Ed Process Int J

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ISSN 2147-0901 (Print), 2564-8020 (Online)

EDUCATIONAL PROCESS
INTERNATIONAL JOURNAL

Research Article

Cite this article: Gayrama, V. P. (2025). Motivation in Self-regulated Learning and Technology-use Efficacy among Filipino University Students on an Island: Indirect Effects of Perceived Value, Pressure, Interest, and Effort. *Educational Process: International Journal, 15*, e2025112. https://doi.org/10.22521/edupij.2025.15.112

Received February 3, 2025
Accepted March 15, 2025
Published Online March 24, 2025

Keywords: Motivation, self-regulated learning; technology-use efficacy, online learning modality, higher education, perceived value

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Motivation in Self-regulated Learning and Technology-use Efficacy among Filipino University Students on an Island: Indirect Effects of Perceived Value, Pressure, Interest, and Effort

Vilma P. Gayrama

Abstract

Background. This study underscores the importance of motivation in self-regulated learning and technology-use efficacy, particularly in the context of online learning modality. The transition to blended and hybrid learning modalities has necessitated a reevaluation of the factors influencing student success.

Methods. This quantitative survey study was conducted at Biliran Province State University (BiPSU) in the Philippines. Using a convenience sampling approach, data were collected through a Likert scale questionnaire to 800 respondents' undergraduate students enrolled in the second semester of the 2022-2023 academic year. The study employed Partial Least Squares - Structural Equation Modeling (PLS-SEM) through SmartPLS to explore the relationships between perceived competence, value, pressure/tension, interest, effort, and technology-use efficacy. The measurement model was validated by assessing indicator reliability, internal consistency, construct reliability, and discriminant validity. The study's exploratory nature and statistical approach enabled a robust analysis of factors influencing students' technology-use efficacy.

Results. The results revealed that reducing pressure/tension and enhancing the perceived value of tasks are significant pathways to improving technology-use efficacy. Specifically, perceived choice and relatedness reduce pressure/tension, and both perceived choice and competence increase the value of the task, leading to higher technology-use efficacy. Effort/importance and interest/enjoyment did not significantly mediate the relationships between the predictors and technology-use efficacy.

Conclusion. Fostering a sense of autonomy, competence, and relatedness may be more critical to promoting effective technology use than focusing solely on effort or enjoyment.

1. Introduction

Educators are noticing a growing trend among students to take control of their learning and achievement through a range of self-directed activities. This shift involves students actively engaging in setting goals, selecting learning strategies, and maintaining motivation to accomplish their objectives. Students exercise greater autonomy in their educational journey by tailoring their approaches to suit their individual needs and preferences. However, this change also poses challenges, as educators need to ensure that students have the right tools, guidance, and support to effectively direct their learning and persist in the face of obstacles. The increasing emphasis on self-regulation in learning reflects a broader move toward fostering lifelong learning skills and preparing students for success in a rapidly changing world. Self-regulated learning is not new, yet its value and benefit were indisputable as it remained relevant and responsive to the limitations. In like manner, online and distance education, although sharing similar overall goals with traditional face-to-face education, cater to distinct groups of learners and educators (Stern, 2004). This modality necessitates different teaching and learning skill sets to effectively engage and support students in a virtual environment (Kocdar et al., 2018).

Research on self-regulated learning (SRL) and technology-use efficacy has largely focused on direct relationships (Bandura, 1997; Deci & Ryan, 2000), but then examining indirect effects through mediators like pressure/tension and value remains an important area of study, as these factors may influence technology-use efficacy. This study takes a more detailed approach to motivation into specific components—perceived competence, choice, relatedness, value, pressure/tension, effort/importance, and interest/enjoyment—to determine which factors have the greatest impact on technology-use efficacy. Though previous research has examined SRL and motivation in relation to general academic performance (Schunk & Usher, 2019), this study applies these concepts specifically to technology-use efficacy given the increasing relevance of digital and remote learning (Sun & Rueda, 2012), particularly on the Filipino University students in an island.

Despite varying levels of preparedness, educational institutions at all levels were required to adopt blended or hybrid learning modalities. In line with the Philippine Commission on Higher Education's (CHED) mandate to implement flexible learning approaches nationwide (CHED, 2020, p.2), universities embraced learning modalities that incorporated elements of self-regulated learning. This includes BiPSU, which adopted flexible learning modalities to ensure the continuity of education. These modalities, characterized by elements of self-regulated learning, included face-to-face and remote, both online and offline (Biliran Province State University, 2020). This study investigates motivation in self-regulated learning and its influence on technology-use efficacy within these flexible learning contexts. It specifically examines the indirect effects of perceived value, pressure, interest, and effort on technology-use efficacy in online learning, highlighting the interplay between motivational factors and students' ability to effectively use technology.

2. Literature Review

2.1. Motivation in self-regulated learning

Motivation plays a vital role in students' ability to self-regulate their learning. According to Deci and Ryan (2000), human motivation is driven by fulfilling three core psychological needs: competence, autonomy, and relatedness. Competence refers to the ability to perform tasks effectively and with skill; autonomy involves having control and choice over one's actions; and relatedness emphasizes a sense of belonging and connection with others. In this study, perceived choice relates to students' ability to select their preferred learning platform, adopt new learning modes, and choose supplementary materials for different courses. Perceived competence encompasses proficiency in tasks like creating video presentations, managing time, handling course requirements, understanding course content, and being satisfied with one's performance across various course modules. Relatedness is defined by trust and frequent interactions with classmates, fostering a sense of closeness and connection within the learning environment.

