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Linking Motivation and Technology Beliefs to Perceived Learning Outcomes: A Moderated Mediation Model in Business Information Systems Education

Dan Liu
liu5dx@jmu.edu

Yugun Zhong
zhongyx@jmu.edu

Ping Wang
wangpx@jmu.edu

Thomas W. Dillon
dillontw@jmu.edu

James Madison University
Harrisonburg VA

Abstract

This study investigates the cognitive and motivational factors that shape students' perceived learning outcomes in technology-enhanced learning environments. Drawing on the Unified Theory of Acceptance and Use of Technology (UTAUT), Self-Regulated Learning theory, and Bandura's Social Cognitive Theory, we propose and test a structural equation model incorporating perceived usefulness, ease of use, perceived behavioral control, effort regulation, and self-efficacy.

Survey data were collected from first-year business students enrolled in an introductory computer information systems course at a public university in the southeastern United States. Among the 678 students surveyed, 642 provided valid responses. Structural equation modeling results reveal that Behavior Intension is significantly predicted by perceived usefulness and perceived behavioral control, while effort regulation and ease of use show limited predictive power. Behavior Intension strongly predicts perceived learning outcomes, which are also directly influenced by self-efficacy. The model explains 68.4% of the variance in Behavior Intension and 64.0% in perceived learning outcomes.
These findings offer empirical support for an integrated framework linking technology acceptance, motivational regulation, and learning effectiveness in higher education. Implications for instructional design, technology integration, and learner support strategies are discussed.

Keywords: UTAUT, Self-Efficacy, Effort Regulation, Behavior Intension, Perceived Learning, Structural Equation Modeling, Business Education

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1. INTRODUCTION

Background

The post-pandemic college experience has reshaped the academic landscape for today's first year college students. Entering higher education in the aftermath of COVID-19, many students face the dual challenge of academic unprepared-ness and motivational fatigue due to prolonged remote learning and social isolation during their high school years. These conditions have made the first or second semesters of college a critical turning point for students to (re)develop effective learning habits, self-discipline, and technological adaptability (Means & Neisler, 2021; Zimmer-man, 2000). This is especially true in gateway courses such as introductory business information systems (IS), which not only initiate students into the digital backbone of modern business practice but also lay the foundation for future academic and professional success (Patterson et al., 2024; Topi et al., 2010).

Research Gaps

While today's college students are often labeled as "digital natives," research consistently shows a gap between their everyday digital usage and meaningful academic engagement with techno-logy (Alshare & Lane, 2011; Ghazal et al., 2018; Kennedy et al., 2008; Margaryan et al., 2011; Prensky, 2001). Instructors frequently observe a paradox: despite ubiquitous access to digital tools, students' sustained engagement, persistence, and regula-tion of learning in technology-supported environ-ments remain limited (Ng, 2012; Lai, 2011). These challenges underscore the importance of understanding the motivational and cognitive factors that influence students' use of educational technology and their learning outcomes (Selwyn, 2021).

Theoretical Framework

To investigate these dynamics, this study integ-rates three theoretical frameworks: the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), Bandura's Social Cognitive Theory (Bandura, 1997), and the Self-Regulated Learning (SRL) framework (Pintrich,1991). We examine how students' beliefs about technology—namely perceived usefulness, ease of use, and behavioral control—interact with motivational constructs such as self-efficacy and effort regulation to shape their Behavior Intension and ultimately their perceived learning outcomes (Artino, 2008; Komarraju & Nadler, 2013).

Theoretical and Practical Contributions

Although UTAUT and SRL theories have been widely applied in educational technology research (Liaw, 2008; Šumak et al., 2011; Teo, 2011), few studies have focused specifically on first-year undergraduate business students in foundational IS courses. Even fewer have integrated both technology acceptance and motivational regula-tion constructs within a structural model that explains perceived learning outcomes in this context. This study addresses this gap and offers contributions at both theoretical and practical levels. Theoretically, we extend the UTAUT framework by incorporating effort regulation and self-efficacy (Pajares, 1996; Pintrich, 2004). Practically, our findings inform instructional strategies that promote self-regulated learning, intentional use of educational technologies, and stronger academic self-efficacy among incoming students (Panadero, 2017; Zimmerman & Schunk, 2013).

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK DEVELOPMENT

Technology Acceptance and UTAUT

The Unified Theory of Acceptance and Use of Technology (UTAUT) provides a robust framework to understand individual adoption of digital tools, particularly in learning environments (Venkatesh et al., 2003). Rooted in earlier models including TAM, TRA, and TPB, UTAUT posits that four core constructs—performance expectancy (perceived usefulness), effort expectancy (perceived ease of use), social influence, and facilitating conditions (perceived behavioral control)—predict behavioral intention and technology use. In academic contexts, these constructs have been widely applied to examine students' adoption of learning management systems, e-learning tools, and mobile applications (Al-Rahmi et al., 2018; Liaw, 2008; Šumak et al., 2011; Teo, 2011).

