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Factors Affecting Students' Acceptance of Learning Simulation Tools in Computing Education Courses from Social, Technology, and Personal Trait Perspectives

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ABSTRACT

This study presents a theoretical model to explore the factors influencing students' acceptance of simulation tools in computing education. These factors include social influences, technology-related aspects, and personal characteristics. The term "simulation tools" refers to systems that can replicate complex processes and situations, providing students with realistic, hands-on experiences without the risks or costs associated with physical setups. To validate the proposed model, 312 responses from university students were collected. A cross-sectional online survey was conducted, and the participants were selected through purposive sampling. The findings indicated that subjective norms have the most significant direct effect on students' perceptions of usefulness, influencing their views on learning outcomes from using simulation tools in computing education courses. Additionally, social support and self-efficacy were also found to have significant effects. However, the impacts of fidelity and innovativeness were not supported. This study sets itself apart from previous research by using a comprehensive approach to explore the factors influencing student acceptance of simulation tools in computing education. Specifically, this research develops a theory based on the Technology Acceptance Model (TAM) and expands it by incorporating environmental factors and personal characteristics of students.

Keywords: Simulation tools, Learning, SEM, Social influence, Personal characteristics, TAM

1. Introduction

In today's digital era, technological advancements have reached almost every part of life, including education. The use of technology in education has opened new paths for innovative learning methods (Haleem et al., 2022a), especially in fields that require both theoretical understanding and practical skills, such as computing, medicine, and engineering. In these areas, traditional learning often relies on expensive equipment, complex setups, and various supplies that may not always be available or affordable (Haleem et al., 2022b; Soliman et al., 2021). Therefore, simulation tools have become a practical and popular solution (Lavrentieva et al., 2020; Tang et al., 2022; Abdulrahaman et al., 2020). Simulation tools create an immersive learning environment where students can experiment, make decisions, and see realistic results without the risks and costs of real-life situations. For example, in medicine, simulations allow students to practice surgical procedures in a controlled and repeatable setting, helping them build essential skills before working with actual patients. Similarly, in engineering and computer science, simulations let students design and test complex systems, like digital circuits or network configurations, enhancing their technical skills and problem-solving abilities. By providing interactive, hands-on learning experiences, simulations bridge the gap between theoretical knowledge and practical application, making them an essential part of modern education and expanding opportunities for hands-on learning within educational institutions.

In addition to their many benefits, simulation tools address several challenges present in traditional lab-based learning environments. Physical labs and real-world exercises often demand expensive equipment, take significant time to set up and supervise, and are typically limited to small groups due to the need for specialized tools and instructor guidance (Brinson et al., 2015; Wei et al., 2019). These limitations can restrict students' opportunities for hands-on practice, which is crucial for mastering practical skills in fields like engineering, medicine, and computer science. In contrast, virtual simulations allow students to practice repeatedly and at their own pace, promoting deeper learning and reducing the need for constant supervision, which helps institutions manage their resources more efficiently (Brinson et al., 2015; Wei et al., 2019).

As simulation tools have evolved, they now offer more than simple task-based exercises; many features sophisticated interactive models and virtual scenarios that closely mimic real-world systems (Zheng et al., 2022). These tools can simulate complex processes and situations, giving students realistic, hands-on experiences without the risks or costs associated with physical setups. For instance, students can conduct virtual experiments, solve problems, and test various scenarios in a safe, controlled digital environment. This advancement has spurred researchers to investigate the factors that may impact the effectiveness of simulation tools, including ease of use, user satisfaction, perceived usefulness, and other user-centered aspects (Adams et al., 1992). Understanding these factors is crucial, as they are believed to positively influence students' engagement, motivation, and learning outcomes.

The growing integration of simulation-based learning tools in higher education is reshaping the learning landscape across diverse fields such as engineering, nursing, and business. Studies consistently highlight the role of simulation in bridging theoretical knowledge with practical skills, offering students immersive experiences that can boost confidence, self-efficacy, and skill acquisition. For example, Mwansa et al. (2024) and Campos et al. (2020) explore the use of simulation in resource-constrained environments and online STEM (Science, Technology, Engineering, and Mathematics) education, respectively, noting that simulation can effectively supplement traditional labs by enhancing practical skills and motivation. Similarly, in nursing education, Hung et al. (2020) demonstrate that repeated simulation exposures can significantly increase perceived competence and learning satisfaction, suggesting that experiential learning principles enable students to move from "knowing" to "doing" through hands-on practice.

The increased use of simulation tools in education has prompted many scholars to investigate the adoption and acceptance of this technology in educational practice, particularly from the student perspective. Research related to how Studies applying theoretical frameworks like the Technology Acceptance Model (TAM) reveal that students' acceptance of simulation tools is heavily influenced by factors such as perceived usefulness, ease of use, and enjoyment. This is particularly evident in the work of Yu (2017) in a merchandising context and Lisana and Suciadi (2021) with high school physics students, where enjoyment emerged as a crucial predictor for sustained engagement. Altalbe (2019) adds to this discourse by integrating TAM with ABET objectives to assess simulation-based virtual laboratories for engineering students, finding that perceived usefulness and instrumentation directly impacted performance outcomes. These findings align with Chernikova et al. (2020), who, through a meta-analysis, showed that well-designed simulations, when paired with proper scaffolding and instructional support, could maximize learning gains across cognitive, procedural, and affective domains. The literature also underscores the importance of contextual and pedagogical factors in leveraging simulation for educational efficacy. Wong et al. (2022) and Hamilton et al. (2021) illustrate that realism and usability in simulation design greatly impact learning outcomes by making learning tools more relevant and effective. Furthermore, studies by Yang et al. (2022) and Hung et al. (2020) emphasize the role of self-efficacy and social aspects in driving students' engagement and performance. Overall, the current literature highlights simulation as a versatile and impactful educational tool that, when implemented thoughtfully with attention to usability, realism, and targeted learning objectives, can significantly enhance student engagement, learning satisfaction, and academic performance across fields.

While many studies demonstrate that the quality of simulation tools can enhance learning, few investigate how social, technological, and personal influences interact to shape students' willingness to use these tools in computing courses. Previous research, summarized in Table 1, shows that factors such as realism, intuitive interfaces, and well-designed simulations contribute to increased learning gains (Chernikova et al., 2020; Hamilton et al., 2021; Wong et al., 2022). However, student acceptance is often treated as a secondary concern. Meanwhile, Yu (2017) and Altalbe (2019) focus on factors like perceived usefulness, ease of use, and enjoyment in predicting the intention to use simulations, yet they rarely explore how classroom dynamics affect these perceptions. Additionally, research by Yang et al. (2022) and Hung et al. (2020) emphasizes the role of self-efficacy in driving student engagement and performance but overlooks other aspects that influence engagement, such as the role of the instructor.