Self-regulated learning (SRL) refers to the ability to set goals, track progress, and modify strategies to effectively reach those goals. Motivation plays a crucial role in driving these processes, as it impacts students' willingness to engage with learning tasks, persist through challenges, and regulate their behavior and thought processes to enhance learning outcomes. Zimmermann and Schunk (1989) defined self-regulated learning as the self-directed generation of thoughts, emotions, and actions aimed at achieving personal goals. A more recent definition by Zimmerman (2015) describes SRL as learners actively applying mental skills to improve academic performance through self-determined goals and strategies.

Several existing studies have examined self-regulated learning and the acceptance and use of technology. Artino (2007) highlighted a significant link between students' motivational beliefs about learning tasks, their application of learning strategies, and their preferences for online learning environments. The research revealed that students with higher self-regulation tend to perform better in settings where they have control over their own learning process. A recent study by Chiu (2022) showed that perceived autonomy, competence, and relatedness significantly boost learner engagement. Equally, Wang et al. (2013) discovered that undergraduate and graduate students with higher levels of motivation demonstrate greater technology self-efficacy, resulting in improved final grades. Areepattamannil and Santos (2019) found that perceived competence and autonomy in using information and communication technology were strong predictors of a positive attitude toward science. Pan (2020) identified technology acceptance and self-efficacy as key factors influencing positive attitudes toward technology-based self-directed learning. Gagné et al. (2022) emphasized that for technology to be effectively utilized in the workplace, it must be perceived as both easy to use and beneficial (i.e., competent). Additionally, individuals should experience a sense of control and minimal pressure (i.e., perceived choice). Organizations should also promote a sense of care and connection among employees (i.e., relatedness). In this study, the researcher hypothesizes that undergraduates will thrive in self-regulated learning when they perceive the technology as easy and convenient to use, have the autonomy to select learning platforms and supplementary materials and feel trust and a sense of closeness with their classmates.

2.2. Technology and Acceptance Model

The Technology Acceptance Model (TAM) has been instrumental in advancing information systems research (Hsiao & Yang, 2011). It was developed to provide a user-centered framework for understanding technology adoption and acceptance. Davis (1989) introduced in his seminal paper "Perceived Usefulness, Perceived Ease of Use, and User Acceptance Information Technology" on the Technology and Acceptance Model that a user's intention to adopt technology is primarily influenced by two key factors: perceived usefulness (PU) and perceived ease of use (PEOU). Perceived usefulness (PU) refers to the degree to which a person believes that using a technology will enhance their performance, emphasizing its practical advantages. Perceived ease of use (PEOU) represents the extent to which a user views the technology as straightforward and easy to operate. A system that is perceived as user-friendly is more likely to gain acceptance. In the Technology Acceptance Model (TAM), intention to use (ITU) acts as an intermediary between perceived usefulness (PU), perceived ease of use (PEOU), and actual use (AU), playing a crucial role in predicting user behavior. Actual use (AU) refers to the real-world adoption of a technology-driven by the user's behavioral intention. Attitude towards technology (ATT) represents a person's overall emotional and evaluative reaction to using a specific technology, encompassing their feelings, tendencies, and personal assessment of its value and effectiveness. Or (2024) employs one-step meta-analytic structural equation modeling to examine the Technology Acceptance Model (TAM) in education, evaluating perceived usefulness, ease of use, intentions, and actual technology use. The study integrates previous findings to confirm

TAM's effectiveness and predictive power. It reveals that perceived ease of use can directly impact actual use, bypassing intention and challenging the traditional TAM framework. The findings reinforce TAM's relevance and provide insights for educational technology adoption.

2.3. Theory of Distance Learning

The Theory of Distance Learning explains how learners engage with educational content, instructors, and peers in a setting where physical separation exists. Several models contribute to this theory: Moore's (1993) Theory of Transactional Distance emphasizes that physical and psychological distance in online learning environments can create a communication gap between students and educators. The level of dialogue, structure, and learner autonomy determines how effectively students engage with learning. Anderson's (2003) Interaction Equivalency Theorem highlights the importance of interaction (student-content, student-teacher, and student-student) for meaningful learning experiences. Garrison et al.'s (2000) Community of Inquiry (CoI) Framework suggests that learning in online environments depends on social, cognitive, and teaching presence to maintain engagement. Distance learning requires self-regulation and motivation, as learners must manage their own progress with less direct supervision. It necessitates self-regulated learning and motivation, with perceived value, effort, pressure, and interest indirectly shaping students' technology-use efficacy. These factors influence students' willingness to adopt and integrate technology effectively into their learning process.

2.4. Technology-use efficacy

During the peak of online learning, the Internet was essential for maintaining the continuity of teaching and learning. It facilitated access to educational resources and enabled communication between teachers and students. Research indicates that effective self-regulated learning is linked to technology-use efficacy (Pan, 2020). Learners with high technology-use efficacy are more likely to excel in self-regulated learning, as evidenced by their superior academic performance (Joo et al., 2000; Pan, 2020). Additionally, there is growing acknowledgment among scholars that students who can effectively self-regulate their learning tend to achieve better academic outcomes (Li et al., 2018; Nota et al., 2004). Technology-use efficacy is defined as learners' perception of their capability to effectively utilize various learning technologies, including both hardware and software, to support their learning and achieve educational goals (Bandura, 1977; Pan, 2020). In this study, technology-use efficacy refers to undergraduates' ability to navigate and explore websites, comprehend instructions for using online platforms, utilize various ICT resources such as online applications and platforms, and manage technical issues.

