

Within this context, technology-enhanced educational approaches have been increasingly positioned as potential means of supporting inquiry-oriented science education. In particular, simulation-based learning and gamification have gained prominence due to their capacity to create interactive, learner-centered environments that foster exploration and experimentation (Monauni & Götte, 2022). Simulation-based learning enables students to manipulate variables, test hypotheses, and visualize otherwise inaccessible scientific phenomena in safe and repeatable digital environments (Sun et al., 2022). Gamification, by contrast, embeds motivational design elements such as challenges, feedback, and progression systems into learning activities, aiming

to sustain students' engagement during cognitively demanding inquiry processes (Ateş & Polat, 2025a; Bennani et al., 2022). Although pedagogically distinct, both approaches serve a common function in science education by mediating inquiry through interactive digital environments that support exploration, experimentation, and sense-making (Kefalis et al., 2025; Na et al., 2025).

Despite their increasing availability and strong alignment with inquiry-based pedagogies, the classroom adoption of gamification and simulation-based learning (GSBL) remains uneven. Empirical evidence suggests that the success of such approaches depends less on their technological sophistication and more on teachers' perceptions, beliefs, and educational intentions (Ateş & Kölemen, 2025a). As key pedagogical decision-makers, science teachers ultimately determine whether these tools are meaningfully integrated into inquiry-oriented education or remain peripheral add-ons. In practice, teachers frequently report challenges related to pedagogical alignment, perceived educational value, classroom feasibility, and institutional support, particularly within the demanding context of science curricula (Hu et al., 2025).

Although a substantial body of research has documented the positive effects of GSBL on student motivation and conceptual understanding (Ateş & Kölemen, 2025b; Bouriami et al., 2025), their sustained adoption by in-service science teachers has not kept pace with technological advancement. Moreover, existing research has predominantly examined GSBL from a learner-centered perspective, focusing on student outcomes rather than the educational decision-making processes of teachers (Thi Binh et al., 2025). Studies that do address teacher adoption often conceptualize technology acceptance as a generic phenomenon, overlooking the domain-specific demands of science teaching, such as inquiry facilitation, experimentation, and conceptual modeling (Özdemir & Ateş, 2025). Consequently, there remains limited empirical understanding of why science teachers choose to adopt, or refrain from adopting, GSBL as integral components of inquiry-oriented science education.

Based on the research problem outlined above, this study examined in-service science teachers' intentions to adopt GSBL through a theory-driven model and addressed specific research questions and hypotheses derived from the UTAUT2 framework.

Literature Review

Gamification and Simulation-Based Learning in Science Inquiry

Research on technology-enhanced science education consistently highlights the potential of GSBL to support inquiry-oriented pedagogies rather than merely increasing surface-level engagement (Cheng et al., 2024; Tassilova et al., 2025). In science education, learning is inherently linked to processes such as hypothesis generation, variable manipulation, evidence-based reasoning, and conceptual modeling (Malone, 2023). Digital simulations have been shown to be particularly effective in supporting these processes by allowing learners to visualize invisible phenomena, test causal relationships, and iteratively refine their understanding in ways that are difficult to achieve through traditional education alone (Pang et al., 2024). Empirical studies in physics and chemistry education demonstrate that simulations can reduce misconceptions by making abstract processes such as molecular motion or electric fields explicit and manipulable, thereby supporting conceptual change (Feyzioğlu, 2009).

Gamification, while pedagogically distinct from simulations, complements inquiry-based science learning by sustaining students' engagement during cognitively demanding tasks (Zourmpakis et al., 2024). Research indicates that game design elements such as immediate feedback, progression systems, and goal structures can encourage persistence in problem-solving and experimentation, particularly in complex scientific investigations (Machmud et al., 2023). When embedded within inquiry activities, gamification has been found to support formative assessment practices and to motivate students to engage more deeply with scientific reasoning tasks (Morris et al., 2013).

Despite these pedagogical affordances, the integration of GSBL in science classrooms remains uneven. Prior research has identified barriers related to curricular alignment, time constraints, teachers' perceived workload, and limited professional support (Hora, 2016). Importantly, these barriers are not merely technical but pedagogical in nature, underscoring the need to examine teachers' adoption decisions through a theory-driven lens that accounts for educational value, effort, and contextual constraints (Tseng et al., 2022).

Adapting UTAUT2 for Teachers in Science Education

The UTAUT2 has been widely employed to explain technology adoption in voluntary usage contexts (Tamilmani et al., 2017). While the model offers a comprehensive set of determinants influencing behavioral intention, its original formulation reflects consumer-oriented assumptions that do not fully align with school-based teaching environments. In K–12 education, technology adoption is shaped by institutional expectations, pedagogical accountability, and collective norms rather than individual consumer choice alone (Du & Liang, 2024).

In the context of science education, performance expectancy extends beyond general job efficiency to encompass perceived pedagogical value, specifically, whether a technology enhances inquiry processes, supports conceptual understanding, and aligns with curriculum standards (Ateş & Gündüzalp, 2025). Studies examining teachers' adoption of digital laboratories and simulations consistently report performance expectancy as a primary determinant when technologies demonstrably improve students' understanding of complex scientific concepts (Nzabahimana et al., 2024).

