ความตั้งใจเชิงพฤติกรรมของนักศึกษาพยาบาลในการฝึกปฏิบัติโดยใช้สถานการณ์จำลอง
Behavioral Intentions of Nursing Students in Simulation-Based Practice

ชมพูนุช โสภาจารีย์[1], ภูตะวัน โฮ วงศ์ใหญ่[2], ธีริศ เทพเฉลิม[2], สร้อยฟ้า ปิ่นสุวรรณ[1*]
Chompunut Sopajaree[1], Phutawan Ho Wongyai[2], Teeris Thepchalerm[2], Soifah Pinsuwan[1*]
[1]สำนักวิชาพยาบาลศาสตร์ มหาวิทยาลัยแม่ฟ้าหลวง, [2]สำนักวิชาการจัดการ มหาวิทยาลัยแม่ฟ้าหลวง
[1]School of Nursing, Mae Fah Luang University, [2]School of Management, Mae Fah Luang University

(Received: *April 7, 2025*: Revised: *November 6, 2025*; Accepted: *December 19, 2025*)

บทคัดย่อ

การศึกษาเชิงปริมาณแบบภาคตัดขวางนี้มีวัตถุประสงค์เพื่อวิเคราะห์ความตั้งใจเชิงพฤติกรรมของนักศึกษาพยาบาลในการฝึกปฏิบัติ โดยใช้สถานการณ์จำลอง การศึกษาพัฒนาแบบจำลองการยอมรับเทคโนโลยี (Technology Acceptance Model: TAM) ให้ครอบคลุมถึงการรับรู้ความเพลิดเพลิน และสมรรถนะแห่งตนด้านเทคโนโลยี กลุ่มตัวอย่างคือ นักศึกษาพยาบาลจำนวน 208 คน เครื่องมือในการวิจัย ได้แก่ แบบสอบถามความตั้งใจเชิงพฤติกรรมของนักศึกษาพยาบาลในการฝึกปฏิบัติโดยใช้สถานการณ์จำลอง ซึ่งมีความตรงเชิงเนื้อหาเท่ากับ 1.00 วิเคราะห์ข้อมูลโดยใช้เทคนิคการวิเคราะห์โมเดลสมการโครงสร้างด้วยวิธีถดถอยแบบน้อยที่สุดบางส่วน (Partial Least Squares Structural Equation Modeling) ผลการวิจัยพบว่า

1. การรับรู้ประโยชน์ และความเพลิดเพลินมีอิทธิพลต่อความตั้งใจในการใช้การฝึกอบรมด้วยสถานการณ์จำลองอย่างมีนัยสำคัญทางสถิติ (p-value < .05)

2. ความเชื่อมั่นในตนเองด้านเทคโนโลยีมีผลต่อการรับรู้ความง่ายในการใช้งาน

การศึกษานี้แสดงให้เห็นถึงความสำคัญของการออกแบบเครื่องมือจำลองที่มีความน่าสนใจและมีประสิทธิภาพ เพื่อส่งเสริมการเรียนรู้ของนักศึกษา ทั้งนี้ควรมีการศึกษาวิจัยเพิ่มเติมในบริบทและกรอบแนวคิดทางการศึกษาที่หลากหลายยิ่งขึ้น

คำสำคัญ: การยอมรับเทคโนโลยี ความตั้งใจเชิงพฤติกรรม นักศึกษาพยาบาล สถานการณ์จำลอง

*ผู้ให้การติดต่อ (Corresponding e-mail: soifah.pin@mfu.ac.th)

Abstract

This cross-sectional quantitative study aimed to analyze the behavioral intentions of nursing students to engage in simulation-based practice. The study extended the Technology Acceptance Model (TAM) by incorporating perceived enjoyment and technological self-efficacy. The sample consisted of 208 nursing students. The research instrument was a questionnaire measuring nursing students' behavioral intentions toward simulation-based practice, with a content validity index of 1.00. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings were as follows.