In the foregoing study, the researcher hypothesized that in the context of motivation in self-regulated learning and technology-use efficacy, perceived competence, choice, and relatedness predict technology-use efficacy; perceived value, pressure, interest, and effort mediate between perceived competence and technology-use efficacy; perceived value, pressure, interest, and effort mediate between perceived choice and technology-use efficacy; and perceived value, pressure, interest, and effort mediate between relatedness and technology-use efficacy. Figure 1 shows the specifics of the model.

Figure 1 shows the Model Specification.

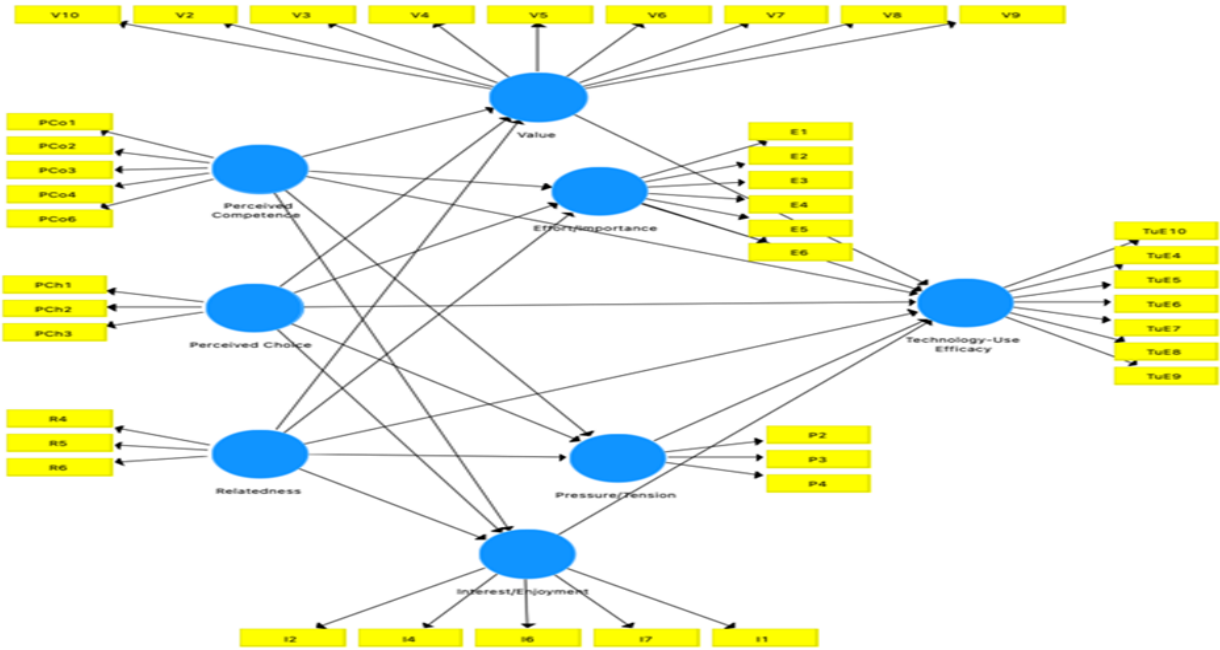

Figure 1. Model Specification

3. Methodology

3.1. Study design, samples, setting

This quantitative survey study was conducted at Biliran Province State University (BiPSU), a state university in the Eastern Visayas Region located in Biliran Province, Philippines. BiPSU operates across two campuses, one in Naval and the other in Biliran, and consists of ten schools: Engineering, Teacher Education, Computer Studies, Arts and Sciences, Criminal Justice Education, Management and Entrepreneurship, Nursing and Health Sciences, Agri-Fishery, Agribusiness and Forest Management, and Graduate Studies. The respondents in the study were undergraduate students enrolled during the second semester of the 2022-2023 academic year. They were selected based on their accessibility and willingness to participate using online Google forms with consent, and it's voluntary on their part.

To ensure the validity of the statistical analysis, this study calculated the minimum required sample size using the gamma exponential method with the G*Power 3.1 calculator (Faul et al., 2009). The analysis was based on the F-test family, employing a fixed model for linear multiple regression to assess R^2 deviation from zero. As shown in Table 1, 800 undergraduate students participated in the study.

Table 1. Age and Sex Distribution

	Sex		
Age	Male	Female	Total
≥ 30	12	16	28
25-29	30	25	55
21-24	93	148	241
≤20	115	361	476

3.2. Instrument

Data from the respondents were collected using a Likert scale questionnaire, which was adapted from existing literature by combining elements from two sources. The sections covering perceived competence, perceived choice, relatedness, value, effort/importance, pressure/tension, and interest/enjoyment were derived from the Intrinsic Motivation Inventory, created by the Center for Self-Determination Theory. Additionally, items related to technology-use efficacy were sourced from the Online Technologies Self-Efficacy Scale, originally developed by Miltiado and Yu (2000).

The questionnaire consisted of six items for perceived competence, eight for perceived choice, seven for relatedness, ten for value, six for effort/importance, five for pressure/tension, seven for interest/enjoyment, and ten for technology-use efficacy. Respondents indicated their level of agreement with each item on a five-point Likert scale, ranging from Strongly Agree (5) to Strongly Disagree (1). The survey questionnaire was pilot-tested on education pre-service teachers who were not part of the main study to assess its clarity and reliability. To determine the factor structure of the adapted items, an Exploratory Factor Analysis (EFA) was conducted.