Effort expectancy, by contrast, is closely tied to teachers' workload and time pressures. Science teachers often balance laboratory preparation, assessment demands, and classroom management, making perceived complexity a critical factor in adoption decisions. Research suggests that even pedagogically powerful tools are likely to be rejected if they are perceived as difficult to implement or disruptive to established educational routines (Ranellucci et al., 2020).

Social influence in school settings is frequently manifested through school leadership expectations, peer collaboration, and professional learning communities rather than informal social norms (Liou & Daly, 2020). Empirical evidence indicates that administrative support and peer modeling play a significant role in shaping teachers' willingness to experiment with innovative educational technologies, particularly in science departments where collaborative planning is common (Ateş & Polat, 2025b).

Facilitating conditions are especially salient in science education due to the infrastructural demands of laboratory-based education (Jere & Mpeta, 2024). Access to reliable internet connectivity, suitable devices, and technical support has been shown to condition whether teachers can realistically integrate simulations or gamified platforms into inquiry activities (Vetrivel et al., 2024).

UTAUT2 constructs related to affective and evaluative dimensions also require contextual reinterpretation. Hedonic motivation, in educational contexts, reflects not only enjoyment but also teachers' intrinsic satisfaction derived from observing students' engagement and conceptual growth. Prior studies suggest that teachers who perceive technology use as professionally rewarding are more inclined to sustain its use (Ateş & Garzón, 2022).

Crucially, this study reconceptualizes price value to address the educational context. Rather than monetary cost, price value is interpreted as perceived educational return on investment, namely, teachers' judgments regarding whether the pedagogical benefits of GSBL justify the time, preparation effort, and classroom resources required (Ateş & Kölemen, 2025a). This interpretation aligns with findings that teachers frequently evaluate technologies in terms of educational payoff rather than financial expenditure.

Finally, habit is conceptualized as routine engagement with digital educational tools rather than habitual use of gamification or simulations specifically (Gómez-García et al., 2020). Teachers with established digital teaching routines have been shown to integrate new technologies more readily, suggesting that habitual technology use may lower adoption thresholds for GSBL. In the present study, habit therefore reflects teachers' general digital teaching routines and contextual readiness for technology integration, rather than post-adoption inertia associated with continued use of GSBL. Prior research indicates that teachers with established digital instructional routines are more likely to experiment with and integrate new educational technologies, suggesting that habitual technology use may lower psychological and practical thresholds for the adoption of GSBL.

Despite the growing body of research highlighting the pedagogical affordances of GSBL in inquiry-oriented science education, existing studies have predominantly focused on student-level outcomes, offering limited insight into teachers' educational decision-making processes. Moreover, research examining teachers' adoption of GSBL has often treated technology acceptance as a generic phenomenon, insufficiently accounting for the domain-specific demands of science teaching, such as inquiry facilitation, experimentation, and conceptual modeling. Although UTAUT2 provides a robust framework for understanding technology adoption, its application in K–12 science education remains under-theorized, particularly with respect to contextual reinterpretations of key constructs. Consequently, there is a clear need for a theory-driven and context-sensitive investigation into the factors shaping in-service science teachers' intentions to adopt GSBL within inquiry-based science education.

Research Aim and Research Questions

The aim of this study was to examine the mechanisms underlying in-service science teachers' intentions to adopt GSBL within inquiry-oriented science education. Specifically, this study addressed how cognitive (e.g., performance expectancy), affective (e.g., hedonic motivation), social (e.g., social influence), and contextual (e.g., facilitating conditions) determinants shaped teachers' adoption intentions within a contextually adapted UTAUT2 framework.

Accordingly, the study addressed the following research questions:

1. To what extent did the proposed UTAUT2-based model explain in-service science teachers' intentions to adopt GSBL within inquiry-oriented science education?
2. How well did a contextually adapted UTAUT2 model fit the empirical data in explaining science teachers' adoption intentions?

Hypothesis Development

Performance Expectancy and Inquiry Support

In science education, teachers prioritize educational approaches that enhance students' ability to engage in inquiry, experimentation, and evidence-based reasoning (Brown et al., 2010). Technologies that demonstrably improve conceptual understanding and inquiry efficiency are therefore more likely to be adopted (Bumbacher et al., 2018). Prior studies on digital simulations and virtual laboratories indicate that perceived educational effectiveness is a strong predictor of teachers' adoption intentions (Tarmo, 2022). Accordingly, this study posits: **H1:** Performance expectancy positively affects science teachers' intention to adopt GSBL.

Effort Expectancy and Teacher Workload

Given the intensive preparation demands associated with science teaching, perceived ease of use plays a critical role in technology adoption (Moses et al., 2013). Tools that are perceived as complex or time-consuming are often avoided, regardless of their pedagogical potential. Empirical evidence suggests that lower perceived effort increases teachers' willingness to integrate technology into regular education (Sang et al., 2023). Therefore:

H2: Effort expectancy positively affects science teachers' intention to adopt GSBL.

Social Influence and School Culture

Technology adoption in schools is strongly embedded within organizational culture. Support from school leadership and encouragement from colleagues can legitimize experimentation with innovative pedagogies (Stumbrienė et al., 2024). Studies in K–12 contexts indicate that peer modeling and administrative endorsement significantly influence teachers' educational decisions (Lai et al., 2022). Thus, it is hypothesized that:

H3: Social influence positively affects science teachers' intention to adopt GSBL.