1. Perceived usefulness and perceived enjoyment had statistically significant effects on the intention to use simulation-based training (*p-value* < .05).

2. Technological self-efficacy significantly influenced perceived ease of use.

The study highlights the importance of designing simulation tools that are both engaging and effective in order to enhance student learning. Further research should be conducted across diverse educational contexts and theoretical frameworks.

Keywords: Technology Acceptance, Behavioral Intention, Nursing Students, Simulation-Based Learning

Introduction

One of the primary objectives of nursing education is to ensure that graduates are well-equipped with the knowledge and skills necessary to perform nursing practices effectively and efficiently. The urgency of this objective is highlighted by global data: 1 in 10 patients is harmed in healthcare, resulting in over 3 million deaths annually, with more than 50% of these cases being preventable (World Health Organization, 2023), underscoring the urgent need for practical training to ensure practitioner competency. Therefore, nursing schools must provide both theoretical lectures and hands-on practice to enable students to develop their cognitive and psychomotor skills. While lectures can be conducted appropriately in the classroom, the practice parts have several limitations (Koukourikos, Tsaloglidou, Papathanasiou, Kourkouta, Iliadis, Fratzana et al., 2021). Students are unable to practice with real patients. They need to practice in a controlled environment that traditionally relies on basic training devices. However, modern simulation-based approaches in these controlled settings offer enhanced learning opportunities and better preparation for clinical practice (Mishra, Trivedi, 2023).

Nursing educators have recently implemented various innovative technologies to enhance their students' learning experiences. For example, utilizing virtual reality technology to teach post-appendectomy wound care resulted in increased student engagement (Izza, Firman, Rahman, Gayatri, Yetti, Boro et al., 2022). A scoping review study (Barbosa, Atanasio, Medeiros, Saraiva, Santos, 2021) also confirmed the positive impact of simulation, mobile applications, web platforms, and hypermedia on nursing education. Several studies support the use of technology in education. Simulation-based technology is powerful and can significantly enhance student learning outcomes, particularly in practical sessions (Bowtell, Kist, Osbourne, Parker, 2013). This technology is designed

to simulate key features of real-world experiences, with a focus on interactivity (Lateef, 2010). It can range from mannequins to computer-generated characters, aiming to provide a realistic patient care experience (Alinier, Oriot, 2022). Numerous studies have demonstrated the benefits of simulation-based technology.

A growing body of research underscores the advantages of technology in nursing education. However, a critical gap exists in understanding how nursing students accept and integrate technology into their learning. Simulation technology is not a single, uniform concept; students' acceptance depends on factors beyond just usefulness. Confusing interfaces or glitches affect Perceived Ease of Use, while a lack of confidence in operating hardware highlights Technology Self-Efficacy (Chow, Hung, Chu, Lam, 2022). Unrealistic scenarios lead to low Perceived Enjoyment, reducing motivation (Cohen, Boni, 2018). A comprehensive model is needed to understand this complex issue of acceptance. A study on the Intention to Use (IU) clinical simulation applied the Technology Acceptance Model (TAM) framework to examine the Intention to Use virtual clinical simulation in clinical nurses (Choi, Tak, 2022). However, the study relied on the original TAM model, which posits that only Perceived Ease of Use and Perceived Usefulness directly influence Intention to Use. At the same time, other factors are unrelated to Intention to Use. The original Technology Acceptance Model (TAM) has been the dominant framework in prior investigations (Forehand, Benson, Chance, Armstrong, 2021; Shanmugapriya, Seethalakshmi, Zayabalaradjane, Rani, 2023). It presents a limited viewpoint. Although the TAM is valuable, it can be further enhanced to provide a more comprehensive understanding. Therefore, this study aims to enrich the comprehension of technology acceptance among nursing students concerning the use of simulation technology by extending the TAM framework.

Objective

To develop and empirically test an extended Technology Acceptance Model (TAM) by integrating Perceived Enjoyment and Technology Self-Efficacy to explain nursing students' behavioral intention to use simulation-based training.