In IS curriculum design, UTAUT is particularly valuable because the framework aligns closely with how students engage with emerging technologies that mirror workplace tools. Perceived usefulness reflects the degree to which students believe that technology use enhances their academic performance and prepares them with relevant digital competencies (Davis, 1989a). This construct is highly applicable to IS education, where demonstrating the career relevance of tools (e.g., ERP systems, data analytics platforms, and collaborative software) strengthens student engagement (Park, 2009; Salloum et al., 2019a; Unal & Uzun, 2021). Perceived ease of use refers to the effort required to use a tool and remains relevant when introducing complex enterprise systems or advanced analytics software that may initially intimidate students (Venkatesh et al., 2003). Finally, perceived behavioral control, derived from Ajzen's (1991, 2020) theory of planned behavior, represents students' perception of the resources and ability they have to use educational technology effectively. In IS contexts, this includes not only system accessibility and technical support but also the self-efficacy to apply digital tools in authentic problem-solving scenarios, directly mapping to AACSB competency requirements for technological agility.

Figure 1 shows the theoretical framework for the study. The following hypotheses are to be tested.

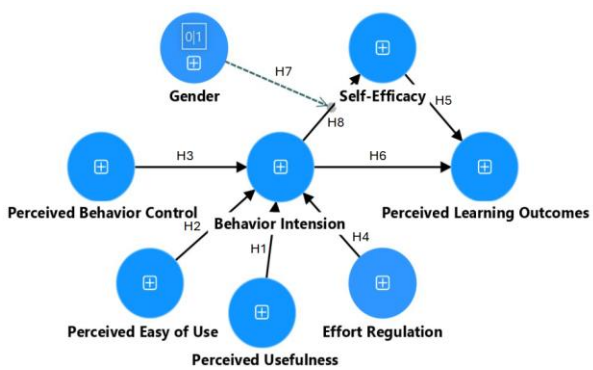

Figure 1. Theoretical Framework - A Moderated Mediation Model

H1: Perceived usefulness positively influences students' Behavior Intension to use learning technologies.

H2: Perceived ease of use positively influences students' Behavior Intension to use learning technologies.

H3: Perceived behavioral control positively influences students' Behavior Intension to use learning technologies.

Effort Regulation and Behavior Intension

Effort regulation is a motivational strategy within the Self-Regulated Learning (SRL) framework, defined as students' ability to persist and maintain effort during learning tasks, especially when faced with distractions or difficulty (Pintrich, 2004; Wolters, 1998). Research shows that students with stronger effort regulation tend to achieve better outcomes and engage more effectively in self-paced, technology-based environments (Barnard-Brak et al., 2010; Broadbent & Poon, 2015). However, its effect on technology adoption intention remains underexplored.

Meta-analytic evidence confirms that effort regulation remains a significant self-regulated learning strategy positively linked with academic performance in online and blended environments (Zhao et al., 2025).

H4: Effort regulation positively influences students' Behavior Intension to use learning technologies.

Self-Efficacy and Learning Outcomes

Self-efficacy, a central construct in Social Cognitive Theory (Bandura, 1997), refers to an individual's belief in their capability to succeed in specific tasks. In education, higher self-efficacy has been shown to predict motivation, persistence, strategic learning behaviors, and academic achievement (Pajares, 2002; Schunk & DiBenedetto, 2020, 2022). Within IS education, self-efficacy is particularly relevant to discipline-specific competencies such as programming, database management, systems analysis, and data analytics. Students with stronger IS-related self-efficacy are more likely to engage with complex enterprise systems, persist in mastering technical tools, and demonstrate confidence in applying IS concepts to problem-solving tasks. In digital learning environments, this confidence not only facilitates smoother adaptation to technology but also leads to more favorable learning perceptions and stronger performance outcomes (Compeau & Higgins, 1995; Torkzadeh & Van Dyke, 2002).

H5: Self-efficacy positively influences students' perceived learning outcomes.

Behavior Intension and Learning Outcomes

Behavior Intension is a well-established predic-tor of actual technology use and subsequent learning in models such as TAM, TPB, and UTAUT (Ajzen, 1991, 2020; Venkatesh et al., 2003). In higher

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education, intention to use learning technologies correlates with deeper engagement, task completion, and self-reported academic gains (Cheung & Vogel, 2013; Taghizadeh et al., 2022). H6: Behavior Intension positively influences students' perceived learning outcomes.

Gender as a Moderator
Prior research has suggested that gender may influence technology adoption and learning behaviors, particularly through its impact on self-efficacy and motivational processes. For example, women have often reported lower technology-related self-efficacy but higher persistence and learning engagement in some contexts, while men have been found to report stronger confidence but not always higher achievement (Ong & Lai, 2006; Venkatesh & Morris, 2000). More recent studies continue to confirm gender-linked differences in technology use and learning outcomes, though these effects tend to be modest (Ameen et al., 2021). We therefore interpret gender as a contextual factor that warrants further investigation rather than as a central theoretical contribution of this study.

This study examined whether gender moderates the indirect effect of Behavior Intension (BI) on perceived learning (PL) via self-efficacy (SEF). The hypothesized moderated mediation (H7) proposes that the strength of the mediation pathway from BI → SEF → PL varies by gender.

H7: Gender moderates the mediation effect of behavior intention on self-efficacy.