Facilitating Conditions

The successful integration of GSBL in science classrooms depends on the availability of technological and organizational support. Adequate infrastructure and technical assistance reduce implementation barriers and increase teachers' confidence in using digital tools (Wangdi et al., 2023). Accordingly:

H4: Facilitating conditions positively affect science teachers' intention to adopt GSBL.

Hedonic Motivation

Teachers' intrinsic enjoyment and professional satisfaction derived from using technology can influence their adoption decisions (Ateş & Garzón, 2022). When GSBL tools enhance classroom dynamics and student engagement, teachers may experience greater educational enjoyment, which in turn supports sustained use. Therefore:

H5: Hedonic motivation positively affects science teachers' intention to adopt GSBL.

Price Value as Educational Return on Investment

In educational settings, teachers evaluate technologies based on whether the educational benefits outweigh the required investment of time and effort (Hernández-Leo & Ginoyan, 2025). When GSBL is perceived as yielding substantial learning gains relative to preparation demands, adoption is more likely. Consequently:

H6: Perceived educational return on investment (price value) positively affects science teachers' intention to adopt GSBL.

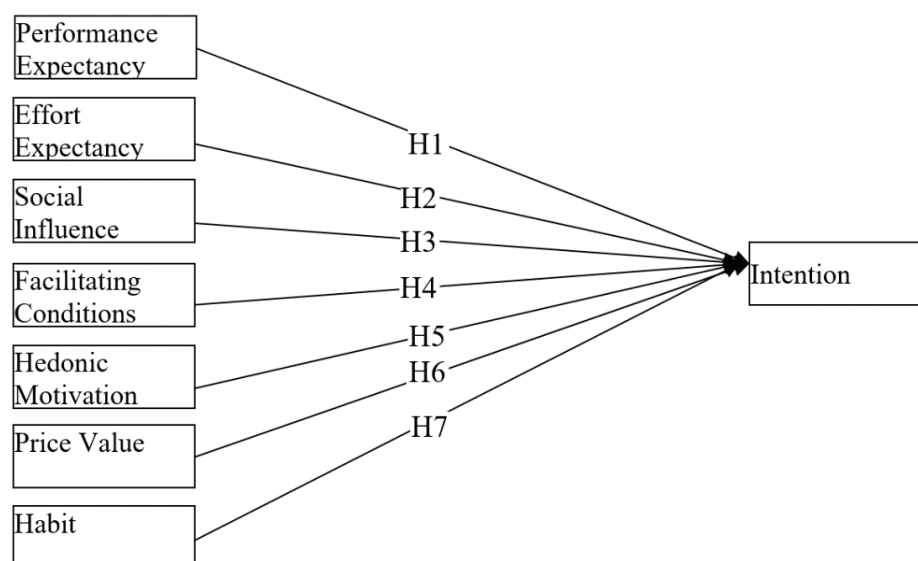
Habit and Technological Routine

Teachers with established routines of using digital technologies are more inclined to experiment with new educational tools (Liu et al., 2025). Habitual engagement with educational technologies can reduce uncertainty and lower perceived adoption barriers. Hence:

H7: Habitual use of digital educational technologies positively affects science teachers' intention to adopt GSBL.

The proposed research model is presented in Figure 1.

Figure 1
The Conceptual Research Model



Research Methodology

General Background

This study adopted a quantitative research approach employing a cross-sectional survey design to examine in-service science teachers' intentions to adopt GSBL. A survey-based methodology was considered appropriate given the study's aim to examine latent psychological and contextual factors derived from the UTAUT2 framework and to test theoretically hypothesized relationships among these constructs.

A cross-sectional research time frame was adopted because the study sought to capture teachers' adoption intentions as they exist at a specific point in time, reflecting prevailing perceptions, beliefs, and contextual conditions rather than changes or developments over time. This approach is consistent with prior technology acceptance research, which commonly employs cross-sectional designs to address determinants of behavioral intention (Hair et al., 2022; Venkatesh et al., 2012).

The research was grounded in a post-positivist paradigm, which assumes that social phenomena can be systematically addressed through empirical observation while acknowledging that knowledge claims are probabilistic and theory-laden (Creswell & Creswell, 2018; Phillips & Burbules, 2000). Within this paradigm, teachers' adoption intentions are conceptualized as latent constructs that can be measured indirectly through observable indicators and statistically modeled to explain underlying relationships.

Covariance-based structural equation modeling (CB-SEM) was employed as the primary analytical technique because it enables rigorous theory testing through the simultaneous assessment of measurement validity and structural relationships among latent variables (Kline, 2016; Hair et al., 2022). Overall, the methodological design was structured to ensure rigor, transparency, and replicability, thereby providing a solid empirical basis for the study's conclusions.

Sample

The target population of the study consisted of in-service science teachers employed at middle and secondary school levels within the national education system. Participants were enrolled through a nationwide in-service professional development program designed to support teachers' integration of innovative educational technologies, with particular emphasis on GSBL in science education. This participant selection approach was deliberately selected because it provided access to a professionally relevant and geographically diverse group of practicing teachers for whom GSBL adoption is pedagogically meaningful, thereby ensuring close alignment between the study's purpose and the participant group.