Taken together, these summaries highlight that no single line of inquiry captures the interplay of social support, tool qualities, and learner dispositions. This is especially critical in introductory computer courses, where limited physical resources make effective simulations essential. To address this gap, this study expands the Technology Acceptance Model (TAM) by distinguishing three overarching aspects and detailing their components. The social aspect assesses peer and instructor support, ranging from informal encouragement to shared classroom norms. The technology aspect evaluates simulator features such as realism, reliability, and accessibility, which shape students' judgments of value and effort. And last, but not least, the personal aspect reflects learners' confidence in using new software and their curiosity about innovation, influencing how they perceive benefits and usability. By analyzing how these aspects jointly influence perceived usefulness, ease of use, and ultimately, learning outcomes, our model provides a theory-driven yet practical understanding of simulation acceptance. This approach offers educators and designers actionable guidance based on a more comprehensive view of student behavior.

This study, therefore, aims to fill the research gap by examining the factors influencing students' acceptance of simulation tools in computing education from three main perspectives: social factors, technology-related factors, and personal traits. To anchor the investigation in an educational context, data were collected from students enrolled in introductory computer networking courses that utilize Cisco's Packet Tracer simulator and EC-Council's iLabs as part of the Certified Secure Computer User (CSCU) Version 3 curriculum. Cisco's Packet Tracer helps students learn core networking concepts, including routing, subnetting, and network configuration. In contrast, iLabs offers an interactive, hands-on environment where students can practice security skills through real-world simulated scenarios that involve security threats and countermeasures. By providing a comprehensive analysis of these diverse factors, this study seeks to deepen the understanding of what drives students to adopt and effectively use simulation tools in computing education. The findings are anticipated to offer valuable insights for educators, instructional designers, and policymakers, helping them create and promote simulation-based learning tools that are not only accessible and functional but also tailored to the varied needs and expectations of students in today's digital learning environments. This study, therefore, formulates the following research question: RQ. What factors significantly influence students' acceptance of learning simulation tools in computing education courses?

2. Literature Study and Hypotheses Development

Table 1 summarizes the current understanding of students' acceptance of simulation-based learning tools and identifies areas where knowledge is still lacking. The first group of studies, grounded in the Technology Acceptance Model (TAM), demonstrates that perceived usefulness, ease of use, and, increasingly, enjoyment are reliable predictors of behavioral intention across various disciplines, ranging from fashion merchandising (Yu, 2017) to engineering (Altalbe, 2019) and immersive virtual reality (Hamilton et al., 2020). The second group employs learning and cognitive theories to show that well-designed scaffolding and realistic interfaces promote competence, self-efficacy, and satisfaction (Hung et al., 2021; Chernikova et al., 2020; Wong et al., 2022). The third group emphasizes contextual constraints, such as equipment shortages or the adequacy of infrastructure, to illustrate that simulations can mitigate limited physical resources (Campos et al., 2020; Mwansa et al., 2024). Lastly, a smaller but growing number of studies connect personal traits (e.g., self-efficacy, innovativeness) to learning outcomes (Yang et al., 2020).

Collectively, these strands confirm that each aspect, technology, pedagogy, context, and individual characteristics, plays a significant role. However, no prior research integrates all these elements within a single explanatory model, nor do any studies specifically focus on computing courses where simulations replace expensive hardware. Our work addresses this gap by expanding TAM to include social-support variables that operationalize peer and instructor influence (technology qualities that capture realism, reliability, and accessibility, and personal dispositions like motivation and self-confidence. By analyzing the combined effects of these constructs, we aim to provide a comprehensive, theory-driven, and practically useful account of simulation acceptance in computing education.

The focus of the study	Basic Theory	Variable	Result	Reference
To examine students' acceptance and perceptions of simulation software technology in a fashion merchandising course and its effect on critical thinking skills.	Technology Acceptance Model (TAM)	The model includes perceived usefulness, ease of use, enjoyment, attitude toward technology use, and improvements in critical thinking skills.	Findings show that students who perceived the simulation software as useful, easy to use, and enjoyable had more positive attitudes and reported improvements in critical thinking skills; enjoyment had the strongest influence on attitudes.	(Yu, 2017)
The study focuses on examining students' acceptance of simulation-based learning (SBL) using an extended Technology Acceptance Model (TAM) within nursing and prehospital emergency care education	Technology Acceptance Model (TAM)	Attitude toward use, behavioral intention, perceived ease of use, perceived usefulness, subjective norm, facilitating conditions, self-efficacy, and fidelity	Attitude, self-efficacy, fidelity, and subjective norm significantly influenced students' acceptance of SBL	(Lemay, et al., 2018)
This study examines the impact of simulation-based virtual laboratories on the performance of engineering students, specifically in the context of Electrical Engineering education in Australia	Technology Acceptance Model (TAM)	Perceived ease of use (PEOU), perceived usefulness (PU), instrumentation (INSTR), creativity and innovation (CI), and performance impact (IMPT)	Perceived usefulness and instrumentation are the most significant factors impacting students' performance	(Altalbe., 2019)
The study investigates how student self-efficacy affects learning outcomes in a business simulation mobile game course, comparing hierarchical teaching and general teaching methods	Self-System Model of Motivational Development (SSMMD)	Self-efficacy, student engagement, and learning outcomes	Self-efficacy directly and indirectly affected learning outcomes through engagement in the hierarchical method	(Yang, et al., 2020)
The study examines simulation-based education (SE) and its application in STEM fields across different European universities, including both online and on-campus models	-	Student motivation, engagement, skill acquisition, as well as practical knowledge of complex systems like logistics and engineering processes	The study finds that SE significantly benefits student engagement, problem-solving skills, and practical knowledge, though it requires careful implementation to avoid distraction and ensure effective learning	(Campos, et al., 2020)
The study focuses on the effectiveness of simulation-based learning in higher education, specifically its role in developing complex skills across	A Meta-Analysis	The type of simulation, technology use, duration, authenticity, and scaffolding methods, along with the	The study finds that simulation-based learning is highly effective in fostering complex skills, especially when using high authenticity simulations and targeted scaffolding	(Chernikova, et al., 2020)