Behavior Intension as a Mediator
In UTAUT and related models, behavioral intention often mediates the link between belief constructs (e.g., usefulness, ease, control) and learning outcomes (Salloum et al., 2019b; Šumak et al., 2011). This study tests whether intention transmits the influence of motivational and technological beliefs to perceived academic success.

H8: Behavior Intension mediates the relation-ship between UTAUT constructs and perceived learning outcomes.

Self-Efficacy as a Mediator
Self-efficacy may mediate the relationship in the technology acceptance process. Learners with high academic self-efficacy are more likely to use support systems and perceive tools as more useful (Hsu et al., 2007; Joo et al., 2011). This suggests that self-efficacy may amplify the relationship between behavioral control and intention.

H9: Self-efficacy mediates the relationship between Behavior Intension and perceived learning outcomes.

3. METHODOLOGY

Research Design and Context
This study employed a quantitative, cross-sectional survey design to examine the relationships among technology acceptance beliefs, motivational regulation, and perceived learning out-comes. The research setting was a required intro-ductory business information systems course at a large public university in the southeastern United States. This course introduces foundational digital competencies, including spreadsheet modeling, data literacy, and information systems concepts relevant to business practice. All study procedures were reviewed and approved by the Institutional Review Board (IRB) at a public university in the Southeastern part of the United States.. Participation was voluntary, with informed consent obtained electronically prior to participate in the survey. Students were assured that their responses would remain anonymous and would not influence their course grades or standing. The study was conducted in the context of a required introductory business information systems course for undergraduate business majors. This course integrates foundational concepts in computer information systems, delivered through a combination of lectures, hands-on labs, and team projects. The setting provides a relevant environment for examining technology adoption and learning behaviors, as all students are required to use digital platforms and engage with technology-supported learning activities as part of their coursework.

A total of 678 students completed the survey, and after screening for missing or invalid data, 642 responses were retained for analysis (valid response rate = 94.7%). The participants were primarily first-year undergraduate business majors. Data collection occurred between weeks 13 and 14 of the semester to ensure that students had sufficient exposure to both course content and instructional technologies. Participation was voluntary, with a small amount of course credit offered as an incentive. Institutional Review Board (IRB) approval was secured, and informed consent was obtained.

Table 1 summarizes the demographic characteristics of the 642 student participants. The sample consisted of 56.7% male and 43.3% female students. In terms of age, the majority were 19

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years old (44.1%), followed by 18-year-olds (32.2%) and 20-year-olds (16.8%), with 6.9% older than 20. Most students were enrolled in face-to-face courses (62.9%), while 36.9% participated online. The participants represented a broad range of business majors, with Marketing (23.2%), Finance/Quantitative Finance (21.5%), and Management (20.7%) being the most common. Other majors included CIS (12.8%), Accounting (8.3%), International Business (3.6%), and Economics (2.3%), with 7.6% indicating "Others" or "Undecided."

Table 1. Demographic Data

Gender		Frequency	Percentage %
Male		364	56.7
Female		278	43.3
Age	**Years**	**Frequency**	**Percentage %**
	18	207	32.2
	19	283	44.1
	20	108	16.8
	>20	44	6.9
Major		**Frequency**	**Percentage %**
Marketing		149	23.2
Finance or Quantitative finance		138	21.5
Management		133	20.7
Computer Information Systems		82	12.8
Accounting		53	8.3
International Business		23	3.6
Economics		15	2.3
Others or Undecided		49	7.6
Mode		**Frequency**	**Percentage %**
Online		237	36.9
Face to face		404	62.9

Instrumentation and Measures

The survey instrument was developed by adapting validated measurement scales from prior studies. Perceived Usefulness, Ease of Use, and Behavioral Control items were adapted from (Ajzen, 1991; Davis, 1989b; Venkatesh et al., 2003). Effort Regulation was measured using the effort management scale from the Motivated Strategies for Learning Questionnaire (Pintrich, 1991, 2004). Self-Efficacy was adapted from (Bandura, 1997), with additional items from (Artino, 2008; Pajares, 2002). Behavior Intension followed the UTAUT operationalization (Teo, 2011). Perceived Learning Outcomes were measured using items from (Cheung & Vogel, 2013; Liaw, 2008). All items were measured on a seven-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree). A pilot test with 25 students was conducted for clarity and item relevance, leading to minor adjustments.

To reduce the potential bias associated with self-reported measures, several safeguards were implemented. First, all constructs were measured using previously validated scales, which were pilot tested with students for clarity and contextual relevance. Second, anonymity and confidentiality were emphasized during data collection to reduce social desirability effects. Third, we conducted statistical tests to assess Common Method Bias (CMB), including Harman's single-factor test and full collinearity variance inflation factors (VIF). Both approaches indicated that CMB was not a significant concern in this study (Podsakoff et al., 2003; Kock, 2015). While self-report measures inherently carry some limitations, these procedures enhance confidence in the validity of the responses.

Data Screening and Assumptions

Data were screened for missing responses, outliershalanobis distance), and multivariate normality. Cases with more than 10% missing values were removed. Harman's single-factor test and full collinearity variance inflation factors (VIF) were used to assess potential common method bias (Kock, 2015; Podsakoff et al., 2003). No substantial bias was detected.