A total of 800 in-service science teachers participated in the study (see Table 1). The sampling strategy can be characterized as voluntary, non-probabilistic, and purposive, as participation was limited to teachers actively engaged in technology-focused professional development. This approach was considered appropriate given the study's aim to examine adoption intentions among potential users of GSBL, rather than the general teacher population. While this strategy may involve some degree of self-selection, it is consistent with prior technology adoption research and is explicitly acknowledged when interpreting the findings.

With respect to school level, 58% of participants were taught at the middle school level and 42% at the secondary school level. The gender distribution was relatively balanced, with 54% female and 46% male teachers, closely reflecting the national gender composition of the teaching workforce. Participants also represented a broad range of professional experience: 24% had 5 years or less teaching experience, 37% had between 6 and 15 years, and 39% had more than 15 years of experience.

In terms of school context, 63% of participants were employed in urban or suburban schools, whereas 37% worked in rural or semi-rural settings. Additionally, 68% of teachers reported having regular access to digital educational technologies (e.g., interactive whiteboards, computer laboratories, or tablet-supported classrooms), while 32% indicated limited or inconsistent access, highlighting meaningful variability in contextual facilitating conditions relevant to GSBL adoption.

Participation was entirely voluntary, and all respondents provided informed consent prior to data collection. To ensure data quality, questionnaires containing substantial missing data or response patterns indicative of inattentive responding were excluded from the final dataset.

The final sample size of 800 participants was considered methodologically adequate and reliable for the purposes of this study. Sample size adequacy was evaluated with reference to established guidelines for covariance-based structural equation modeling (CB-SEM), which requires relatively large samples to ensure stable parameter estimation, accurate assessment of model fit, and sufficient statistical power, particularly in models involving multiple latent constructs.

Methodological authorities commonly recommend a minimum of 200 cases for CB-SEM, with larger samples preferred as model complexity increases. Given the complexity of the adapted UTAUT2 model tested in this study, the achieved sample size substantially exceeds recommended thresholds, providing strong statistical power for hypothesis testing, robust estimation of structural paths, and reliable evaluation of global model fit indices. Accordingly, the sample size can be considered sufficient to support valid and reliable conclusions regarding the determinants of GSBL adoption among in-service science teachers.

Table 1
Demographic Characteristics of the Participants

Characteristic	Category	<i>n</i>	%
Gender	Female	432	54.0
	Male	368	46.0
School Level	Middle School	464	58.0
	Secondary School	336	42.0
Teaching Experience	≤ 5 years	192	24.0
	6–15 years	296	37.0
	> 15 years	312	39.0
School Context	Urban / Suburban	504	63.0
	Rural / Semi-rural	296	37.0
Access to Digital Technologies	Regular access	544	68.0
	Limited / inconsistent access	256	32.0

Note. Percentages may not total 100 due to rounding.

Instrument and Procedures

Data were collected using a structured self-administered questionnaire adapted from validated UTAUT2 instruments originally developed by Venkatesh et al. (2012) and subsequently employed in teacher and educational technology adoption studies. As the original UTAUT2 items were developed in English, a rigorous translation and back-translation procedure was employed following Brislin's (1970) guidelines to ensure semantic and conceptual equivalence in Turkish. Discrepancies between the original and back-translated versions were resolved through expert consensus involving specialists in science education and educational technology.

The questionnaire consisted of two sections. The first section gathered demographic information, including gender, years of teaching experience, school level, and general frequency of digital technology use in teaching. The second section measured the UTAUT2 constructs, including performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value (conceptualized in this study as perceived educational return on investment), habit (defined as routine engagement with digital educational technologies), and behavioral intention, using items adapted to the science education context.

21 items were measured using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Although seven-point scales are frequently used in technology acceptance research, a five-point scale was selected to reduce cognitive load and response fatigue, given the length of the instrument and the professional constraints of the participants.

To support construct validity and ensure a shared understanding of key terms, participants attended a brief, neutral standardization briefing prior to survey administration. This briefing was limited to operational definitions distinguishing GSBL from general educational technology and did not include evaluative language, persuasive content, or demonstrations intended to promote adoption. Accordingly, the study captures teachers' behavioral intentions within the context of professional development while minimizing potential priming effects.

Prior to the main data collection, a pilot study was conducted with a group of in-service science teachers ($n = 145$) to evaluate the clarity, relevance, and contextual appropriateness of the adapted questionnaire items. The pilot participants were selected to reflect variability

in teaching experience and school level, ensuring that the instrument was comprehensible across different professional profiles. The pilot study served multiple purposes: (a) to assess the linguistic clarity of the translated items, (b) to examine the suitability of the items for the science education context, and (c) to identify potential issues related to survey length and respondent burden. Participants were invited to provide written feedback on item wording, ambiguity, and perceived redundancy. Based on the pilot feedback, minor revisions were made to several items, primarily involving simplification of phrasing and alignment with terminology commonly used in science teaching practice. No items were removed or added at this stage, as the pilot results indicated satisfactory content coverage and construct representation. Preliminary reliability analysis conducted on the pilot data yielded Cronbach's alpha values exceeding .70 for all constructs, suggesting acceptable internal consistency prior to the main study. In addition, the average completion time was monitored during the pilot phase and was found to be approximately 20–25 minutes, which was deemed appropriate given the professional constraints of the target population. The finalized questionnaire was subsequently administered electronically to the full sample. Responses were collected anonymously to encourage honest reporting and to reduce potential social desirability bias.