3.3. Data collection and analysis

This study utilized convenience sampling, a non-probability sampling technique, to collect data. The deans of various schools were requested to assist in distributing a Google survey to their students. Given the exploratory nature of the research, Partial Least Squares - Structural Equation Modeling (PLS-SEM) was employed for data analysis using the SmartPLS software (Hair et al., 2017; Ringle et al., 2015). PLS-SEM is well-suited for exploratory studies as it enables researchers to assess complex relationships between latent variables. It offers flexibility in its assumptions, allowing for hypothesis testing, identification of key predictors, emphasizing explained variance (R^2) rather than strict model fit criteria since it examines technology-use efficacy and its antecedents (perceived competence, value, pressure/tension, interest, and effort) perform well in a small to moderate sample size, provides robust estimates despite sample size limitations (Hair et al., 2019), and evaluation of model fit.

The data were analyzed using partial least squares structural equation modeling (PLS-SEM) through SmartPLS. In the initial phase, the researchers validated the measurement model (Ringle et al., 2015). The initial phase of the study involved assessing the measurement model. By utilizing the PLS algorithm, the researchers confirmed several key criteria: indicator reliability (with outer loadings ≥ 0.708), internal consistency (Cronbach's $\alpha \geq 0.70$), composite reliability (≥ 0.70), construct reliability and validity (average variance extracted ≥ 0.50), discriminant validity (heterotrait-monotrait ratio ≤ 0.90), and collinearity (variance inflation factors ≤ 3.3) (Hair et al., 2017). The second phase involved evaluating the structural model. Using the PLS algorithm and bootstrapping procedure in SmartPLS, the study assessed path coefficients (p-value ≤ 0.05; t-value ≥ 1.654), predictive accuracy ($R^2 = 0.75$ for substantial, 0.50 for moderate, 0.25 for weak), effect size ($f^2 = 0.35$ for substantial, 0.15 for moderate, 0.02 for small), and predictive relevance ($Q2>0.35$ - strong, between 0.15 and 0.35 moderate, between 0.02 and 0.15 weak, and <0.02 no predictive relevance (Hair et al., 2017). The final phase focused on assessing indirect effects. By running the indirect effects procedure in SmartPLS, the study measured the indirect influence of perceived value, pressure, interest, and effort on motivation in self-regulated learning and technology-use efficacy (p-value ≤ 0.05; t-value ≥ 1.654) (Hair et al., 2017).

4. Results

4.1. Assessment of measurement model

Tables 2 and 3 display the results for indicator reliability (outer loadings), internal consistency (Cronbach's α), composite reliability, rho_A (average-item correlation), construct reliability and validity, discriminant validity, and collinearity. Items with outer loadings below 0.708 were excluded to ensure indicator reliability. Table 2 lists the number of items retained for each variable. Internal consistency was confirmed, as all Cronbach's α values were above 0.700, showing moderate reliability for perceived value, pressure, interest, and effort related to motivation in self-regulated learning and technology-use efficacy (Nunnally & Bernstein, 1994). Additionally, composite reliability exceeded 0.700 for all variables, and the average variance extracted (AVE) was above 0.500, affirming convergent validity (Hair et al., 2017). Discriminant validity was verified, with all heterotrait-monotrait ratios below 0.900, and collinearity was confirmed with variance inflation factors under the 3.300 threshold (Hair et al., 2017) (see Table 3).

Table 2. Indicator reliability, convergent validity, and reliability

	Outer loading	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Effort/Importance		0.893	0.894	0.918	0.651
E1	0.77				
E2	0.829				
E3	0.823				
E4	0.835				
E5	0.785				
E6	0.797				
Interest/Enjoyment		0.82	0.824	0.874	0.581
I1	0.787				
I2	0.753				
I4	0.776				
I6	0.717				
I7	0.777				
Pressure/Tension		0.836	0.941	0.896	0.745
P2	0.697				
P3	0.941				
P4	0.929				
Perceived Choice		0.714	0.716	0.84	0.636
PCh1	0.797				
PCh2	0.783				
PCh3	0.813				
Perceived Competence		0.835	0.838	0.883	0.603
PCo1	0.703				
PCo2	0.772				
PCo3	0.796				
PCo4	0.821				
PCo6	0.785				
Relatedness		0.797	0.797	0.881	0.711
R4	0.838				
R5	0.833				
R6	0.859				
Technology-Use Efficacy		0.898	0.902	0.92	0.621
TuE10	0.785				

TuE4	0.796				
TuE5	0.791				
TuE6	0.82				
TuE7	0.782				
TuE8	0.793				
TuE9	0.746				
Value		0.928	0.928	0.94	0.635
V10	0.805				
V2	0.746				
V3	0.804				
V4	0.77				
V5	0.816				
V6	0.836				
V7	0.83				
V8	0.775				
V9	0.784				

Figure 2 shows the Outer loadings and predictive accuracy.