Measurement Model Evaluation

Reliability and validity of the constructs were assessed before testing the structural model. Internal consistency was examined via McDonald's Omega (ω), both expected to exceed 0.70 (Hayes & Coutts, 2020; McDonald, 2013). As shown in Table 2, the reliability assessment indicated that most constructs met or exceeded recommended thresholds for internal consistency (ω, CR ≥ 0.70) and convergent validity (AVE ≥ 0.50). For Effort Regulation, McDonald's omega (ω = 0.679, 95% CI: 0.626–0.725) and composite reliability (CR = 0.698) fell just below the

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conventional 0.70 threshold. However, these values are close to the acceptable range and the AVE (0.543) exceeded the recommended 0.50 cut-off, indicating satisfactory convergent validity (Hair et al., 2019). Given the theoretical importance of effort regulation in self-regulated learning (Pintrich, 2004; Broadbent & Poon, 2015), we retained this construct while noting this limitation. Future research with refined items may strengthen its reliability. Convergent validity was evaluated using composite reliability (CR > 0.70) and average variance extracted (AVE > 0.50).

Table 2. Measurement Model Evaluation

Con-struct	Omega (ω) (95% CI)	CR	AVE
PUSE	0.943 (0.936, 0.950)	0.943	0.735
PEUSE	0.927 (0.918, 0.936)	0.927	0.679
PBC	0.907 (0.894, 0.918)	0.907	0.710
ER	0.679 (0.626, 0.725)	0.698	0.543
SEF	0.907 (0.896, 0.918)	0.909	0.590
BI	0.918 (0.907, 0.928)	0.919	0.741
PLO	0.778 (0.749, 0.805)	0.806	0.582

Notes:

Perceived Usefulness = PUSE
Perceived Ease of Use = PESUE
Perceived Behavioral Control = PBC
Effort Regulation = ER
Self-Efficacy = SEF
Behavior Intension = BI
Perceived Learning Outcomes = PLO
McDonald's Omega (ω) = Omega (ω)
Composite Reliability (rho-c) = CR
Average Variance Extracted = AVE

Discriminant validity was established using the Fornell-Larcker criterion and the HTMT ratio (Henseler et al., 2015), with a threshold of 0.85.

****** Table 3. Discriminant Validity – Fornell - Larcker Criterion is here.******

Table 3 (Fornell–Larcker Criterion) confirms discriminant validity. The square root of the Average Variance Extracted (AVE) for each construct (diagonal values) is consistently higher than the correlations with other constructs (off-diagonal values). For example, Behavioral Intention (0.897) exceeds its correlations with PBC (0.673) and PLO (0.638), supporting the distinctiveness of the constructs.

Table 4 (HTMT) shows that all heterotrait–monotrait (HTMT) ratios are well below the conservative threshold of 0.85, indicating strong discriminant validity among the constructs. The highest HTMT value observed was between Perceived Usefulness (USE) and Behavior Intension (BI) at 0.776, which is still comfortably below the threshold.

Together, these two tests provide robust evidence that the study constructs demonstrate adequate discriminant validity, supporting the reliability of the structural model results.SmartPLS is used to assess the measurement and structure models.

Table 4. Discriminant Validity - Heterotrait – monotrait Ratio (HTMT)

	BI	EUSE	ER	PBC	PLO	SEF
BI						
EUSE	0.614					
ER	0.345	0.317				
PBC	0.737	0.741	0.441			
PLO	0.740	0.635	0.380	0.739		
SEF	0.515	0.712	0.463	0.711	0.649	
USE	0.776	0.629	0.463	0.687	0.702	0.578

Common Method Bias Assessment: To assess potential Common Method Bias (CMB), both statistical and diagnostic approaches were employed. First, we conducted Harman's single-factor test by loading all measurement items into an unrotated exploratory factor analysis. The results (Appendix [X]) showed that the first factor accounted for 46.6% of the variance, which is below the 50% threshold commonly used as an indication of CMB (Podsakoff et al., 2003). Multiple factors with eigenvalues greater than 1 emerged, suggesting that variance was distributed across constructs rather than dominated by a single factor. Second, we examined Variance Inflation Factor (VIF) values for all items. All VIFs ranged between 1.36 and 4.00, majority VIFs well below the conservative cutoff of 3.3 suggested for PLS-SEM (Kock, 2015) and comfortably under the general threshold of 5.0 (Hair et al., 2019). Together, these results indicate that CMB and multicollinearity are not serious concerns in this study.

Structural Model and Hypothesis Testing
Partial Least Squares Structural Equation Modeling (PLS-SEM) was conducted using SmartPLS 4. The bootstrapping procedure (5,000 resamples) was used to generate path estimates,

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standard errors, and significance levels for direct and indirect effects. R² values were calculated for endogenous constructs (Behavior Intension and perceived learning outcomes), with values above 0.25 considered acceptable for educational research (Hair et al., 2019).