Table 2 presents the measurement items used in the study along with descriptive statistics and reliability and validity indices.

Table 2
Measurement Items, Descriptive Statistics, and Reliability Indices

Construct / Item	M	SD	Factor loading	Cronbach's α	AVE	CR
Performance Expectancy (PE)				.89	.68	.91
PE1: Using GSBL enhances students' understanding of science concepts.	3.87	.81	.82			
PE2: GSBL improves the effectiveness of my science teaching.	3.79	.84	.85			
PE3: GSBL supports inquiry-based learning in science.	3.92	.78	.83			
Effort Expectancy (EE)				.87	.64	.90
EE1: Learning to use GSBL is easy for me.	3.61	.88	.81			
EE2: I find GSBL easy to integrate into my science lessons.	3.55	.91	.79			
EE3: It is easy for me to become skillful at using GSBL.	3.68	.86	.83			
Social Influence (SI)				.85	.66	.89
SI1: School administrators encourage me to use GSBL.	3.42	.97	.82			
SI2: Colleagues whose opinions I value support the use of GSBL.	3.58	.89	.84			
Facilitating Conditions (FC)				.88	.69	.91
FC1: I have access to the necessary resources to use GSBL.	3.71	.83	.85			
FC2: I receive adequate technical support for GSBL.	3.46	.92	.81			
FC3: My school infrastructure supports GSBL use.	3.62	.87	.84			
Hedonic Motivation (HM)				.90	.72	.93
HM1: I enjoy using GSBL in science teaching.	3.88	.79	.86			
HM2: Using GSBL makes teaching science more enjoyable.	3.94	.76	.88			
HM3: I find GSBL interesting to use.	3.90	.80	.84			
Price Value (PV – Educational ROI)				.86	.63	.89
PV1: The educational benefits of GSBL justify the time required.	3.67	.85	.81			
PV2: GSBL is worth the effort invested for student learning.	3.74	.82	.83			
Habit (HT – Digital Routine)				.84	.61	.88
HT1: Using digital technologies is a natural part of my teaching routine.	3.81	.84	.79			
HT2: I regularly use digital tools in my science lessons.	3.76	.86	.82			
Behavioral Intention (BI)				.92	.74	.94
BI1: I intend to use GSBL in my future science teaching.	3.89	.77	.87			
BI2: I plan to integrate GSBL into my science lessons.	3.85	.79	.88			
BI3: I will make an effort to use GSBL regularly.	3.91	.75	.86			

Data Analysis

Data analysis proceeded in a two-step approach, beginning with an assessment of the data's distributional properties and measurement quality, followed by testing of the hypothesized structural relationships. In the first step, descriptive statistics (means, standard deviations, skewness, and kurtosis) were computed to examine the distributional properties of

the observed variables and to ensure compliance with assumptions of multivariate normality. No severe deviations from normality were observed, supporting the use of maximum likelihood estimation.

The measurement model was subsequently evaluated through confirmatory factor analysis (CFA). Standardized factor loadings were examined to assess indicator reliability, with values exceeding the recommended threshold of .60, indicating that all items adequately represented their intended latent constructs. Internal consistency reliability was assessed using both Cronbach's alpha and composite reliability (CR), with values above .70 for all constructs, demonstrating satisfactory reliability.

Convergent validity was evaluated by examining average variance extracted (AVE) values. All constructs exhibited AVE values greater than the .50 criterion, indicating that a substantial proportion of variance was captured by the latent construct relative to measurement error. Discriminant validity was assessed by comparing the square root of each construct's AVE with the inter-construct correlations, in accordance with the Fornell–Larcker criterion. The results confirmed that each construct shared more variance with its indicators than with other constructs, supporting discriminant validity.

Given the cross-sectional and self-reported nature of the data, common method bias was explicitly examined using Harman's single-factor test. The unrotated factor solution revealed that no single factor accounted for more than 50% of the total variance, suggesting that common method bias was unlikely to substantially influence the results.

Following validation of the measurement model, the structural model was tested using covariance-based SEM to examine the hypothesized relationships among UTAUT2 constructs. Overall model fit was evaluated using multiple goodness-of-fit indices, including the chi-square to degrees of freedom ratio (χ^2/df), Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). The obtained fit indices met or exceeded commonly accepted thresholds ($\chi^2/df < 3$, CFI and TLI $\geq .90$, RMSEA $\leq .08$, SRMR $\leq .08$), indicating an acceptable to good model fit.

Finally, standardized path coefficients, corresponding standard errors, and significance levels were examined to test the proposed hypotheses, while the results of the measurement model including inter-construct correlations, square roots of the average variance extracted ($\sqrt{AVE}$), and descriptive statistics are summarized in Table 3. All analyses were conducted using IBM SPSS Statistics 26.0 and IBM SPSS AMOS 26.0, following established best practices for covariance-based structural equation modeling (CB-SEM).