Hypothesis

Based on the review of TAM and nursing education literature, seven hypotheses were formulated to predict nursing students' intention to use simulation training. This study extends the framework by adding Perceived Enjoyment and Technology Self-Efficacy for a more comprehensive understanding of technology adoption factors.

H1: Nursing students' Intention to use simulation devices increases as their Perceived Ease of Use increases.

H2: Perceived Usefulness increases as Perceived Ease of Use increases.

H3: Nursing students' Intention to use simulation devices increases as their Perceived Usefulness increases.

H4: Perceived Usefulness increases as Perceived Enjoyment increases.

H5: Nursing students' Intention to Use simulation devices increases as their Perceived Enjoyment increases.

H6: Perceived Ease of Use increases as Technology self-efficacy increases.

H7: Nursing students' Intention to use simulation devices increases as their Technology self-efficacy increases.

Conceptual Framework

The Technology Acceptance Model (TAM), introduced in 1986 by Fred Davis (1986), suggests that Perceived Ease of Use and Perceived Usefulness are key factors in determining a user's Intention to Use a new technology, and this intention leads to actual usage (Davis, 1989). Both Perceived Usefulness and Perceived Ease of Use positively impact the Intention to Use technology. The model was refined by including Technology self-efficacy and system characteristics (Venkatesh, Davis, 2000). The model's validity and robustness have been confirmed through meta-analysis studies (King, He, 2006). Recognizing its potential for further explanation, Venkatesh and Davis (2000) developed TAM2 by incorporating social influences (subjective norms) and cognitive instrument factors (results from demonstrability and job relevance). This expansion demonstrates TAM's adaptability and potential for improvement, enabling a more comprehensive understanding of technology adoption.

The Technology Acceptance Model (TAM) has served as a foundation for understanding technology adoption; however, researchers have identified additional factors that influence user intention. Two key additions are Perceived Enjoyment and Technology self-efficacy (Marangunić, Granić, 2015). Studies across various contexts support this notion. Another study found a positive link between enjoyment and the Intention to use web-based training (Park, Son, Kim, 2012). Similarly, a study reported that enjoyment has a positive impact on university students' use of e-learning platforms. Balog and Pribeanu (2010) further confirm this connection for students in the context of augmented reality.

Technology self-efficacy also plays a significant role. Studies demonstrate its positive influence on e-learning effectiveness and technology-based self-directed learning (Chien, 2012). Additionally, nursing education research suggests a link between students' Technology self-efficacy and positive attitudes toward technology.

Considering these findings, this study expands the TAM framework by incorporating Perceived Enjoyment and Technology self-efficacy to investigate their impact on students' technology adoption.

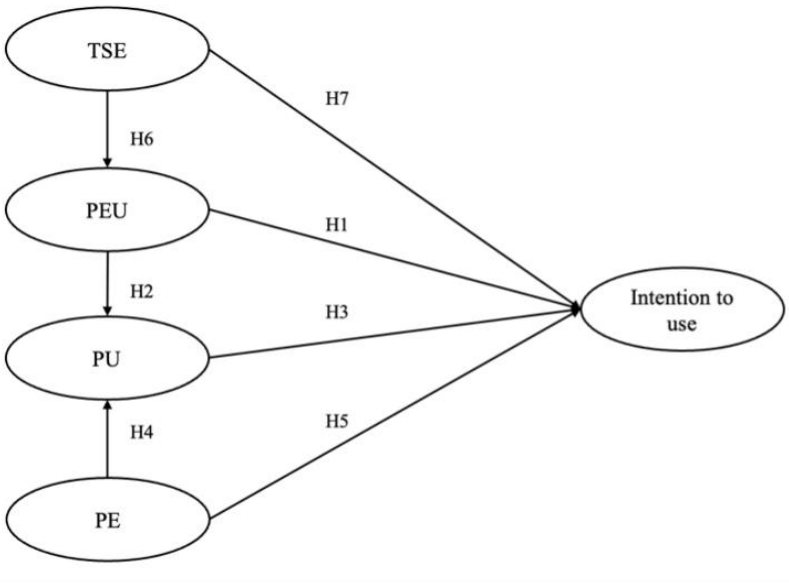


Figure 1: Conceptual Framework

Methodology

Research Design

This study utilized a cross-sectional quantitative research design to examine the factors influencing nursing students' behavioral intention to use simulation-based training. The study population consisted of nursing students, with a sample of 208 nursing students.