diverse academic domains		learners' prior knowledge and familiarity with the subject matter	approaches, though the effects vary based on learners' prior knowledge and the specific instructional supports used	
To evaluate the effectiveness of immersive virtual reality (I-VR) as an educational tool through a systematic review of quantitative learning outcomes and experimental design in various academic fields.	Technology Acceptance Model and Bloom's taxonomy of educational objectives	Key variables include cognitive learning outcomes, procedural skills, affective learning outcomes, intervention characteristics, assessment measures, and methodological quality scores of the studies reviewed.	The study finds that I-VR generally improves cognitive learning outcomes, particularly in fields requiring spatial understanding, although its benefits vary by subject and study design.	(Hamilton. et al., 2020)
The study investigates the effects of simulation-based learning (SBL) on nursing students' perceived competence, self-efficacy, and learning satisfaction across repeated exposures	Kolb's Experiential Learning Theory	Nursing competence, self-efficacy, and learning satisfaction	Repeated simulation exposures significantly improved nursing students' competence, self-efficacy, and learning satisfaction	(Hung et al., 2021)
This study examines the factors influencing high school students' acceptance of a 3D simulation Android app for learning physics as a form of mobile learning	Technology Acceptance Model (TAM)	Perceived Usefulness, Perceived Ease of Use, Perceived Enjoyment, and Behavioral Intention	Perceived Enjoyment and Perceived Usefulness positively influenced students' intention to use the app	(Lisana, L., & Suciadi, 2021).
To investigate students' perceptions and acceptance of simulation games as a learning tool in higher education, particularly in STEM learning contexts	Human cognition and information processing theories	Students' perceptions of simulation games as valid representations of reality, the application of theoretical knowledge, and ease of use of the game interface	The study found that students generally have positive perceptions of simulation games as learning tools, with high satisfaction levels and perceived learning benefits.	(Wong, et al., 2022)
The study evaluates the impact of simulation tools, especially Cisco Packet Tracer, on enhancing practical computer networking skills in a resource-constrained higher education context in South Africa.	The CIPP (Context, Input, Process, Product) model.	Practical skill acquisition, theoretical understanding, tool effectiveness, infrastructure adequacy, and learning outcome sustainability.	The study concludes that simulation tools significantly improve practical skills, theoretical comprehension, and preparedness for professional networking work, despite occasional software and compatibility challenges.	(Mwansa, et al., 2024)

Table 1. Overview of prior studies

2.1. Literature Study and Hypotheses Development

This study uses the Technology Acceptance Model (TAM) as the foundation for developing a proposed theoretical model to explain student acceptance of Learning Simulation Tools. This framework comprises two main constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). These constructs address two critical questions in a required lab setting: whether the simulator effectively aids students in learning the subject and whether students can use it with minimal effort. In settings where simulation tools are mandatory components of the curriculum (e.g., virtual labs, training simulators), PEOU and PU remain the primary levers of acceptance, while constructs such as Facilitating Conditions (from UTAUT) become relatively constant, as all students have access to the same equipment and support.

Previous studies have also confirmed that TAM is an effective framework for exploring the acceptance of simulation tools in educational settings through its two key components, PU and PEOU (Yu, 2017; Lemay et al., 2018; Altalbe, 2019; Hamilton et al., 2020; Lisana & Suciadi, 2021). These two variables have been shown to have a strong influence on users' attitudes and intentions regarding the use of specific technologies (Fussell & Truong, 2022). In the context of learning, Bagdi et al. (2023) highlighted that TAM effectively explains how students adopt specific technologies in education. Based on this, we propose that both perceived usefulness and ease of use significantly influence students' positive perceptions of learning outcomes when using simulation tools in computing education courses. Perceived usefulness refers to the belief that using simulation tools will help students understand the learning material better (Lisana & Suciadi, 2021). This indicates that learning simulation tools can significantly benefit student learning activities. Meanwhile, ease of use refers to the degree to which an individual believes that using a particular system will require minimal effort (Estriegana et al., 2019). This implies that users can expect that utilizing simulation tools in their learning activities will not require excessive effort to become familiar with them (Fussell & Truong, 2022). Thus, the following hypotheses are proposed:

H1. Perceived usefulness positively and significantly affects learning outcomes from learning simulation tools in computing education courses

H2. Perceived ease of use positively and significantly affects learning outcomes from learning simulation tools in computing education courses

In educational environments, social pressure from influential individuals—particularly those students consider important and significant- influences their perceptions of technology use (Nofita et al., 2024). Binyamin et al. (2018) note that in high school settings, students' attitudes toward certain technologies are shaped by the opinions of individuals they respect, such as teachers and close friends. This concept is referred to as Subjective Norms. In university contexts, Ermilinda et al. (2024) demonstrate that the behavior of lecturers has a significant impact on students' technology usage. Consequently, this study adopts the definition of Subjective Norms from Kim et al. (2021) and adjusts it for the context of this research, defining it as the extent to which students believe their lecturers think they should use simulation tools. The study, therefore, posits that subjective norms have a substantial effect on users' perceptions of the usefulness and ease of use of these tools, consistent with previous research (Aji et al., 2020; Al Kurdi et al., 2021; Kim et al., 2021), lead to following hypotheses:

H3: Subjective Norms positively and significantly affect Perceived usefulness

H4: Subjective Norms positively and significantly affect Perceived ease of use

A recent study in higher education emphasizes the importance of positive support in student learning activities, which fosters effective teaching methods (Wilson et al., 2024). Specifically, support from individuals in the academic environment, such as peers, teaching assistants, and professors, can have a positive effect on students, enhancing their confidence in conducting academic activities (Khan et al., 2024). This support, known as social support, refers to an individual's perception that they are cared for, valued, and part of a mutually supportive community (Wang et al., 2023). In the context of this study, when students believe they will receive help or support from their peers, teaching assistants, or lecturers when facing challenges in their academic activities, it enhances their positive perception of using learning tools. This assertion is supported by Shen et al. (2006), who indicate that the influence of users in different roles within higher education, such as lecturers, peers, or teaching assistants, affects students' perceptions of the perceived usefulness and perceived ease of use of learning tools. According to Huang and Zhang (2022), this construct also explains the perceived available assistance, or the actual support received, which can increase positive feelings, especially when students encounter challenges in their studies. Thus, this study believes that social support from individuals in different roles, such as lecturers or teaching assistants, enhances students' perceptions of system usage, including its usefulness and ease of use. Therefore, this study proposes the following hypothesis:

H5: Social Support positively and significantly affects Perceived usefulness

H6: Social Support positively and significantly affects Perceived ease of use

One significant factor in determining the quality of a simulation program is fidelity. This concept refers to the extent to which a virtual environment resembles the real world (Jiang et al., 2024; Wen & Wang, 2020). Specifically, it explains how closely simulation tools can replicate the original experience found in reality (McMahan et al., 2012). According to Mahalil et al. (2020), this aspect influences user acceptance of the tools, including their perceived usefulness and ease of use. Jiang et al. (2024) emphasize that the level of fidelity will affect the tools' ability to deliver better outcomes, ultimately leading to improved performance expectations for simulator tools. Therefore, we propose the following hypothesis:

H7: Fidelity positively and significantly affects Perceived usefulness

H8: Fidelity positively and significantly affects Perceived ease of use

Prior research highlights the impact of personal traits on students' acceptance of technology usage in higher education, particularly their self-belief in using specific systems. Ermilinda et al. (2024) argue that students with confidence in their ability to utilize a particular system are more likely to maximize the platform's benefits for their learning activities. This concept is known as self-efficacy, which refers to "people's judgment of their capabilities to organize and execute courses of action required to attain designated types of performance" (Bandura, 1977). In the context of simulation education tools, Xie et al. (2022) emphasize the importance of self-efficacy in system usage. Specifically, self-efficacy helps students mitigate negative perceptions regarding the complexity of successfully using a system (Lisana & Handarkho, 2024). Individuals with high self-efficacy also tend to believe in their likelihood of succeeding while using a particular system (Cardullo et al., 2021). Additionally, Ali et al. (2021) note that self-efficacy influences students' perceptions of the effort required to use the system for their learning activities effectively. Fathema et al. (2015) also state that if individuals doubt their ability to use a system, they are likely to view it as less useful and more difficult to use. This study, therefore, proposes the following hypothesis:

H9: Self Efficacy positively and significantly affects Perceived usefulness

H10: Self Efficacy positively and significantly affects Perceived ease of use

Other factors that influence technology adoption include innovativeness. In an educational context, innovativeness refers to students' willingness to take on challenges, explore new ideas, and seek out additional learning opportunities (Wang & Lin, 2021). Maki et al. (2016) note that individuals who possess this trait often adopt innovative technology on a daily basis. According to Kim et al. (2021), people with this characteristic are more likely to embrace systems that offer unique or novel approaches. In this study, we believe that students who exhibit higher levels of innovativeness are more likely to embrace learning technologies such as simulation tools. This embrace leads to positive perceptions of these technologies, including their usefulness and ease of use (Wu & Liu, 2023; Akour et al., 2022). Based on this, we formulate the following hypothesis:

H11: Innovativeness positively and significantly affects Perceived usefulness

H12: Innovativeness positively and significantly affects Perceived ease of use

3. Research Design and Methodology

This study conducted an online, cross-sectional survey of university students who had used a simulation tool as part of their learning. The participants were students in their first, second, and third years of study in informatics or computer science. They had completed courses that utilized simulation tools, including computer networking courses that used Cisco's Packet Tracer simulator and iLabs for the Certified Secure Computer User (CSCU) certification. We selected participants using the purposive sampling method based on the criteria outlined in Neuman's (2014) sampling frame. This approach was necessary to ensure that participants had experience with simulation tools in their university computing courses. The focus constructs of the proposed model (perceived usefulness, ease of use, and learning outcomes) can only be assessed by students who have actually worked with a simulation tool. If novices were asked to respond hypothetically, it would weaken construct validity. Without hands-on experience, respondents could only guess how useful or easy the tool might be. Thus, hypothetical questions may introduce systematic response bias, known as hypothetical bias, leading to measurement error (Kaderabek & Sinibaldi, 2022). However, we recognize that excluding inexperienced students could result in self-selection bias, which might inflate favorable ratings and reduce the spread of scores. Therefore, we invited every eligible student to participate in order to capture the widest possible range of experiences, and we acknowledge this limitation for future research that could include first-time users or pre- or post-exposure designs.

The sample size for this study was determined using the formula provided by Kline (2016), which specifies a minimum of 20 respondents for each factor in the model. Since our model includes eight latent constructs, this necessitates at least $8 \times 20 = 160$ respondents. However, Kline (2016) further recommends a minimum of 200 cases for stable estimation in structural equation modeling (SEM), the method employed in this study. The confirmatory factor analysis (CFA) involved calculating the average variance extracted (AVE) and composite reliability (CR) to ensure the convergent validity of the data, following the criteria proposed by Fornell and Larcker (1981). In addition, George and Mallery's (2003) guidelines were used to assess data reliability through the coefficients of Cronbach's alpha. Meanwhile, discriminant validity was evaluated by ensuring that the square roots of the AVE values were greater than the correlations among the latent variables (Barclay et al., 1995). Lastly, this study used AMOS software to analyze the data and validate the proposed effects in the theoretical model through SEM based on guidance from Kline (2016).

In line with recent SEM guidelines (Kline, 2016), we estimated our model using covariance-based SEM in AMOS with a latent structural-regression (LSR) specification. This approach was chosen over alternatives such as path analysis, partially latent structured regression (PLSR), or variance-based PLS-SEM. LSR treats all seven theoretical constructs as fully latent variables, each measured by a complete set of reflective indicators. This enables us to test the entire Technology Acceptance Model extension, covering both measurement and structural relationships, within a single likelihood-based framework. This choice aligns with our goal of theory confirmation. CB-SEM/LSR provides global fit indices (e.g., χ^2, CFI, RMSEA) that are essential for evaluating how well the hypothesized model reproduces the observed covariance matrix. In contrast, PLS-SEM primarily focuses on prediction and is mainly recommended for formative or exploratory research (Schumaker & Lomax, 2016). Furthermore, the complexity of our model, including eight latent constructs and twenty-seven indicators, fits well within the analytical scope of LSR. Utilizing path analysis or PLSR would oversimplify the measurement component by collapsing some latent variables into single composite scores. Additionally, we set threshold values for skewness and kurtosis at less than three and seven, respectively, to meet the distributional assumptions for covariance-based SEM (Kline, 2016). All these factors confirm that covariance-based SEM with an LSR measurement model is the most rigorous and appropriate approach for testing our theoretically grounded hypotheses. Finally, a consent form has been incorporated into the survey to guarantee that all participants have given informed consent to engage in the study. This research utilized a voluntary and anonymous survey that did not capture sensitive or personal data. We ensured adherence to ethical norms by obtaining explicit consent from individuals.

4. Theoretical Model and Measurement

Figure 1 shows the theoretical model. Meanwhile, all the measuring instruments used to validate the model can be seen in Table 2. The questionnaire was adopted from several prior studies and developed with input from a focus group of student representatives who have varying levels of experience with simulation tools, ranging from novice to expert. To ensure the accuracy and contextual relevance of the Indonesian version of the questionnaire, bilingual experts with experience in this type of research were involved in the translation process. Additionally, a pilot study was conducted to gather feedback from selected respondents, which helped to refine the questionnaire to better align with the specific objectives of the study.