Table 3
Discriminant Validity, Correlations, and Descriptive Statistics

Construct	1	2	3	4	5	6	7	8	$\sqrt{AVE}$	<i>M</i>	<i>SD</i>
1. Performance Expectancy	–								.82	3.86	.81
2. Effort Expectancy	.54	–							.80	3.61	.88
3. Social Influence	.48	.42	–						.81	3.50	.93
4. Facilitating Conditions	.51	.46	.49	–					.83	3.60	.87
5. Hedonic Motivation	.58	.44	.41	.47	–				.85	3.91	.78
6. Price Value	.53	.40	.38	.42	.55	–			.79	3.71	.84
7. Habit	.46	.39	.36	.41	.43	.44	–		.78	3.79	.85
8. Behavioral Intention	.61	.52	.49	.50	.58	.54	.51	–	.86	3.88	.77

Note. Off-diagonal elements represent inter-construct correlations. The square root of the average variance extracted ($\sqrt{AVE}$) appears in the rightmost column. Discriminant validity is supported because the $\sqrt{AVE}$ for each construct exceeds its correlations with other constructs. *M* = mean; *SD* = standard deviation.

Research Results*Structural Model Analysis*

Following the validation of the measurement model, the structural model was evaluated using covariance-based structural equation modeling with maximum likelihood estimation. The goodness-of-fit indices indicated that the proposed UTAUT2 model demonstrated an acceptable to good fit with the data. The chi-square to degrees of freedom ratio (χ^2/df) was below recommended thresholds, and both absolute and incremental fit indices met established criteria. Overall, the model explained a substantial proportion of variance in science teachers' behavioral intention to adopt GSBL.

The detailed results of the structural model fit indices are presented in Table 4.

Table 4
Goodness-of-Fit Indices for the Structural Model

Fit indices	Suggested value	Model fit indices
χ^2	–	465.12
df	–	162
χ^2/df	≤ 2 to ≤ 5	2.87
GFI	$\geq .90$	.91
IFI	$\geq .90$	.93
TLI	$\geq .90$	.92
CFI	$\geq .90$	.93
RMSEA	$\leq .08$	.04
SRMR	$\leq .08$	.04
R ² (Behavioral Intention)	–	.54

Note. Suggested cutoff values are based on Hair et al. (2018), Hu and Bentler (1999), and Kline (2005). χ^2 = chi-square; df = degrees of freedom; GFI = goodness-of-fit index; IFI = incremental fit index; TLI = Tucker–Lewis index; CFI = comparative fit index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

Hypothesis Testing and Structural Path Results

The hypothesized relationships of the adapted UTAUT2 model were examined using covariance-based structural equation modeling with maximum likelihood estimation. Hypothesis testing was conducted by evaluating standardized regression weights (β), standard errors (S.E.), and corresponding *t*-values. The statistical significance and magnitude of each structural path were assessed to determine the relative influence of UTAUT2 determinants on science teachers' behavioral intention to adopt GSBL.

The results indicate that all seven UTAUT2 constructs exerted statistically significant effects on behavioral intention, although the strength of these effects varied. Performance expectancy emerged as the strongest predictor of behavioral intention ($\beta = .28$, $t = 6.83$), suggesting that science teachers are more likely to adopt GSBL when they perceive clear educational benefits for enhancing inquiry, conceptual understanding, and student engagement. Hedonic motivation also demonstrated a strong positive influence ($\beta = .26$, $t = 6.67$), indicating that intrinsic enjoyment and professional satisfaction associated with GSBL use play a substantial role in adoption decisions.

Facilitating conditions had a moderate but significant effect on behavioral intention ($\beta = .19, t = 5.59$), highlighting the importance of institutional infrastructure, technical support, and access to digital resources in enabling GSBL integration. Effort expectancy similarly showed a significant effect ($\beta = .17, t = 4.72$), suggesting that perceived ease of learning and implementation remains a relevant, though secondary, consideration for science teachers.

Social influence exhibited a positive and statistically significant, yet comparatively weaker, effect on behavioral intention ($\beta = .14, t = 4.38$), reflecting the role of school leadership expectations and peer norms in shaping teachers' technology adoption behaviors. Price value, conceptualized as perceived educational return on investment, also significantly predicted behavioral intention ($\beta = .16, t = 4.85$), indicating that teachers evaluate GSBL adoption by weighing anticipated pedagogical gains against the time and effort required for implementation.

Finally, habit, defined as routine engagement with digital educational technologies, had a modest but significant effect on behavioral intention ($\beta = .13, t = 4.33$). This finding suggests that teachers with established digital teaching routines are more inclined to incorporate GSBL into their educational practices, even when the technology itself is relatively novel.

Collectively, the seven UTAUT2 constructs explained 54% of the variance in behavioral intention, demonstrating strong explanatory power of the adapted model in the context of in-service science teachers. A summary of the hypothesis testing results is presented in Table 5 and Figure 2.