Research instrument

The research instrument was a questionnaire consisting of two sections (1) collecting respondents' demographics and (2) collecting students' perceptions of using interactive devices. The questions and underlying concepts were grounded in the Technology Acceptance Model and the existing literature. The final survey incorporated 20 measurement items across five constructs. Key TAM constructs were sourced from previous studies (Davis, 1989; Demoulin, Djelassi, 2016). At the same time, measures for Perceived Enjoyment (PENJ) were adapted from several studies (Mubuke, Ogenmungu, Masaba, Andrew 2017; Park, Son, Kim, 2012), while Technology Self-Efficacy (TSE) measures were adapted from studies by Compeau and Higgins (1995) and Wangpipatwong, Chutimaskul and Papasratorn (2008). The content validity index was 1.00.

Data Collection

Data were collected from third- and fourth-year nursing students at Mae Fah Luang University. The researchers distributed an online questionnaire via email to the students. Out of 228 emails sent, 208 responses were received. The respondents ranged in age from 19 to 21 and consisted of 185 female and 23 male students. This research focused on third- and fourth-year students because they possessed prior knowledge and understanding of simulation-based learning through their nursing coursework, specifically, interactive mannequins and high-fidelity perineal wound repair simulators. In contrast, first- and second-year students had only completed general education courses without exposure to simulation concepts.

To calculate the appropriate sample size, the researchers used the power analysis method using G*Power 3.1 software (Hair, 2014). The calculation incorporated Cohen's recommendations: an average effect size (ES) of .15, an alpha level of .05, and a power of .95 (Cohen, 2013). This analysis determined that a minimum sample size of 129 was required. The study's final sample of 208 responses, therefore, exceeded the minimum requirement, ensuring adequate statistical power for the analysis.

Data Analysis

The researchers employed the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique for data analysis using SmartPLS 4. Before analysis, the dataset (N = 208) was screened. Since the online questionnaire required complete responses, there was no missing data. Mahalanobis distance was used to identify multivariate outliers, and no extreme cases were removed. This method is widely recognized in behavioral research for its high validity, reliability, and robustness (Hair, 2014; Sarstedt, Ringle, Hair, 2021).

Ethical Considerations

The Research Ethics Committee at Mae Fah Luang University reviewed and approved this study, with approval number EC 24103-19. After all participants were advised of the voluntary nature of their participation, written informed consent was obtained.

Results

1. Measurement Model Evaluation

Following the initial model evaluation, the researchers removed the PE1 and PU3 items to improve overall model fit. Regarding indicator reliability, all items achieved standardized outer loadings greater than 0.708 (Table 2), and Cronbach's alpha exceeded 0.70 (Table 2), indicating good indicator reliability and internal consistency. The results showed that AVE exceeded 0.5 for all constructs, indicating that each construct accounts for more than half of the variance in its indicators. In the collinearity analysis, the VIF values for each variable were below 0.5, indicating no multicollinearity (Hair, 2014).

The researchers employed the heterotrait-monotrait (HTMT) method to assess discriminant validity. Table 2 details the HTMT results. While an HTMT value below 0.85 is preferable, the acceptable threshold is below 0.90 (Hair, 2014; Sarstedt et al., 2021). All constructs had HTMT values below 0.85, except for the pair of PU and PE, which had an HTMT value of 0.863. This value is slightly above the preferable threshold but remains acceptable. Overall, these results indicate strong support for acceptable discriminant validity.