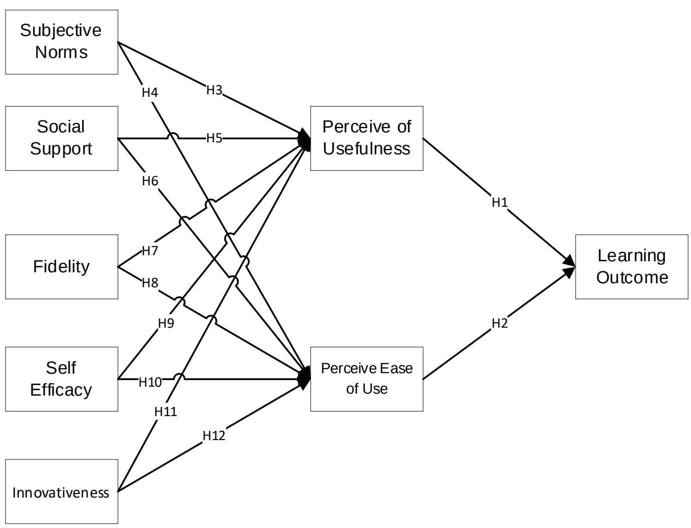

Figure 1. The theoretical model

Variable (Symbol)	Indicator	Measuring Instrument	Adopted from
Learning outcomes	LO1	The simulation tool made me learn to apply theory to practice	(Yang et al., 2022)
	LO2	This simulation tool helped me understand the course material	
	LO3	The simulation tool gave me insight into the course material	
Ease of Use	EOU1	Learning how to use the simulation tool is easy.	(Hong et al., 2006)
	EOU2	The simulation tool is clear and understandable to use.	
	EOU3	I find the simulation tool easy to use.	
Perceived usefulness	PU1	The use of the simulation tool to fulfill my learning activities will improve my performance.	(Handarkho, 2020)
	PU2	The use of the simulation tool to fulfill my learning activities will improve my effectiveness.	
	PU3	The use of the simulation tool helps me to carry out my learning activities.	
	PU4	In general, the use of the simulation tool is beneficial for fulfilling my learning activities.	
Subjective Norm	SN1	The simulation tool is important for my learning in class	(Binyamin et al., 2018)
	SN2	The lecturer thought that I needed the simulation tool to help me study.	
	SN3	I want to do what my lecturer thinks I should do.	
	SN4	The lecturer thinks that with the simulation tool, my learning will increase.	
Social support	SS1	When I am faced with difficulties, some people (peers, lecturer, lecturer assistant) in class comfort and encourage me.	(Shanmugam et al., 2016)
	SS2	When I am faced with difficulties, some people (peers, lecturer, lecturer assistant) in class show interest and concern for my well-being.	
	SS3	In the class, some people (peers, lecturer, lecturer assistant) offer suggestions when I need help.	
	SS4	When I encounter a problem, some people in class (peers, lecturer, lecturer assistant) give me information to help me overcome the problem.	
Fidelity	FD1	The scenario used in the simulator resembled a real-life situation	(Lemay et al., 2018)
	FD2	Real-life factors, situations, and variables were built into the simulation scenario.	
Self-efficacy	SE1	I believe that I can use the simulation tool to get the learning information I need.	(Chen & Tseng, 2012)
	SE2	I believe that I can use the simulation tool to unlock lecturer-given assignments.	
	SE3	I believe that the experience when I use the simulation tool help me to take quizzes given by the lecturer.	
Innovativeness	IN1	If I find out about a new technology, I seek ways to experience it	(Handarkho, & Harjoseputro, 2020)
	IN2	I can usually figure out new technology without help from others	
	IN3	I enjoy the challenge of figuring out a new technology	
	IN4	In general, I am among the first in my circle of friends to acquire new technology when it appears	

Table 2. Indicators and measuring instrument

5. Data Preparation & Descriptive Analyses

A total of 312 responses were collected to validate the proposed model. We conducted a Confirmatory Factor Analysis (CFA) using AMOS software to determine the loading factors, which were then used to calculate the Average Variance Extracted (AVE) and Composite Reliability (CR) to assess convergent validity. The results indicate that all values of AVE and CR meet the minimum thresholds established by Fornell and Larcker (1981), as shown in Table 3. Additionally, Cronbach's alpha coefficient also meets the standard values proposed by George and Mallery (2003), demonstrating that the collected responses exhibit data reliability.

However, the results for discriminant validity (Table 4) show a cross-correlation between the constructs of Ease of Use and Learning Outcome, suggesting that these two constructs are highly correlated and may overlap significantly. This implies that they may not be distinct from each other as originally intended (Fornell & Larcker, 1981). To thoroughly investigate these issues, we conduct the HTMT (Heterotrait–Monotrait Matrix Test), which has a higher power to detect problematic overlaps by analyzing the factor loadings associated with each construct (Henseler et al., 2015). After running every combination of indicators for Ease of Use (EOU1 to EOU3) and Learning Outcome (LO1 to LO3), while ensuring that we maintain at least two indicators per construct (the minimum typically recommended for Structural Equation Modeling), the results indicate that all HTMT values surpass the 0.90 threshold. This is above the commonly accepted cut-off for discriminant validity, where HTMT values should be below 0.85 for conceptually distinct constructs or below 0.90 for constructs that are more closely related, as suggested by Henseler et. al. (2015), even after excluding indicators with loadings below 0.70.

Indicator	Factor loadings	AVE	CR	CA	Indicator	Factor loadings	AVE	CR
LO1	0.521	0.576	0.796	0.831	SS1	0.784	0.687	0.898
LO2	0.835				SS2	0.85		
LO3	0.871				SS3	0.843		
EOU1	0.859	0.760	0.907	0.813	SS4	0.837		
EOU2	0.884				FD1	0.757	0.652	0.789
EOU3	0.426				FD2	0.855		
PU1	0.794	0.671	0.891	0.889	SE1	0.856	0.704	0.877
PU2	0.839				SE2	0.842		
PU3	0.833				SE3	0.818		
PU4	0.809				IN1	0.74	0.517	0.810
SN1	0.79	0.597	0.856	0.854	IN2	0.647		
SN2	0.749				IN3	0.765		
SN3	0.752				IN4	0.718		
SN4	0.799							

Note: CA refers to Cronbach's alpha

Table 3. Factor analysis and Cronbach's alpha coefficient.

	LO	EOU	PU	SN	SS	FD	SE	IN
Learning outcomes	0.759							
Ease of Use	.911**	0.872						
Perceived usefulness	.626**	.702**	0.819					
Subjective Norm	.578**	.633**	.711**	0.773				
Social support	.404**	.431**	.547**	.541**	0.829			
Fidelity	.487**	.521**	.544**	.614**	.538**	0.807		
Self-efficacy	.570**	.620**	.658**	.692**	.563**	.621**	0.839	
Innovativeness	.452**	.502**	.507**	.507**	.443**	.576**	.563**	0.719

Notes: **. Correlation is significant at the 0.01 level (2-tailed); Highlighted columns indicate a cross-correlation between the constructs of Ease of Use and Learning Outcome

Table 4. Discriminant validity

This finding confirms that the overlap between Learning Outcome (LO) and Ease of Use (EOU) is structural rather than being driven by one or two anomalous items. Table 5 shows all the HTMT ratios for each subset that retains at least 2 items per construct. Consequently, this study has decided to drop the construct of Ease of Use since the Learning Outcome is the dependent variable we aim to explain. As a result, we have adjusted the proposed theoretical model, as illustrated in Figure 2, which details the final indicator and factor loadings values presented in Table 6. The final indicator still maintains a factor loading value under 0.7 (LO1). Loadings as low as 0.50 or 0.60 are acceptable if the Average Variance Extracted (AVE) exceeds 0.50 and the Composite Reliability (CR) is above 0.70. These criteria indicate sufficient convergent validity and internal consistency reliability (Hair et al., 2010).