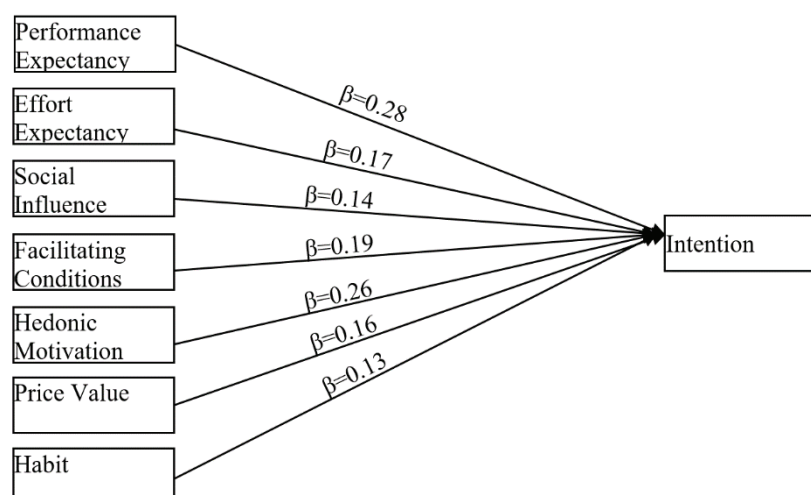
Table 5
Structural Path Estimates and Hypothesis Testing Results

Hypothesis	Structural path	β	t-value	Result
H1	Performance Expectancy → Behavioral Intention	.28	6.83	Supported
H2	Effort Expectancy → Behavioral Intention	.17	4.72	Supported
H3	Social Influence → Behavioral Intention	.14	4.38	Supported
H4	Facilitating Conditions → Behavioral Intention	.19	5.59	Supported
H5	Hedonic Motivation → Behavioral Intention	.26	6.67	Supported
H6	Price Value → Behavioral Intention	.16	4.85	Supported
H7	Habit → Behavioral Intention	.13	4.33	Supported

Note. All coefficients are standardized regression weights. All t-values are significant at $p < .001$.

Figure 2

Results of the structural equation model for science teachers' adoption of GSBL.



Discussion

The present study examined the factors shaping in-service science teachers' intention to adopt GSBL through a contextually adapted UTAUT2 framework. Overall, the model accounted for 54% of the variance in behavioral intention, indicating strong explanatory power in a school-based teaching context. This level of explained variance is broadly consistent with, and in some cases higher than, that reported in international teacher-focused technology acceptance studies (Cao et al., 2025; Khoshtaria et al., 2026; Nikolopoulou et al., 2021), supporting the position that UTAUT2 can be informative in education when constructs are appropriately contextualized.

Performance expectancy emerged as the strongest predictor of behavioral intention. A plausible explanation is that science teachers are likely to prioritize approaches that support core disciplinary goals such as inquiry, modelling, and conceptual understanding of abstract or unobservable phenomena. In science education, where learning often depends on visualization and dynamic representation (National Research Council, 2012), teachers may evaluate GSBL chiefly in terms of perceived pedagogical contribution rather than novelty or external pressure. This pattern is consistent with international findings showing performance expectancy as a dominant determinant of teachers' technology acceptance (Cao et al., 2025; Khoshtaria et al., 2026; Nikolopoulou et al., 2021). The present study extends these studies by interpreting performance expectancy as reflecting pedagogical-content alignment, which resonates with the logic of technological pedagogical content knowledge (Mishra & Koehler, 2006).

Hedonic motivation was the second strongest predictor of behavioral intention. One possible reason is that GSBL may enhance teachers' professional satisfaction by making classroom experiences more engaging and by enabling more varied teaching approaches, which can be particularly valuable in a cognitively demanding subject area. This result is broadly consistent with motivational perspectives emphasizing the role of intrinsic satisfaction in sustaining professional behaviors (Deci & Ryan, 2000). At the same time, prior research has reported mixed results regarding hedonic motivation in teacher adoption models (Ateş & Kölemen, 2025a), suggesting that its influence may vary by subject domain, tool type, or contextual conditions. In comparison with student-centered gamification literature, where hedonic motivation is often prominent (Luarn et al., 2025), the present findings clarify that enjoyment and professional vitality can also be consequential for teachers' adoption intentions.

Facilitating conditions demonstrated a moderate but significant influence on behavioral intention. A likely explanation is that, even when teachers perceive GSBL as beneficial, adoption remains contingent on access to adequate technological resources and organizational support. This result is consistent with international work indicating that infrastructure, technical support, and school-level enablers shape teachers' willingness and capacity to adopt digital approaches (Du & Liang, 2024; Tseng et al., 2022). The present findings support this line of evidence by showing that enabling conditions remain consequential even when other determinants (e.g., perceived value and motivation) are strong, thereby confirming that adoption decisions are embedded within organizational realities rather than being purely individual choices.

Effort expectancy and social influence were statistically significant but comparatively weaker predictors. One possible reason is that baseline digital competence among teachers may reduce the salience of ease-of-use concerns, while adoption decisions may rely more heavily on perceived pedagogical contribution than on colleagues' or administrators' expectations. This pattern aligns with findings from some teacher-focused acceptance studies where effort expectancy and social influence play secondary roles once teachers are familiar with digital tools (Nikolopoulou et al., 2021; Tseng et al., 2022). However, this finding may differ from contexts where technology use is mandated or where peer norms are stronger, suggesting that the influence of social influence may be more context-dependent than universal.