Table 1: *Heterotrait-monotrait*

	PEU	PU	PE	TSE
PU	0.645			
PE	0.678	0.863		
TSE	0.746	0.533	0.672	
IU	0.536	0.751	0.798	0.581

2. Evaluation of the Structural Model

Figure 2 illustrates the model overview, and Table 3 provides a detailed breakdown of the model results. Based on the model's results, the independent variables can explain 39.7%, 60.6%, and 57.4% of the variance in the dependent variables PEU, PU, and IU, respectively. The PEU's effect on IU is insignificant (*p-value* > .05), so H1 was rejected. However, PEU has a positive impact on PU with a small effect size (t = 2.838, *p-value* < 0.05, f^2 = 0.044), so H2 was accepted. The results confirmed that PU has a positive effect on IU, with a small effect size (t = 3.441, *p-value* < 0.01, f^2 = 0.092), supporting H3. PE positively affects PU with a large effect size (t = 13.394, *p-value* < .01, f^2 = 0.770). Thus, H4 was accepted. PE positively affects IU with a medium effect size (t = 3.911, *p-value* < .01, f^2 = 0.133). Thus, H5 was accepted. TSE positively affects PEU with a large effect size (t = 12.559, *p-value* < 0.01, f^2 = 0.659). Thus, H6 was accepted. Unfortunately, the effect of TSE on IU was not found (*p-value* > .05), so H7 was rejected. Regarding the model's predictive power, the Q^2 value in Table 5 indicates that the model exhibits sufficient predictive power.