Moderation was tested using product-indicator interaction terms, and mediation was tested using the indirect effect approach with confidence intervals. Model fit was evaluated using SRMR (standardized root mean square residual), aiming for a value < 0.08.

*** Table 5 Hypothesis Testing Results is here ***

4. DISCUSSION

As shown in Figure 2 and Table 5, the findings of this study provide meaningful insights into how motivational and technological beliefs influence students' perceived learning outcomes in a foundational business information systems course. Through structural equation modeling, we validated the role of UTAUT constructs and motivational regulation in shaping Behavior Intension and perceived learning, revealing both expected and unexpected patterns.

These patterns are especially meaningful given our focus on first- and second-year students. Compared to upperclassmen or graduate learners, early-stage undergraduates are still developing academic habits and digital learning fluency. The non-significant effect of perceived ease of use may reflect a generational baseline of digital familiarity, where ease is assumed rather than consciously evaluated. This aligns with recent observations that younger students prioritize outcome utility over usability (Liaw, 2008; Park, 2009), distinguishing them from earlier cohorts studied in foundational UTAUT applications. Furthermore, the observed gender moderation effect on the BI–SEF path may also be more salient in early college years, where self-efficacy development is in flux. These findings underscore the importance of examining motivational and behavioral patterns within specific educational transitions, reinforcing our study's focus on entry-level business students as a distinct and underexplored population in technology-enhanced learning research.

Our study applies UTAUT and SRL by examining their predictive power in a business information systems learning context, while also extending and challenging certain assumptions. Consistent with UTAUT, perceived usefulness, behavioral control, and behavioral intention strongly predicted learning outcomes; however, ease of use showed no explanatory value, suggesting that for digital-native students this construct has limited relevance. From the SRL perspective, self-efficacy emerged as a robust predictor of perceived learning, while effort regulation was negligible, indicating that motivational confidence may outweigh volitional persistence in technology-supported learning. These findings both support and refine the models, highlighting boundary conditions that warrant further theoretical adaptation.

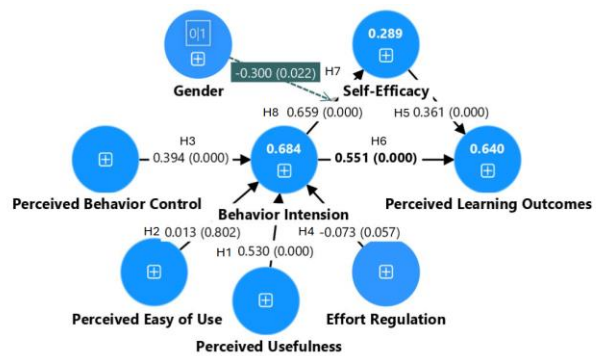

Figure 2. Path-Coefficients

Perceived usefulness and perceived behavioral control were found to be strong predictors of Behavior Intension, confirming hypotheses H1 and H3. These results support previous studies that highlight the critical roles of performance expectancy and facilitating conditions in predicting students' engagement with educational technologies (Salloum et al., 2019b; Teo, 2011; Venkatesh et al., 2003). Students who believe that using technology improves their academic performance and who feel confident in their ability to access and use digital tools are more inclined to adopt them consistently.

Contrary to expectations, perceived ease of use did not significantly influence Behavior Intension (H2 not supported). This aligns with emerging literature suggesting that ease of use may be a less salient factor for today's "digitally fluent" students, who often assume a baseline level of functionality and focus instead on value-added outcomes (Liaw, 2008; Park, 2009). Thus, ease of use may be necessary but not sufficient to motivate active engagement.

Unexpectedly, effort regulation also showed marginal significant influence on Behavior Intension (H4 marginally supported). Figure 3 shows the interactive effect of Gender and Behavior Intension. This inverse relationship may

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suggest that students who need to exert more self-regulatory effort to stay engaged may perceive the CIS content as more demanding or less intuitive—thus reducing their intention to continue using it. Similarly, the gender moderation analysis indicates that male students in the red line benefitted more from intention-driven self-efficacy building than females in the dark line, a dynamic that may relate to confidence formation patterns in early college years. This result diverges from earlier studies (Broadbent & Poon, 2015; Pintrich, 2004) which emphasized that persistence and effort sustain engagement with challenging tasks and tools. One possible explanation is that students who exhibit strong effort regulation may already possess independent learning strategies and therefore feel less need to rely on technological aids. Alternatively, their motivation may be intrinsic and not linked to external systems.

Recent studies emphasize that IS-related self-efficacy extends beyond general confidence to encompass discipline-specific competencies such as data analysis, programming, and systems thinking. Students with higher IS self-efficacy not only adapt more readily to digital learning environments but also demonstrate stronger professional readiness and problem-solving capacity (Schunk & DiBenedetto, 2020; Schunk & DiBenedetto, 2022; Ameen et al., 2021). In line with previous research, self-efficacy was found to be a robust predictor of perceived learning outcomes (H5 supported). Students who believe in their academic capabilities are more likely to engage meaningfully with course materials and evaluate their own learning positively (Artino, 2008; Bandura, 1997; Pajares, 2002). Similarly, Behavior Intension significantly predicted perceived learning (H6 supported), confirming its pivotal role in facilitating active use and benefit from educational tools (Ajzen, 1991).