The results provide clear support for the reinterpretation of price value as perceived educational return on investment. A plausible explanation is that teachers evaluate GSBL not as consumers weighing monetary cost, but as professionals balancing time, preparation effort, and classroom disruption against perceived pedagogical gains. This interpretation is consistent with arguments that teachers' technology decisions are shaped by perceived payoff relative to workload constraints rather than financial expenditure (Scherer et al., 2019; Teo, 2011). Importantly, earlier school-based applications of UTAUT2 have often reported weak or inconsistent effects for price value (Du & Liang, 2024; Tseng et al., 2022). The present findings therefore differ from those studies in form but help clarify them theoretically: when the construct is conceptually aligned with teachers' professional evaluations, it becomes empirically meaningful.

Finally, habit, conceptualized as general digital teaching routine, had a modest but significant effect on behavioral intention. One possible explanation is that teachers with established digital routines experience lower uncertainty and fewer barriers when adopting new digital approaches. Prior research has highlighted conceptual challenges in applying habit to teachers when it is defined as repeated use of a specific technology (Ateş & Garzón, 2022; Ifenthaler & Schweinbenz, 2013). In contrast, the present study's findings support treating habit as contextual readiness rather than post-adoption continuation, clarifying how habit can be relevant even in adoption-focused research.

Limitations and Suggestions for Future Studies

Despite the theoretical and methodological rigor of the present study, several limitations should be acknowledged, which also indicate directions for future research. First, the study employed a cross-sectional survey design, which restricts the ability to draw causal inferences regarding the relationships among the UTAUT2 constructs. Although the proposed model was theoretically grounded and empirically supported, future studies adopting longitudinal or experimental designs would be valuable for examining how teachers' adoption intentions translate into actual classroom use over time, particularly as digital routines and organizational conditions evolve.

Second, the study relied exclusively on self-reported measures, which may be subject to common method bias and social desirability effects, despite the procedural and statistical

controls implemented. Future research could strengthen validity by incorporating additional data sources, such as system log data, classroom observations, or teaching artefacts, to triangulate teachers' reported intentions with observed classroom practices.

Third, although the sample size was large and geographically diverse, participants were recruited through a national professional development program focused on educational technologies. As a result, the sample may overrepresent teachers who are relatively open to innovation. Future studies could examine more heterogeneous teacher populations, including those with limited prior exposure to digital technologies, to explore whether adoption mechanisms vary across levels of technological readiness.

Fourth, the construct of habit was conceptualized as general digital teaching routine rather than prior or continued use of gamification or simulation-based learning specifically. While this adaptation was theoretically appropriate within a pre-adoption context, future longitudinal research could examine how GSBL-specific habits develop over time and how they relate to continuation intention and sustained classroom use once these practices become more institutionalized. Such work would further refine understanding of the temporal dynamics of habit formation in educational technology adoption.

Finally, this study focused exclusively on science education, where the epistemic demands of inquiry, visualization, and experimentation are particularly salient. While this domain-specific focus represents a strength, future research should examine whether the adapted UTAUT2 framework, particularly the interpretation of price value as perceived educational return on investment, extends to other subject areas such as mathematics, social sciences, or language education. Comparative, cross-disciplinary studies would contribute to the development of more nuanced and discipline-sensitive models of technology acceptance in education.

Conclusion and Implications

This study contributes to the literature on educational technology adoption by offering a discipline-sensitive explanation of how and why in-service science teachers decide to integrate GSBL. Situated within the broader challenge of aligning educational technologies with pedagogical practice, the findings demonstrate that teachers' adoption intentions can be systematically explained through a coherent combination of perceived educational value, affective engagement, and contextual support. Collectively, these factors accounted for a substantial proportion of variance in behavioral intention, underscoring that technology adoption in science education is a pedagogically situated and professionally meaningful process rather than a novelty-driven or externally imposed decision.

At a more general level, the results suggest that science teachers' adoption of GSBL is shaped by professional judgments regarding pedagogical alignment, educational payoff, and the conditions that enable sustainable classroom implementation. Rather than being driven primarily by ease of use or social pressure, adoption decisions reflect teachers' evaluations of how well digital technologies support epistemic goals in science teaching and contribute to meaningful learning experiences.

From a theoretical standpoint, this study demonstrates that the applicability of the UTAUT2 framework in educational settings depends on contextual and conceptual refinement. In particular, conceptualizing price value as perceived educational return on investment and habit as routine engagement with digital educational practices provides greater explanatory clarity for understanding teachers' technology adoption behavior. By situating technology acceptance within disciplinary pedagogy and established professional routines, the findings underscore the importance of adapting general technology acceptance models to reflect the realities of teaching practice.

The findings also carry important implications for practice. Professional development initiatives should prioritize demonstrating the pedagogical relevance of GSBL for inquiry-based science education rather than focusing solely on technical functionality. Experiential and design-oriented learning opportunities may further enhance teachers' professional engagement and support sustained adoption. At the school and policy levels, establishing stable digital teaching routines and providing curriculum-aligned GSBL resources can reduce cognitive and educational costs, thereby strengthening perceived educational return on investment and facilitating the integration of GSBL as an embedded educational practice.

In sum, this study demonstrates that science teachers' adoption of GSBL is best understood as a pedagogically grounded, affectively informed, and contextually enabled process. By refining UTAUT2 to reflect the professional realities of science teaching, the study advances both theory and practice and contributes to a more nuanced understanding of educational technology adoption in contemporary classrooms.

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