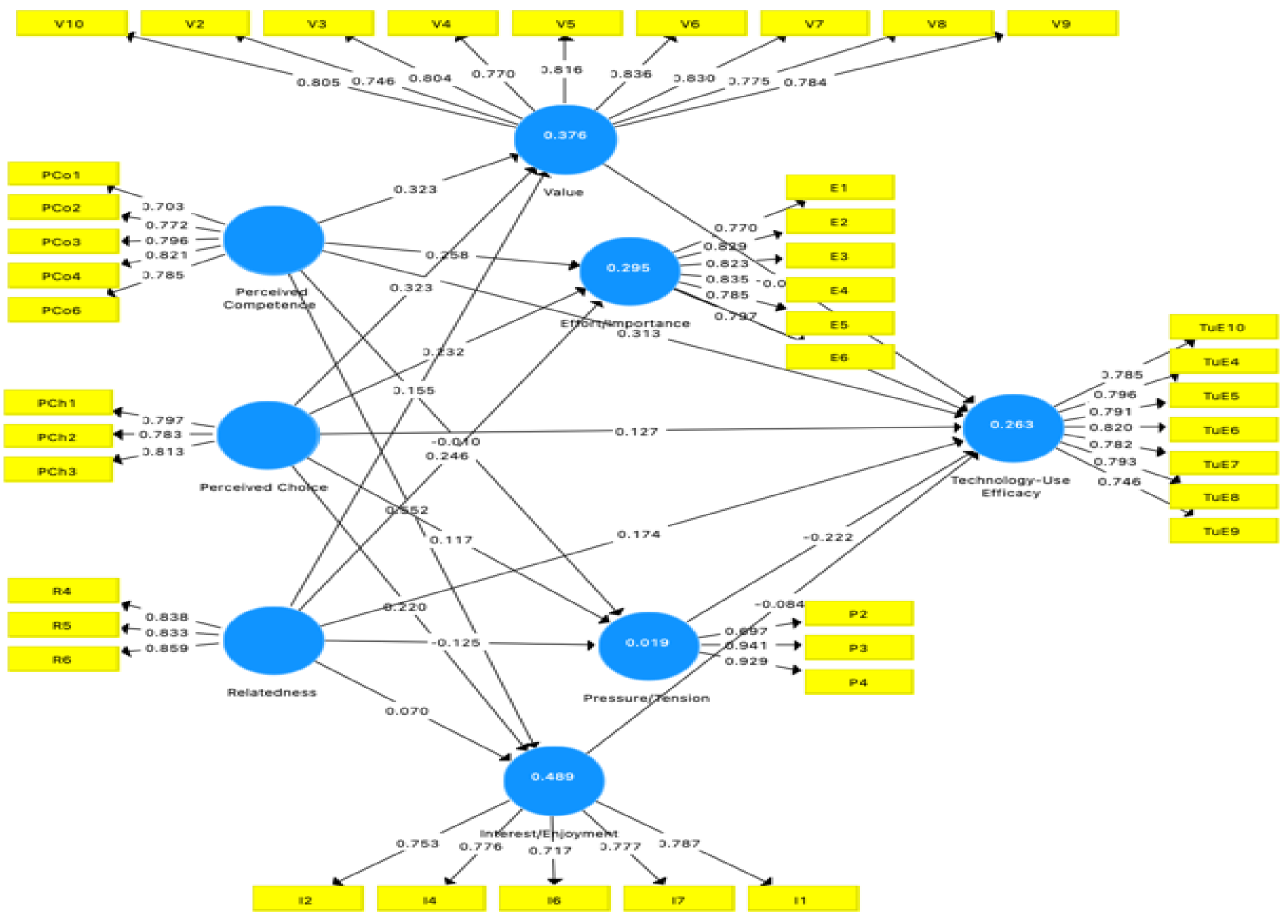

Figure 2. Outer loadings and predictive accuracy

Figure 2 presents a structural equation model (SEM) that visualizes relationships among several variables influencing "technology-use efficacy," which refers to students' effectiveness in using technology.

Table 3. Heterotrait-monotrait ratio

HTMT	Effort/ Importance	Interest/ Enjoyment	Perceived Choice	Perceived Competence	Pressure/ Tension	Relatedness	Technology-Use Efficacy
Interest/ Enjoyment	0.495						
Perceived Choice	0.529	0.632					
Perceived Competence	0.462	0.794	0.566				
Pressure/ Tension	0.112	0.046	0.117	0.048			
Relatedness	0.44	0.306	0.435	0.227	0.107		
Technology-Use Efficacy	0.293	0.307	0.377	0.44	0.234	0.348	
Value	0.56	0.617	0.631	0.555	0.062	0.374	0.338

4.2. Assessment of structural model

Table 4 presents the path coefficients and confidence intervals bias corrected of the specified model. Results reveal that perceived competence (t value = 6.614; p-value = 0.000) has a strong direct effect on technology-use efficacy. When students feel competent in their technological abilities, they are more likely to use technology effectively. This underscores the importance of building students' technological skills and confidence. Perceived choice also shows a significant direct effect (t= 2.892, p=0.002) on technology-use efficacy. Providing students with choices in their learning processes can foster a sense of ownership and motivation. Relatedness (t value = 4.575; p-value = 0.000) significantly impacts technology-use efficacy. Positive social connections and support systems are crucial. Encouraging collaboration and support among peers can enhance students' engagement with technology. Although interest/enjoyment (t=1.577, p= 0.057) it is not a significant direct predictor. While enjoyment is important, it may not directly enhance technology-use efficacy. Efforts to make technology use enjoyable should be coupled with strategies to reduce pressure and increase task value. Pressure/tension also has a significant direct effect (t=1.577, p=0.000). Reducing stress and anxiety related to technology use is essential for improving efficacy. Creating a supportive and low-pressure learning environment can help. Perceived value has a significant effect (t= 1.778, p= 0.038) on technology-use efficacy. Highlighting the relevance and benefits of technology-related tasks can enhance students' motivation and efficacy. Effort/importance does not significantly affect technology-use efficacy (t= 0.184, p= 0.427). Effort alone is insufficient. The focus should be on reducing pressure and enhancing task value rather than solely increasing effort.