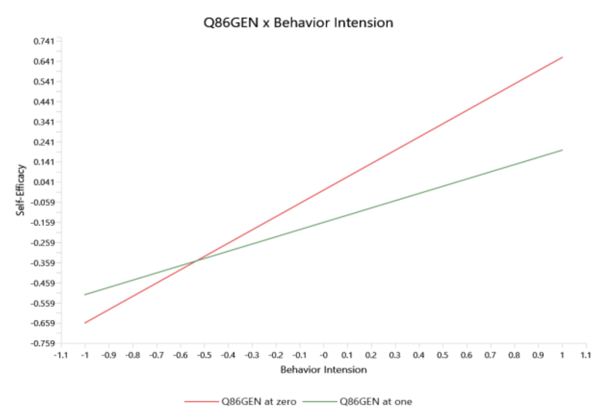

Figure 3. Interactive Effect of Gender and Behavior Intension

The moderation analysis showed that gender strengthened the relationship between perceived behavioral control and self - efficacy (H7 supported). Preliminary analysis suggests that gender significantly moderates the relationship between BI and SEF, indicating that the indirect effect of BI on PL through SEF is stronger for one gender group (e.g., females) than the other. This finding underscores the importance of tailoring motivational and instructional strategies in technology -supported learning environments to account for gender-based differences in self-efficacy development and perceived learning.

Lastly, the mediation analysis confirmed that Behavior Intension mediated the relationship between technology beliefs and learning outcomes (H8 supported). This finding aligns with the logic of the UTAUT model and with prior research that emphasizes intention as the crucial link between motivational/cognitive beliefs and learning outcomes (Cheung & Vogel, 2013; Šumak et al., 2011).

Revised Theoretical Framework and Testing Results

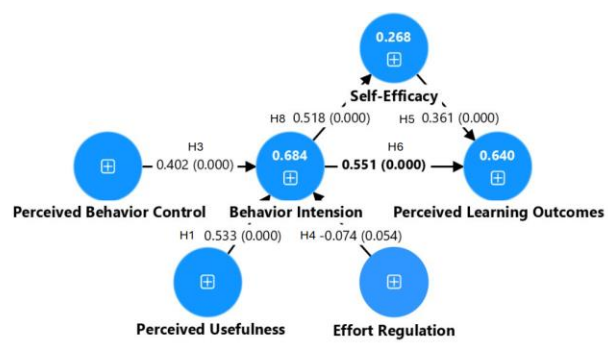

Figure 4. Refined Theoretical Framework

In light of the empirical results, the theoretical framework was refined by removing gender and perceived ease of use, as both constructs exhibited negligible effects and did not contribute meaningfully to the explanatory power of the model. The revised framework, therefore, centers on the more robust UTAUT and SRL drivers—perceived usefulness, perceived behavioral control, behavioral intention, self-efficacy, effort regulation, and perceived learning outcomes. This streamlined structure continues to highlight the central role of behavioral intention as a mediator between technology beliefs and learning, as well as the strong contributions of perceived usefulness and self-efficacy in shaping students' perceived learning outcomes. Importantly, these adjustments do not alter the study's conclusions

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but instead sharpen the theoretical model by focusing on the constructs that demonstrated substantive explanatory value.

Overall, the model explained 68.4% of the variance in Behavior Intension and 64.0% in perceived learning outcomes, demonstrating strong explanatory power. These results contribute to the growing literature at the intersection of UTAUT and motivational regulation by focusing on **first- and second-year IS students**—a population often underexamined in technology acceptance research. Unlike mixed-major or upper-division studies, our results show that perceived usefulness and behavioral control remain dominant drivers of technology engagement, while ease of use is less relevant for digital-native learners. Additionally, the moderated mediation pathway involving gender and self-efficacy reveals nuanced motivational differences that may inform tailored interventions in early IS coursework. These findings respond to recent calls in IS education to better understand how digital motivation and learning technology use evolve across stages of academic development (e.g., Patterson et al., 2024; Zhao et al., 2025).

5. CONCLUSION

This study investigated the psychological and technological drivers of perceived learning outcomes among first-year business students in a technology-enhanced learning environment. By integrating constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT), Self-Regulated Learning theory, and Social Cognitive Theory, we developed and tested a moderated mediation model using Partial Least Squares Structural Equation Modeling.

The findings highlight the significance of perceived usefulness and perceived behavioral control in shaping Behavior Intension, confirming the enduring relevance of UTAUT constructs in the educational domain. Students who perceive educational technologies as beneficial and who feel capable of accessing them are more likely to engage with these tools. Interestingly, perceived ease of use did not significantly predict intention, suggesting that its role may be diminishing among digital-native learners who assume basic usability by default.

Although effort regulation did not significantly predict Behavior Intension, its theoretical importance as a self-regulatory strategy remains. Further exploration may be needed to determine how students balance internal persistence with external technological aids. As expected, self-efficacy directly influenced perceived learning outcomes.