LO items kept	**EOU items kept**	**HTMT for LO–EOU**
LO1, LO2	EOU2, EOU3	0.98
LO1, LO3	EOU1, EOU3	1.04
LO1, LO2	EOU1, EOU2, EOU3	1.06
LO1, LO2	EOU1, EOU2	1.08
LO1, LO2, LO3	EOU1, EOU3	1.09
LO1, LO2, LO3	EOU2, EOU3	1.1
LO1, LO2	EOU1, EOU3	1.1
LO1, LO2, LO3	EOU1, EOU2, EOU3	1.11
LO2, LO3	EOU1, EOU3	1.12
LO1, LO3	EOU1, EOU2, EOU3	1.12
LO2, LO3	EOU2, EOU3	1.15
LO1, LO2, LO3	EOU1, EOU2	1.15
LO1, LO3	EOU1, EOU2	1.15
LO2, LO3	EOU1, EOU2, EOU3	1.16
LO1, LO3	EOU2, EOU3	1.17
LO2, LO3	EOU1, EOU2	1.22

Table 5. Sub HTMT ratios for LO and EOU

Indicator	**Factor loadings**	**AVE**	**CR**	**CA**	**Indicator**	**Factor loadings**	**AVE**	**CR**
LO1	0.521	0.576	0.796	0.831	SS1	0.784	0.687	0.898
LO2	0.835				SS2	0.85		
LO3	0.871				SS3	0.843		
PU1	0.794	0.671	0.891	0.889	SS4	0.837		
PU2	0.839				FD1	0.757	0.652	0.789
PU3	0.833				FD2	0.855		
PU4	0.809				SE1	0.856	0.704	0.877
SN1	0.79	0.597	0.856	0.854	SE2	0.842		
SN2	0.749				SE3	0.818		
SN3	0.752				IN1	0.74	0.517	0.810
SN4	0.799				IN2	0.647		
					IN3	0.765		
					IN4	0.718		

Table 6. Final factor loading, with AVE, CR, and Cronbach's alpha value.

Table 7 presents the detailed characteristics of the respondents. The respondents consist of first-year students (32.1%), second-year students (35.95%), and third-year students (32.15%) who are currently attending classes. Additionally, male respondents dominate the group, making up 80% of the total. All the students have experience with simulation tools in their computing course at the university, indicating they are qualified to be part of the research.

Further, based on the profiles of the respondents, we conducted T-tests and ANOVA to analyze significant differences in mean (M) scores based on gender and student semester, respectively. The results from the T-test revealed a significant difference between males and females, particularly in terms of innovativeness.

Males had a significantly higher mean score (M = 3.87) compared to females (M = 3.57) in this area. While both genders showed a positive response, male innovativeness was notably more pronounced, especially regarding their intention to explore new technology, as indicated by items IN1, IN3, and IN4, which reflect their enjoyment in discovering and acquiring new technological tools. Meanwhile, the ANOVA results indicated significant differences in the mean values for the Fidelity factor. First-year students (M = 4.09) considered this aspect more important than second-year (M = 3.83) and third-year students (M = 3.84), particularly regarding how well the simulator reflects real-life situations (FD1).

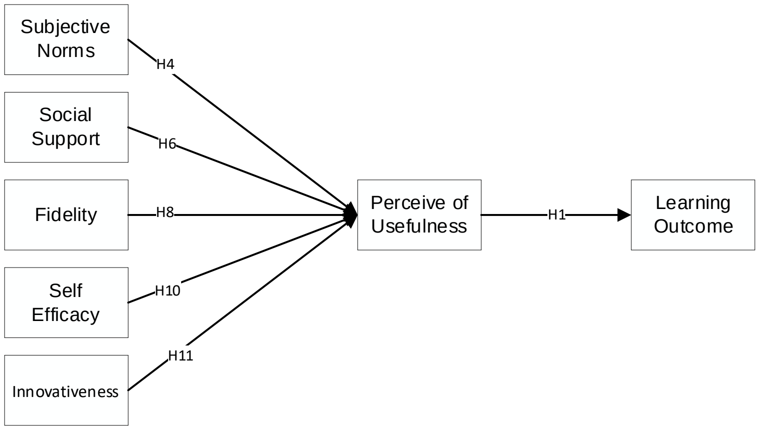

Figure 2. The adjusted theoretical model

Lastly, Skewness and kurtosis values were calculated to ensure the data were suitable for SEM. The recorded values were less than three and seven, respectively, thus satisfying the requirement (Kline, 2016).

		Frequency	Percent	Valid Percent	Cumulative Percent
Age	< =20	236	75.6	75.6	75.6
	>20	76	24.4	24.4	100.0
	Total	312	100.0	100.0	
Semester	1-2	100	32	32	32.
	3-4	112	36	36	68
	5-6	100	32	32	100.0
	Total	312	100.0	100.0	
Gender	Male	252	80.8	80.8	80.8
	Female	60	19.2	19.2	100.0
	Total	312	100.0	100.0	

Table 7. Respondents' characteristics

6. Result of Direct Effects

The results of the Structural Equation Modeling (SEM) analysis are presented in Table 8 and Figure 3. The analysis revealed that the direct effect of Subjective Norms on Perceived Usefulness is the strongest in the model, followed by Self-Efficacy and Social Support. Additionally, Perceived Usefulness was found to significantly predict students' perceptions of learning outcomes resulting from the use of simulation tools. However, two of the proposed hypotheses, specifically those related to Fidelity and Innovativeness, were found to be insignificant. Furthermore, since we removed the Ease-of-Use construct from the model, all hypotheses associated with this factor (H2, H4, H6, H8, H10, and H12) were also excluded from this study. Meanwhile, Table 7 indicates that the data fit the model statistically, based on Kline's (2016) model fit criterion.

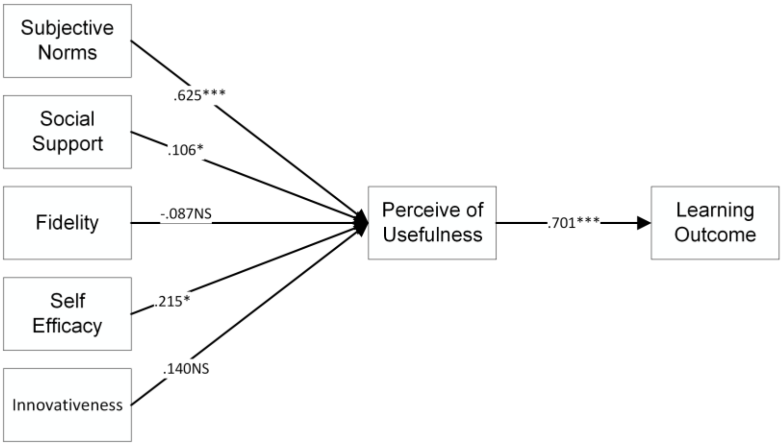

Figure 3. The result of the direct effect in the Theoretical Model

Direct effect	Total Effect	Status
Usefulness ➔ Learning Outcome (H1)	.701***	Accepted
Subjective Norms➔ Usefulness (H4)	.625***	Accepted
Social Support ➔ Usefulness (H6)	.106*	Accepted
Fidelity ➔ Usefulness (H8)	-.087NS	Rejected
Self-efficacy ➔ Usefulness (H10)	.215*	Accepted
Innovativeness ➔ Usefulness (H12)	.140NS	Rejected

Table 8: Hypothesis testing results

Sample Size	**Normed chi-square (NC) = $\chi 2/df$**	**RMR**	**SRMR**	**GFI**	**AGFI**	**NFI**	**IFI**	**CFI**	**TLI**	**RMSEA**
312	424.219/236 = 1.798	.018	.037	.901	.874	.914	.960	.960	.953	.051
	R^2: LO: 0.567; PU:0.727									