Table 4. Path Coefficients. Direct effect

Hypotheses	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Confidence Intervals Bias Corrected	
						5.00%	95.00%
Perceived Competence -> Technology-Use Efficacy	0.313	0.316	0.047	6.614	0.000	0.234	0.389
Perceived Choice -> Technology-Use Efficacy	0.127	0.128	0.044	2.892	0.002	0.057	0.202
Relatedness -> Technology-Use Efficacy	0.174	0.174	0.038	4.575	0.000	0.109	0.234
Effort/Importance -> Technology-Use Efficacy	-0.008	-0.008	0.042	0.184	0.427	-0.079	0.062
Interest/Enjoyment -> Technology-Use Efficacy	-0.084	-0.085	0.053	1.577	0.057	-0.17	0.003
Pressure/Tension -> Technology-Use Efficacy	-0.222	-0.222	0.034	6.62	0.000	-0.274	-0.165
Value -> Technology-Use Efficacy	0.086	0.086	0.049	1.778	0.038	0.008	0.166

Table 5 shows the specific indirect effects of various predictors on technology-use efficacy through different mediators. It aims to identify which pathways significantly influence technology-use efficacy and which do not. It includes the list of specific pathways tested (hypotheses), estimated indirect effect from the original sample data (Original Sample), the average indirect effect from the samples (Sample Mean), variability of the indirect effect estimate (Standard Deviation), ratio of the effect estimate to its standard deviation (T Statistics), probability values (p-values), range likely to contain the true effect (Confidence Intervals), and the decision whether the hypothesis is statistically supported (at 0.05 significance level).

Based on the results, the indirect effect of perceived choice on technology-use efficacy through pressure/tension was significant ($t=2.393$, $p=0.008$). This means that perceived choice reduces pressure/tension, thereby enhancing technology-use efficacy. The effect of perceived choice on technology-use efficacy through value was also significant ($t=1.800$, $p=0.036$), indicating that perceived choice increases the value individuals (or students) devote to the task, thereby enhancing their technology-use efficacy. Learners who feel confident in their technological skills are more likely to explore and utilize digital resources effectively. Pan (2020) suggests that fostering both technology

https://doi.org/10.22521/edupij.2025.15.112 Published online by Universitepark Press

acceptance and self-efficacy is crucial for encouraging positive attitudes and successful engagement in technology-based self-directed learning environments. Perceived competence significantly affects technology-use efficacy through value (t=1.651, p=0.049), denoting that feeling competent enhances the perceived value of the task, which increases technology-use efficacy. Additionally, the effect of relatedness on technology-use efficacy through pressure/tension was also significant (t=2.652, p=0.004), indicating that feelings of connection with others reduce pressure/tension, thereby enhancing technology-use efficacy. Similarly, relatedness to technology-use efficacy through value was marginally significant (t=1.593, p=0.056), suggesting that feeling related increases the value someone devotes to the task that improves technology-use efficacy.

Table 5. Specific indirect effects

Hypotheses	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Confidence Intervals Bias Corrected	
						5.00%	95.00%
Perceived Choice -> Effort/Importance -> Technology-Use Efficacy	-0.002	-0.002	0.01	0.182	0.428	-0.018	0.015
Perceived Choice -> Interest/Enjoyment -> Technology-Use Efficacy	-0.018	-0.019	0.012	1.532	0.063	-0.039	0
Perceived Choice -> Pressure/Tension -> Technology-Use Efficacy	-0.026	-0.026	0.011	2.392	0.008	-0.046	-0.01
Perceived Choice -> Value -> Technology-Use Efficacy	0.028	0.027	0.015	1.8	0.036	0.003	0.053
Perceived Competence -> Effort/ Importance -> Technology-Use Efficacy	-0.002	-0.002	0.011	0.181	0.428	-0.02	0.016
Perceived Competence -> Interest/ Enjoyment -> Technology-Use Efficacy	-0.046	-0.047	0.03	1.55	0.061	-0.096	0.001
Perceived Competence -> Pressure/ Tension -> Technology-Use Efficacy	0.002	0.002	0.01	0.228	0.410	-0.014	0.019
Perceived Competence -> Value -> Technology-Use Efficacy	0.028	0.028	0.017	1.651	0.049	0.003	0.059
Relatedness -> Effort/Importance -> Technology-Use Efficacy	-0.002	-0.002	0.011	0.18	0.429	-0.019	0.016
Relatedness -> Interest/Enjoyment -> Technology-Use Efficacy	-0.006	-0.006	0.005	1.192	0.117	-0.017	0
Relatedness -> Pressure/Tension -> Technology-Use Efficacy	0.028	0.028	0.01	2.652	0.004	0.012	0.046
Relatedness -> Value -> Technology-Use Efficacy	0.013	0.013	0.008	1.593	0.056	0.002	0.03

On the other hand, the effort or importance individuals place on the task does not significantly mediate the relationship between perceived choice (t=0.182, p=0.428), competence (t=0.181, p=0.428), or relatedness (t=0.180, p=0.429) and technology-use efficacy. Also, interest/enjoyment in the task does not significantly mediate these relationships (t=1.532, p=0.063; t=1.550, p=0.061; and t=1.192, p=-.117). The results also showed that pressure/tension does not significantly mediate the effect of perceived competence on technology-use efficacy (t=0.228, p=0.410).

The Variance Accounted For (VAF) ratios presented in Table 6 indicate that mediation effects are weak in this model. First, the VAF for Perceived Choice on Technology-Use Efficacy is -16.5%, suggesting no mediation. The direct effect (0.127) (see Table 4) is significantly stronger than the indirect effect (-0.018) (see Table 5), meaning Perceived Choice primarily influences Technology-Use Efficacy through direct pathways rather than through mediators. Similarly, the VAF for Perceived Competence on Technology-Use Efficacy is -6.1%, further confirming the absence of meaningful mediation. The direct effect (0.313) (see Table 4) is much greater than the indirect effects, indicating that Perceived Competence directly shapes Technology-Use Efficacy with minimal contribution from mediators. Lastly, the VAF for Relatedness on Technology-Use Efficacy is 15.6%, which points to only slight mediation. Overall, the results demonstrate that direct effects dominate, meaning Perceived Choice, Perceived Competence, and Relatedness influence Technology-Use Efficacy primarily on their own, without significant mediation effects.