Importantly, Behavior Intension mediated the relationship between students' beliefs and their reported learning outcomes, underscoring its centrality in the learning process. The model accounted for substantial variance in both intention (68.4%) and perceived learning (64.0%), validating the integrative approach of combining motivational and technological frameworks.

~~This research extends the UTAUT framework by integrating effort regulation and self-efficacy, and by modeling a moderated mediation pathway. It contributes to the growing literature on motivational technology use and demonstrates the explanatory value of connecting cognitive beliefs with perceived learning via Behavior Intension.~~

~~Educators and instructional designers should prioritize interventions that reinforce self-efficacy and perceived value, such as task scaffolding, mastery experiences, and practical demonstrations of technological benefits. Learning technologies should be embedded in ways that align with students' motivational states and provide meaningful, confidence-building interactions.~~

This research extends the UTAUT framework by integrating effort regulation and self-efficacy, and by modeling a moderated mediation pathway that reveals differentiated motivational dynamics among early-stage IS learners. In doing so, it contributes to the growing body of work in IS education that seeks to link students' cognitive beliefs with learning outcomes through a motivation-sensitive lens (Zhao et al., 2025). Specifically, this study highlights that intention and self-efficacy serve as pivotal levers in enhancing perceived learning for new business majors, and that gender plays a moderating role in the strength of these effects.

Importantly, this study contributes specifically to the IS education literature by demonstrating how motivational constructs can inform curriculum design and pedagogical strategies in technology-enhanced learning environments. By linking behavioral intention and self-efficacy to IS-specific competencies such as programming, systems analysis, and data analytics, our findings offer actionable guidance for educators seeking to enhance student engagement, learning outcomes, and alignment with AACSB technology

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competency standards. This contribution underscores the relevance of integrating motivational theory with practical IS curriculum development, providing a framework for future research and teaching practice in IS education.

For IS educators, these insights yield several actionable recommendations. First, instructors should scaffold tasks that demonstrate clear value and relevance (enhancing perceived usefulness), particularly in foundational courses. Second, they should incorporate early mastery experiences and peer modeling to strengthen students' self-efficacy. Third, reducing extraneous cognitive load through streamlined tools and modular learning content can prevent effort regulation from becoming a barrier to continued engagement. Lastly, gender-aware instructional strategies—such as inclusive feedback and differentiated encouragement—may help close motivational gaps observed in early semesters. By translating empirical findings into instructional design, this study supports IS educators in fostering more intentional, confident, and sustained technology use among students at the critical entry point of their academic journey.

Further, these findings have several practical implications for IS curriculum design and accreditation standards. First, the central role of perceived usefulness suggests that educators should emphasize technology's value in achieving concrete learning outcomes, for example by aligning digital tools with core course objectives and AACSB learning competencies. Second, because perceived behavioral control significantly shapes students' engagement, institutions should prioritize technology training, onboarding, and equitable access initiatives, ensuring that all students feel capable of using required systems. Third, the non-significant role of ease of use highlights that today's digital-native students may take usability for granted, shifting the educator's task toward integrating technology in ways that foster deeper learning and professional skill development rather than merely ensuring basic operability. Finally, the strong effect of self-efficacy and behavioral intention on perceived learning outcomes reinforces the need for curriculum designs that cultivate students' confidence, persistence, and motivation, which align closely with AACSB's emphasis on lifelong learning, problem-solving, and technology agility.

Several limitations should be acknowledged. First, the study used self-reported measures, which may introduce bias or overestimate true perceived learning outcomes. Second, the sample was drawn from a single institution, limiting generalizability. Third, actual academic performance was not included as a validation criterion. Future studies should incorporate longitudinal designs, cross-institutional samples, and objective outcome data. In addition, qualitative studies could explore how students interpret and experience the constructs measured in this model.

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APPENDIX

Table 3. Discriminant Validity - Fornell - Larcker Criterion

	BI	EUSE	ER	PBC	PLO	SEF	USE
BI	***0.897***						
EUSE	0.570	***0.857***					
ER	0.280	0.266	***0.868***				
PBC	0.673	0.683	0.352	***0.884***			
PLO	0.638	0.548	0.285	0.631	***0.848***		
SEF	0.475	0.658	0.371	0.651	0.556	***0.806***	
USE	0.723	0.590	0.375	0.635	0.613	0.539	***0.883***

Table 5. Hypothesis Testing Results

	Path-Coef. (p-value)	f-square (p-value)	Total Effect (Standard)
H1: USE -> BI	0.530 (< 0.001)	0.416 (< 0.001)	0.530 (< 0.001)
H2: EUSE -> BI	0.013 (= 0.802)	0.000 (= 0.966)	0.013 (= 0.802)
H3: PBC -> BI	0.394 (< 0.001)	0.175 (= 0.003)	0.394 (< 0.001)
H4: ER -> BI	-0.073 (= 0.057)	0.013 (= 0.365)	-0.073 (= 0.057)
H5: SEF -> PLO	0.361 (< 0.001)	0.265 (= 0.001)	0.361 (< 0.001)
H6: BI - PLO	0.551 (< 0.001)	0.617 (< 0.001)	0.789 (< 0.001)
Gender -> SEF	-0.160 (= 0.026)	0.009 (= 0.300)	-0.160 (= 0.026)
H7: Gen x BI -> SEF	-0.300 (= 0.022)	0.021 (= 0.307)	-0.300 (= 0.022)
H8: BI - SEF	0.659 (< 0.001)	0.267 (= 0.001)	0.659 (< 0.001)

Notes: 1). *f-square (p-value)* indicates the effect size of each predictor on the endogenous variable, assessing the relative impact of removing a given predictor from the model. According to Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively.