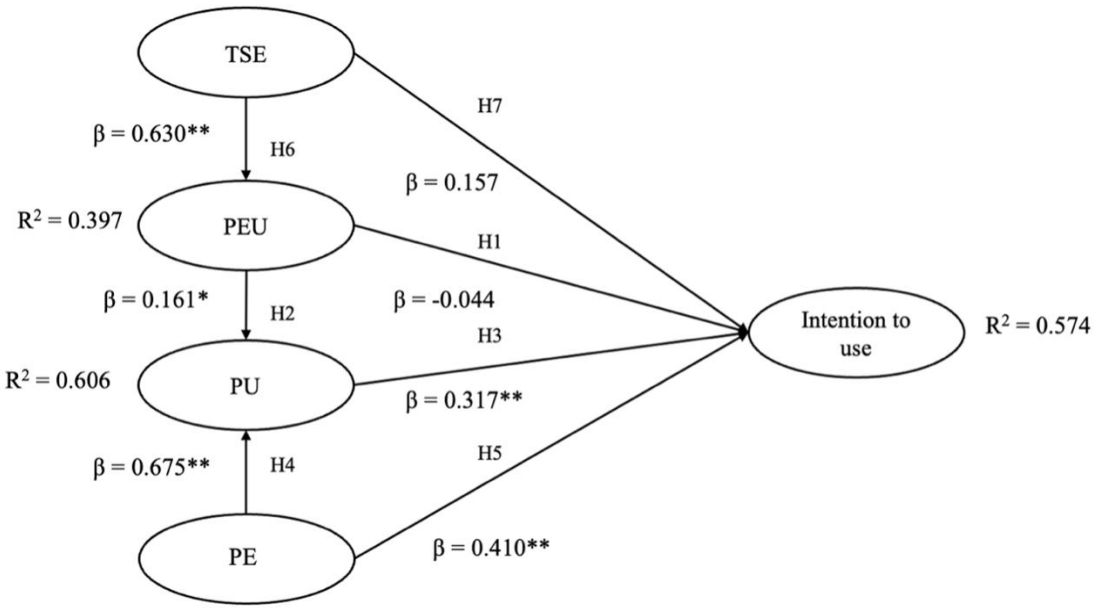


Figure 2: *Overall Results*

Table 2: *Hypothesis testing*

Hypothesis	*Paths*	*β*	*t-value*	*Std.dev.*	*p-value*	f^2	*Decision*
H1	PEU⟶IU	-0.044	0.615	0.071	.539	0.002	reject
H2	PEU⟶PU	0.161	2.838	0.057	.005	0.044	accept
H3	PU⟶IU	0.317	3.441	0.092	.00058	0.092	accept
H4	PE⟶PU	0.675	13.394	0.050	.00032	0.770	accept
H5	PE⟶IU	0.410	3.011	0.092	.00261	0.133	accept
H6	TSE⟶PEU	0.630	12.559	0.050	.00083	0.659	accept
H7	TSE⟶IU	0.157	1.914	0.082	.056	0.030	reject

Discussion

Although it was hypothesized that Perceived Ease of Use (PEU) would influence the Intention to Use, the model's results do not support this hypothesis. This finding contrasts with the results of previous studies. PEU was found to be a significant determinant of IU (Davis, 1986; 1989; Williamson, Muckle, 2018). This result could be explained by the fact that the simulation is typically integrated into the student learning process. As a result, students might view it as a tool to enhance their performance rather than simply an easy-to-use application, so they want to use it to improve their skills regardless of the ease of use.

According to the results, Perceived Usefulness (PU) and Perceived Enjoyment (PE) are the significant factors affecting IU. The results are consistent with previous studies (Davis, 1989; Izza, Firman, Rahman, Gayatri, Yetti, Boro et al., 2022; Venkatesh, Davis, 2000). These results suggest that the more the students believe that simulation devices are useful and enjoyable, the more they are willing to use them. Therefore, the simulation should be coherent with the expected learning outcomes or aim to improve some difficult skills. In addition, the simulation should feature an attractive design, such as intuitive navigation, visually appealing graphics, and engaging interactive elements. The results also reveal that PEU and PE are significant determinants of PU, indicating that when students' PEU and PE increase, their PU also tends to increase. Students who believe that using the simulation is easy and enjoyable might think they can use the simulation more quickly and effectively, thus gaining benefits from it. These results align with the previous studies (Campos, Nogal, Caliz, Juan, 2020; Sun, Zhang, 2008).

Technology Self-Efficacy (TSE) did not significantly influence Intention to Use (IU). This finding does not align with previous studies (Chien, 2012; Williamson, Muckle, 2018). The reason might relate to the connection between Perceived Ease of Use (PEU) and IU. Regardless of students' technology proficiency, they tend to use the simulation to enhance their skills. However, TSE is a key determinant of PEU; students with higher technology proficiency are more likely to believe that the simulation is easy to use.

Implication of the Results

The results indicate that Perceived Usefulness and Perceived Enjoyment significantly predict nursing students' Intention to Use simulation training devices. This suggests that the more students believe that training with simulation is enjoyable and can improve their competency, the more willing they will be to use it. Therefore, to maximize usefulness, instructors should carefully identify students' needs and areas for improvement when designing simulations. They can conduct written assessments on specific topics, review students' feedback, or arrange a group discussion with students. This should ensure that the simulation precisely addresses students' needs and provides a sense of relevance and accomplishment, thus increasing students' Perceived Usefulness.

To enhance engagement and enjoyment, simulations should provide branching scenarios with decision points, enabling personalized learning experiences. This approach aligns with constructivist learning theory, emphasizing active learning and personal meaning-making (Narayan,

Rodriguez, Araujo, Shaqlaih, Moss, 2013). Additionally, incorporating gamification, such as tiered challenges with increasing difficulty, can prevent discouragement and boost enjoyment.