Table 6. Variance Accounted For (VAF) Ratio

Predictor	Indirect Effect	Total Effect	VAF (%)
Perceived Choice→Technology-use Efficacy	-0.018	0.109	-16.5%
Perceived Competence→Technology-use Efficacy	-0.018	0.033	-6.1%
Relatedness →Technology-use Efficacy	0.295	0.207	15.9%

The predictive accuracy of the model is presented in table 7. The R Square and Adjusted R Square values for different constructs in the study indicate how well the predictor variables explain the variance in each dependent (endogenous) variable.

Table 7. Predictive accuracy

	R Square	R Square Adjusted	Predictive Accuracy
Effort/Importance	0.295	0.292	Weak
Interest/Enjoyment	0.489	0.487	Moderate
Pressure/Tension	0.019	0.015	Very Weak
Technology-Use Efficacy	0.263	0.256	Weak
Value	0.376	0.374	Weak to Moderate

Interest/Enjoyment accounts for 48.9% of the variance, while Value accounts for 37.6%, indicating that the independent variables moderately predict these constructs. Effort/Importance explains 29.5% of the variance, and Technology-use Efficacy accounts for 26.3%, reflecting weak predictive accuracy. Pressure/Tension contributes only 1.9% of the variance, demonstrating minimal predictive power. Table 8 presents the effect size, which shows how much each independent variable contributes to explaining the variance in each dependent variable. It measures the strength of the relationship between an independent variable (predictor) and a dependent variable (outcome). To interpret the effect size: 0.02 small effect, 0.015 medium effect, and 0.35 large effect (Cohen, 1998).

Table 8. Effect size

	Effort/ Importance	Interest/ Enjoyment	Pressure/ Tension	Technology-Use Efficacy	Value	Effect Strength
Effort/ Importance				0		No effect
Interest/ Enjoyment				0.005		Negligible Effect
Perceived Choice	0.057	0.07	0.01	0.014	0.124	Small Effect
Perceived Competence	0.076	0.48	0	0.07	0.135	Large Effect
Pressure/ Tension				0.065		Small Effect
Relatedness	0.076	0.009	0.014	0.033	0.034	Small Effect
Value				0.006		Negligible Effect

Perceived Competence has a strong effect on Interest/Enjoyment (f2=0.48). Students who feel competent in using technology are significantly more likely to enjoy using it. Perceived Choice has a small effect on multiple variables. It has the highest effect on Value (f2=0.124), meaning students' sense of choice influences how much they value using technology. It also has small effects on Interest/Enjoyment (f2=0.07), Effort/Importance (f2=0.057), and Technology-Use Efficacy (f2=0.014). Pressure/Tension has a small effect on itself (f2=0.065). This suggests that certain factors might be reinforcing students' feelings of pressure, but their influence is not strong. Relatedness has small effects on multiple constructs. It has a small impact on Effort/Importance (f2=0.076), Technology-Use Efficacy (f2=0.033), and Value (f2=0.034). Effort/Importance and Value have almost no effect on other variables. Value has a negligible effect (f2=0.006) on Technology-Use Efficacy, suggesting that just seeing technology as valuable does not strongly impact students' confidence in using it.

Table 9 presents the model's predictive relevance (Q2) using the blindfolding procedure in PLS-SEM. The Q2 values indicate how well the independent variables predict each dependent variable beyond chance (out-of-sample predictive power).

Table 9. Predictive relevance

Q square	SSO	SSE	Q^2 (=1-SSE/ SSO)	Predictive Relevance
Effort/Importance	4500	3657.283	0.187	Moderate
Interest/Enjoyment	3750	2705.074	0.279	Moderate
Pressure/Tension	2250	2224.791	0.011	None
Technology-Use Efficacy	5250	4421.136	0.158	Weak
Value	6750	5164.693	0.235	Moderate

Table 9 shows Interest/Enjoyment (Q2=0.279) and Value (Q2=0.235) have moderate predictive relevance. The model is moderately good at predicting how much students will enjoy using technology and how much they value it. Effort/Importance (Q2=0.187) has moderate predictive relevance. This suggests that the model is moderately effective in predicting students' effort and perceived importance of using technology. Technology-Use Efficacy (Q2=0.158) has weak predictive relevance. The model has some ability to predict students' confidence in using technology, but it is not very strong. Pressure/Tension (Q2=0.011) has no predictive relevance. The model cannot effectively predict students' stress or tension when using technology.

5. Discussion

This paper presents a study that explored motivation in self-regulated learning and technology-use efficacy: a) perceived competence, choice, and relatedness predict technology-use efficacy, b) perceived value, pressure, interest, and effort mediate between perceived competence and technology-use efficacy, c)perceived value, pressure, interest, and effort mediate between perceived choice and technology-use efficacy, and d)perceived value, pressure, interest, and effort mediate between relatedness and technology-use efficacy. Data were collected from 800 undergraduates in one of the state universities in the Philippines. The results of this are discussed as follows:

Firstly, the direct effects of various motivational factors on technology-use efficacy among students highlight the significant role of perceived competence, choice, relatedness, pressure/tension, and value in shaping students' confidence and ability to use technology. Perceived competence has the strongest positive effect on technology-use efficacy, indicating that students who feel capable and competent in their abilities are more likely to perceive themselves as effective users of technology. This finding aligns with self-determination theory (Deci & Ryan, 1985), which emphasizes competence as a fundamental psychological need that enhances motivation. In the same vein, Chiu (2022) posited that learners' intrinsic motivation increases if they have a choice in their activities and can self-direct their learning, take on challenges, and persist in the face of difficulties, which lead to higher engagement, and more engaged and motivated to participate if supported and valued within their learning community. Similarly, perceived choice and relatedness contribute positively to technology-use efficacy, suggesting that when students have autonomy in their technology-related tasks and feel connected to others, their efficacy improves (Ryan & Deci, 2000). The positive effect of value indicates that students who see the importance and relevance of technology use tend to develop greater efficacy (Eccles & Wigfield, 2002).