Note(s): R^2 is the proportion of the variance explained by the variables affecting it

Table 9. Fit statistic for the proposed model

Table 9 demonstrates that the structural model fits the data well according to all recommended indices. The normed chi-square is 1.80 (χ^2 = 424.219, df = 236), which is comfortably below the conservative ceiling of 3.0, indicating an acceptable fit (Kline, 2016). Both absolute and incremental indices show strong results: the Goodness-of-Fit Index (GFI = .901) exceeds the guideline of .90 (Byrne, 2010), while the Adjusted GFI (AGFI = .874) surpasses the benchmark of .85 for complex models (Hooper, Coughlan, & Mullen, 2008). Incremental measures, including the Normed Fit Index (NFI = .914) and the Incremental Fit Index (IFI = .960), both exceed the threshold of .90, indicating a significant improvement over the null model (Hu & Bentler, 1999). Additionally, the Comparative Fit Index (CFI = .960) and the Tucker-Lewis Index (TLI = .953) both surpass the .95 criterion for a close fit (Hu & Bentler, 1999). Residual-based indices confirm minimal misfit, with a raw root mean square residual (RMR) of .018, where values less than or equal to .05 are considered good. Moreover, the root mean square error of approximation (RMSEA) is .051, with values below .06 indicating a good fit, and the standardized RMR (SRMR) is .038, which is well below the ceiling of .08 (Hu & Bentler, 1999). The model's explanatory power is also significant, accounting for 72.7% of the variance in Perceived Usefulness (R^2 = .727) and 56.7% in Learning Outcome (R^2 = .567). Both proportions exceed Cohen's (1988) "substantial" benchmark of .26.

7. Discussion

The results indicate that social factors play a crucial role in the successful adoption of simulation tools in computing education courses. The findings suggest that lecturers' opinions significantly influence students' perceptions of the usefulness of these tools (H4). In the context of Indonesian higher education, characterized by high power distance and a strong respect for authority, this influence is even more pronounced. When lecturers incorporate tools like Cisco Packet Tracer and iLabs into their lectures, they not only demonstrate technical workflows but also convey institutional legitimacy. This, in turn, enhances student motivation and engagement (Ermilinda et al., 2024; Kim et al., 2021). For instance, one lecturer's enthusiastic demonstration of a virtual network configuration inspired even the most skeptical students to explore advanced features. This suggests that lecturer enthusiasm acts as both an informational and normative influence. These findings support the work of Binyamin et al. (2018), who identified respect for instructors as a key factor in technology acceptance. Additionally, this research expands upon theirs by highlighting the cultural aspects of authority in collectivist contexts.

The findings further show that support from peers, teaching assistants, and professors can positively impact students when they encounter difficulties using simulation tools in their learning activities (H6), which confirms Khan et al. (2024). This indicates that when students believe they will receive support from their peers, teaching assistants, or lecturers while facing academic challenges, it positively affects their perception of learning tools. This notion is backed by Shen et al. (2006), who argue that the involvement of various individuals in higher education influences students' perceptions of the usefulness of these tools. Furthermore, the availability of assistance and the actual support received can enhance students' positive feelings, especially when they encounter difficulties in their studies (Huang and Zhang, 2022).

From a personal perspective, although dispositional innovativeness (H11) was not a significant predictor, self-efficacy (H10) had a strong influence on perceived usefulness. This finding suggests that students' confidence in their ability to use the system impacts their perception of its usefulness (Lisana & Handarkho, 2024; Fathema et al., 2015). It indicates that students who are confident in their ability to navigate a particular system are more likely to fully leverage the platform's benefits for their learning activities (Ermilinda et al., 2024). This result confirms that students with high self-efficacy are more likely to believe in their chances of success when using a specific system (Cardullo et al., 2021).

Meanwhile, the results for H11 indicate that the effect of innovativeness was rejected. This result contradicts prior studies that suggest this construct encourages individuals to use innovative systems (Kim et al., 2021). This difference may be attributed to the tendency for innovation to be linked with technology used outside of education, such as for financial and entertainment purposes. Our respondent, who uses simulator tools as part of the course, may influence the results. When a tool is required rather than selected freely, students' dispositional innovativeness might play a smaller role (Brown et. al., 2002). This could lead them to focus more on adapting to the tool instead of actively exploring its novel features. Furthermore, the effect of fidelity of simulation tools for technology quality is also not supported (H7), which contradicts previous studies (Mahalil et al., 2020; Jiang et al., 2024). This outcome may be attributed to the context of computing education courses, where the realism of simulations is seen as a supplementary feature. In these cases, the primary focus of students is to understand the course material rather than to experience the realism of the simulation. From a statistical perspective, since all students used the same simulator (Cisco Packet Tracer and Ilabs simulator) and had similar exposure to the course, perceived realism ("Fidelity") was uniformly high, creating a ceiling effect that weakened the correlations (Cohen, 1988).

Overall, our findings indicate that the acceptance and effective use of simulation tools primarily depend on supportive social aspects. When lecturers integrate simulations into course objectives and demonstrate their use, they legitimize the technology and set clear expectations for students. Moreover, encouraging collaboration among peers and ensuring that teaching assistants are readily available creates a positive learning environment. In such an environment, students can troubleshoot, exchange strategies, and celebrate their achievements together. This social support enhances their learning experiences and boosts their confidence, making simulation tools vital components of the learning process. Consequently, students feel empowered to experiment, refine their approaches, and confidently grasp complex computing concepts.

The theoretical contribution of this study lies in its comprehensive approach to explaining the factors that influence student acceptance of simulation tools in computing education. Specifically, this research develops a theory based on the Technology Acceptance Model (TAM) and extends it by incorporating environmental aspects and personal characteristics of students. While several previous studies have focused on theoretical frameworks that emphasize the capabilities of simulation software in enhancing the student learning experience from a technological perspective, others have discussed student cognitive processes to explain their perceptions and acceptance of learning tools in educational settings. In contrast, this study offers an alternative approach that also considers the influence of environmental factors, such as lecturers, peers, and teaching assistants, which prior research has yet to explore in depth. This study addresses this gap in the literature. The results indicate that social factors are crucial in students' acceptance of alternative teaching and learning methods in computing education courses that use simulation tools. Consequently, this finding contributes to the theoretical framework of this research area.