2). Perceived Usefulness = PUSE, Perceived Ease of Use = PESUE, Perceived Behavioral Control = PBC, Effort Regulation = ER, Self-Efficacy = SEF, Behavior Intension = BI, Perceived Learning Outcomes = PLO.

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APPENDIX A

TableA1 Measurement Scales

Perceived Behavioral Control (PBC) (Ajzen, 1991; Venkatesh et al., 2003)	Mean	Standard Deviation	Loadings (Standard)	p-value
PBC1 I had the knowledge necessary to use CIS content/concepts in learning.	5.050	1.221	0.880	< 0.001
PBC2 I had control over CIS content/concepts in learning.	4.830	1.295	0.814	< 0.001
PBC3 I had the resources necessary to use CIS content/concepts in learning.	5.290	1.183	0.814	< 0.001
PBC4 I had the skills to use CIS content/concepts in learning.	5.060	1.228	0.862	< 0.001
Behavioral Intention (BI) (Salloum et al., 2019; Teo, 2011; Venkatesh et al., 2003)				
BI1 I consistently tried to use CIS content/concepts in learning.	4.450	1.369	0.786	< 0.001
BI2 I intended to continue using CIS content/concepts beyond this semester.	4.980	1.350	0.893	< 0.001
BI3 I planned to keep using CIS content/concepts frequently.	4.690	1.409	0.886	< 0.001
BI4 I expected to use CIS content/concepts to study my courses this semester.	4.830	1.443	0.873	< 0.001
Perceived Learning Outcomes (PLO) (Cheung & Vogel, 2013; Liaw, 2008)				
PLO1 The time I spent to understand CIS course material was reasonable.	5.010	1.346	0.700	< 0.001
PLO2 The CIS course taught me to view things from different perspectives.	4.990	1.283	0.760	< 0.001
PLO3 The CIS course taught me how to form ideas that enrich knowledge.	5.110	1.193	0.823	< 0.001
Effort Regulation (ER) (Broadbent & Poon, 2015; Pintrich, 1991, 2004; Wolters, 1998)				
ER2 I worked hard to do well in this class even if I didn't like the activities.	5.500	1.136	0.609	< 0.001
ER4 Even when materials were dull or uninteresting, I kept working until I finished.	5.310	1.189	0.846	< 0.001
Perceived Usefulness (PUSE) (Davis, 1989; Venkatesh et al., 2003)				
PUSE1 Using CIS content/concepts improved my academic performance.	5.110	1.274	0.853	< 0.001
PUSE2 Using CIS content/concepts helped me accomplish tasks more quickly.	5.100	1.249	0.838	< 0.001
PUSE3 Using CIS content/concepts enhanced my learning effectiveness.	4.980	1.261	0.849	< 0.001

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PUSE4 Using CIS content/concepts increased my productivity.	5.040	1.240	0.861	< 0.001
PUSE5 Using CIS content/concepts made it easier for me to learn.	4.780	1.317	0.859	< 0.001
PUSE6 I found CIS content/concepts useful in my learning.	5.000	1.307	0.883	< 0.001
Perceived Ease of Use (EUSE) (Davis, 1989; Venkatesh et al., 2003)				
EUSE1 Learning how to use CIS content/concepts was easy for me.	4.340	1.390	0.736	< 0.001
EUSE2 My interaction with CIS content/concepts was clear and understandable.	4.580	1.291	0.848	< 0.001
EUSE3 I found CIS content/concepts easy to use.	4.460	1.326	0.741	< 0.001
EUSE4 It was easy to become skillful at using CIS content/concepts.	4.440	1.372	0.868	< 0.001
EUSE5 I found CIS content/concepts flexible to interact with.	4.600	1.330	0.832	< 0.001
EUSE6 I found it easy to get CIS content/concepts to do what I wanted.	4.550	1.348	0.905	< 0.001
Self-Efficacy (SEF) (Bandura, 1997; Patterson et al., 2024)				
SEF1 I believed I received an excellent grade in this class.	4.070	1.420	0.649	< 0.001
SEF2 I was confident I could understand the basic concepts in this course.	5.300	1.196	0.801	< 0.001
SEF3 I was confident I could understand the most complex material in this course.	4.300	1.543	0.810	< 0.001
SEF4 I was confident I could do an excellent job on assignments and tests.	4.650	1.335	0.804	< 0.001
SEF5 I expected to do well in this class.	4.980	1.241	0.653	< 0.001
SEF6 I was certain I could master the skills taught in this class.	4.910	1.252	0.784	< 0.001
SEF7 Considering the difficulty, instructor, and my skills, I think I did well in this class.	4.770	1.309	0.849	< 0.001