Meanwhile, effort/importance does not significantly predict technology-use efficacy, implying that merely putting in effort or recognizing the importance of technology use does not necessarily translate to higher confidence in using it. Likewise, interest has a negative but marginally insignificant effect, suggesting that intrinsic enjoyment alone may not be sufficient to enhance technology-use efficacy. However, pressure/tension exerts a strong negative effect on technology-use efficacy, meaning that students who experience high pressure or stress when using technology tend to have lower efficacy. This supports previous research indicating that anxiety and stress undermine self-efficacy in learning environments (Pekrun, 2006).

Secondly, the specific indirect effects of perceived competence, choice, and relatedness on technology-use efficacy through mediating variables such as effort/importance, interest/enjoyment, pressure/tension, and value. The results provide insights into the indirect pathways through which these motivational factors influence students' technology-use efficacy. Perceived choice → pressure/tension → technology-use efficacy indicates that greater autonomy in learning reduces pressure/tension, which in turn enhances technology-use efficacy. This aligns with self-determination theory (Deci & Ryan, 1985), which posits that autonomy reduces stress and enhances motivation. Perceived choice → value → technology-use efficacy suggests that when students have more autonomy, they are more likely to find value in technology use, which positively affects their efficacy. Relatedness → pressure/tension → technology-use efficacy shows that stronger social connections may contribute to increased pressure or tension, which then impacts technology-use efficacy. While relatedness generally promotes motivation (Ryan & Deci, 2000), social expectations may sometimes create pressure. Perceived competence → value → technology-use efficacy suggests that when students feel competent, they are more likely to perceive technology use as valuable, which enhances efficacy. This finding aligns with the expectancy-value theory (Eccles & Wigfield, 2002). On the other hand, several indirect pathways, including those through effort/importance and interest/enjoyment, are non-significant, indicating that these factors may not strongly mediate the relationship between motivational constructs and technology-use efficacy. For example, perceived competence and relatedness did not significantly influence efficacy through effort/importance, suggesting that students' awareness of effort alone does not necessarily translate into improved efficacy.

These findings suggest that fostering competence, autonomy, relatedness, and perceived value can enhance students' technology-use efficacy, whereas reducing pressure and stress may prevent negative effects. The results are consistent with motivational theories such as self-determination theory (Deci & Ryan, 1985) and expectancy-value theory (Eccles & Wigfield, 2002), which emphasize the importance of psychological needs and perceived task value in shaping motivation and performance. However, reducing pressure/tension and enhancing perceived value are key mechanisms for improving students' technology-use efficacy. Supporting student autonomy and competence can foster a greater sense of value in technology use while minimizing stress and further enhancing efficacy. These insights reinforce the importance of fostering intrinsic motivation and reducing external stressors in technology-integrated learning environments.

6. Conclusion

The direct effects of various motivational factors on technology-use efficacy among students indicate that perceived competence, choice, relatedness, and value have significant positive effects on technology-use efficacy, suggesting that students who feel competent, autonomous, socially connected, and who perceive value in technology use tend to exhibit higher efficacy in using technology. Pressure/tension has a significant negative impact, indicating that students who experience stress or pressure related to technology use are likely to have lower efficacy. Effort/importance and interest/enjoyment do not show significant effects, implying that merely recognizing the importance of technology use or enjoying it does not necessarily lead to higher efficacy. Meanwhile, the specific indirect effects of perceived competence, choice, and relatedness on technology-use efficacy through mediators such as effort/importance, interest/enjoyment, pressure/tension, and value indicate that pressure/tension and value serve as key mediators, while effort/importance and interest/enjoyment do not significantly mediate the relationships. There is a need for educational strategies that enhance competence, autonomy, relatedness, and perceived value while minimizing pressure and stress to improve students' technology-use efficacy.

7. Limitations of The Study

The researcher recognizes the inherent limitations of survey research in data collection and analysis because, firstly, this study employed convenience sampling and was implemented at one of the state universities in the Philippines. Although the total number of participants is satisfied, the minimum number of participants required for partial least structural-equation modeling, interpretation, and applicability of the findings in similar contexts may require caution. Secondly, this quantitative study employs the bootstrap and moderating effect procedure using SmartPLS. Other equally rigorous data analysis processes may be used to validate the claims of the study. A parallel qualitative and mixed methods study may be relevant not only to prove the claims of the researcher in this study.

8. Suggestions

Based on the findings, it is suggested that interventions are needed to improve students' technology-use efficacy, focusing on enhancing perceived competence, choice, and relatedness while minimizing pressure. Reducing pressure is a key pathway to improving technology-use efficacy, especially in relation to perceived choice and relatedness. Additionally, efforts should be made to increase the perceived value of tasks, particularly for perceived choice and competence. Given that effort and interest do not significantly mediate these relationships, they should not be prioritized in interventions aimed at enhancing technology-use efficacy.

Declarations

Author Contributions. This article is solely authored, with all research, analysis, and writing conducted by a single author.

Conflicts of Interest. The author declares no conflict of interest.

Funding. This research was conducted without external funding.

Ethical Approval. Ethical approval was not required for this study as participation was entirely voluntary.

Data Availability Statement. The datasets produced in this study can be obtained from the author upon reasonable request.

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