Several practical actions can be proposed to enhance students' perception of the usefulness of simulation tools in supporting their learning activities in class. Based on the results regarding subjective norms, lecturers play a crucial role in encouraging students to maximize the use of these tools. Therefore, lecturers need to demonstrate the value of the tools by integrating them into course objectives. By aligning the tools with syllabus guidelines, students will recognize their importance in the course and appreciate their usefulness in the learning process. The results also indicate the importance of support from peers, teaching assistants, and lecturers when students face challenges in their academic activities, particularly in using simulation tools. Faculty or departments should consider creating study groups or incorporating the adoption of these tools as a topic in study sessions. This way, upper-year students can share their experiences with newcomers regarding the use of simulation tools. Ideally, through these groups, students can assist one another in maximizing the effectiveness of the tools to enhance their learning. Additionally, lecturers should ensure that their teaching assistants are properly trained to provide hands-on guidance in using simulation tools during class sessions. This will allow them to assist students who face challenges in operating the simulation tools. To enhance self-efficacy among students, lecturers can provide training and tutorials outside of regular class sessions, particularly for newcomers. This support can be facilitated through student study groups or additional classes, helping students become more familiar with using various tools. The goal is for students to gain confidence in utilizing simulation tools. Lecturers should also design their courses to incorporate these tools gradually. They can start by introducing simpler cases or assignments to help students become familiar with them. By beginning with basic course material that is simple enough, students can build their confidence and reduce any intimidation they may feel when using these tools.

However, even though the effect of fidelity is rejected, the ANOVA result indicates that 1st years students give more attention to this construct. This pattern suggests that newcomers place more weight on surface realism, perhaps because they lack hands-on experience. Therefore, the department needs to design first-year simulation exercises with relatable real-world scenarios, such as simulating a home or small office network setup, along with visual cues and step-by-step tasks that mirror actual field conditions, helping students better grasp how course concepts apply in practical environments.

In order to convert our findings into improvements that benefit all stakeholders, we recommend several interconnected measures. Instructors should incorporate simulation exercises into course objectives and assessment criteria, highlighting their importance and encouraging student engagement. By aligning each simulation with specific syllabus goals, students can view these tools as essential rather than supplementary. Further, given the strong influence of subjective norms on acceptance, departments can bolster peer support by establishing informal study groups or mentoring clinics where senior students offer practical advice to newcomers. Additionally, teaching assistants should receive specialized training to provide practical help during laboratory sessions. Instructors, meanwhile, can boost students' self-efficacy by offering brief optional lessons outside regular class hours and by structuring assignments that progress from low-stakes, basic tasks to more challenging scenarios. This approach allows novices to build their confidence gradually.

Next, developers of educational tools can support pedagogical efforts by optimizing user interfaces with wizard-style workflows, in-line error notifications, and context-sensitive micro-tutorials that facilitate initial use. They should also incorporate adaptive-fidelity controls, enabling instructors to switch between low- and high-fidelity modes to manage cognitive load effectively. Integrating accessibility features, such as keyboard-only navigation, text-to-speech capabilities, and bandwidth-adaptive media, will enhance participation, particularly in resource-limited environments often found in Indonesian higher education institutions. Instructional designers, meanwhile, can further improve these initiatives by implementing dynamic analytics dashboards that showcase competence heat maps. This allows educators to focus feedback on areas where simulation data indicate recurring mistakes. Furthermore, they can package simulation segments as Learning Management System (LMS) content blocks through Learning Tools Interoperability (LTI) or Application Programming Interface (API), supporting spaced-practice schedules that reinforce knowledge retention.

Together, these pedagogical, technical, and design strategies should enhance the perceived utility and user-friendliness of simulation tools while optimizing their effectiveness for learning.

Moreover, broader institutional support, such as establishing dedicated simulation laboratories with standardized quality criteria, regular system updates, and comprehensive training programs, could enhance students' engagement by providing a consistent and reliable learning environment. For instance, universities could implement formal guidelines for the periodic evaluation of simulation software quality, usability assessments involving students and lecturers, and systematic integration of industry-based scenarios. These measures would ensure that simulation tools not only meet educational objectives but also reflect real-world technological advancements.

Universities could further motivate active student adoption of simulation technologies by introducing gamified elements, such as digital badges, leaderboards, or achievement certificates linked directly to course grades or extra credits. Additionally, recognizing outstanding student performance through academic awards or showcasing their simulation projects publicly, for instance, in university exhibitions or open-day events, could reinforce positive perceptions and encourage greater student enthusiasm toward utilizing these educational technologies.

8. Limitation

Several limitations should be considered when interpreting and generalizing our findings. First, although we ensured anonymity to minimize bias, the use of self-reported data introduces the potential for common-method bias. Additionally, since participation was voluntary, students who are more confident with or interested in technology-based learning may be over-represented. This may have resulted in more favorable responses regarding perceived usefulness and learning outcomes than would be observed in a broader, more diverse student population. Second, the study was conducted within a single computing program at an Indonesian university using purposive sampling. This limits the external validity of the findings, particularly when applied to other academic disciplines or institutional contexts. For instance, fields such as medicine or aviation often use more complex simulation environments that emphasize high-fidelity interaction and realism. Moreover, our participants engaged specifically with Cisco's Packet Tracer and EC-Council's iLabs (CSCU v3), so the findings primarily reflect experiences with those platforms. We did not disaggregate responses by tool, which limits our ability to identify platform-specific effects. Third, our assessment of simulation tool quality focused primarily on fidelity, that is, how well the tools replicate real-world tasks. Other important aspects, such as usability, accessibility, or interoperability, were not examined but may also influence student acceptance and learning outcomes.

Finally, we acknowledge the theoretical significance of Perceived Ease of Use as a core construct in the Technology Acceptance Model (TAM). Due to persistent discriminant validity issues with the Learning Outcome, we made the difficult decision to remove Ease of Use from the final model. While this choice ensured construct clarity and statistical robustness, it may reduce comparability with prior TAM-based studies. Future research should consider alternative modeling strategies, such as bifactor or higher-order models, to retain this construct without compromising validity. Recognizing these methodological, contextual, and theoretical limitations is important for accurately interpreting our results. Future studies may benefit from including novice users, comparing different simulation tools, involving more diverse academic programs or institutions, and adopting broader frameworks for evaluating technology acceptance.

9. Conclusion and Future Research

This study shows how various social factors, including the roles and influences of lecturers, peers, and teaching assistants, significantly shape students' perceptions of the effectiveness of simulation tools in enhancing learning outcomes in computing education courses. It also emphasizes the importance of students' self-efficacy, which deserves particular attention. However, the impact of innovativeness and fidelity was found to be insignificant. Overall, the findings suggest that supportive social factors play a crucial role in determining the acceptance and effective use of simulation tools in computing education settings. From a theoretical standpoint, this research enhances the understanding of the factors affecting student acceptance of simulation tools by moving beyond a purely technological perspective. It takes into account environmental influences, such as those from lecturers, peers, and teaching assistants, an aspect that has not been thoroughly explored in previous research. This positions our study as a valuable contribution to the existing body of knowledge.

Future research should focus on longitudinal designs that track perceptions and learning outcomes over multiple semesters. This approach will help clarify how social influence and self-efficacy develop with continued exposure to simulation tools. Additionally, using more representative respondent profiles, considering factors such as gender, age, major, and GPA, will allow for moderating factor analysis, enhancing the findings. Furthermore, researchers could replicate and extend the proposed framework to diverse fields like nursing, finance, and language learning to determine whether the same influencing factors exist or if new ones emerge. Lastly, broadening the concept of technology quality to include aspects like system usability, cognitive load, and interaction richness will provide clearer insights into which technical attributes most significantly affect user acceptance and performance.

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