The results also highlight the importance of Perceived Ease of Use and Technology Self-Efficacy. These two variables do not directly correlate with behavioral intention; rather, they influence other predictors. The easier the simulation, the more useful students perceive it to be. Therefore, simulations should be designed with a clear and intuitive interface, user-friendly controls, and readily accessible help resources. For example, providing step-by-step instructions, interactive tutorials, or on-screen prompts can help students navigate the simulation and understand its functionalities. The design should minimize the cognitive load so the students can focus on learning the clinical content rather than struggling with the technology. This can be achieved by breaking down complex tasks into smaller steps, providing clear visual cues, and minimizing extraneous information. Students' technology competency is also important. Nursing programs could offer dedicated workshops or integrate modules into existing courses to develop essential computer skills, such as navigating software interfaces, troubleshooting basic technical issues, and using simulation-specific functionalities. This is particularly important for students with limited prior experience with technology or those who express anxiety about using simulations.

Limitations and Recommendations for Further Study : This study has three main limitations. First, it used a convenience sample from a single institution, which introduces potential selection bias, as the students who chose to participate may not be representative of all nursing students. This affects the extent to which the findings can be applied broadly. Second, data for both independent and dependent variables were gathered from a single self-report questionnaire at one point in time, creating a risk of common method bias (CMB) that could have artificially inflated the observed relationships between variables. Future research could address this by collecting data at different times. Lastly, this study focused solely on TAM. Other theoretical frameworks, such as the Theory of Planned Behavior (TPB) or the Norms Activation Model (NAM), can be used to test similar hypotheses.

References

Alinier, G., & Oriot, D. (2022). Simulation-based education: Deceiving learners with good intent. *Advances in Simulation, 7*(1), 8. doi.org/10.1186/s41077-022-00117-w

Balog, A., & Pribeanu, C. (2010). The role of perceived enjoyment in the students' acceptance of an augmented reality teaching platform: A structural equation modelling approach. *Studies in Informatics and Control, 19*(3), 319-330. doi.org/10.24846/v19i3y201006

Barbosa, M. L., Atanasio, L. L. d. M., Medeiros, S. G. d., Saraiva, C. O. P. d. O., & Santos, V. E. P. (2021). Evolución de la enseñanza de enfermería en el uso de la tecnología educacional: Una revisión sistemática. *Revista Brasileira de Enfermagem, 74*, e20200422. doi.org/10.1590/0034-7167-2020-0422

Bowtell, L., Kist, A., Osbourne, D., & Parker, V. (2013). Interactive emulator system to aid clinical practice outcomes for nurses. *International Journal of Online Engineering, 9*, 32-37. doi.org/10.3991/ijoe.v9iS5.2771

Campos, N., Nogal, M., Caliz, C., & Juan, A. A. (2020). Simulation-based education involving online and on-campus models in different European universities. *International Journal of Educational Technology in Higher Education, 17*(1), 8. doi.org/10.1186/s41239-020-0181-y

Chien, T. C. (2012). Computer self-efficacy and factors influencing e-learning effectiveness. *European Journal of Training and Development, 36*(7), 670-686. doi.org/10.1108/030905912112 74135

Choi, H., & Tak, S. H. (2022). Nurses' behavioral intention in using virtual clinical simulation training: By structural equation modeling. *Nurse Education in Practice, 65*, 103492. doi.org/10.1016/j.nepr. 2022.103492

Chow, M. C. M., Hung, M. S. Y., Chu, J. W. K., & Lam, S. K. K. (2022). Factors affecting nursing students' intention to use a 3D game to learn field triage skills: A structural equation modelling analysis. *BMC Nursing, 21*(1), 46. doi.org/10.1186/s12912-022-00826-0

Cohen, B. S., & Boni, R. (2018). Holistic nursing simulation: A concept analysis. *Journal of Holistic Nursing, 36*(1), 68-78. doi.org/10.1177/0898010116678325

Cohen, J. (2013). *Statistical Power Analysis for the Behavioral Sciences*. Taylor & Francis.

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly, 19*(2), 189-211. doi.org/10.2307/249688

Davis, F. D. (1986). A technology acceptance model for testing new end-user information systems: Theory and results. *Sloan School of Management,* 291.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340.

Demoulin, N. T., & Djelassi, S. (2016). An integrated model of self-service technology (SST) usage in a retail context. *International Journal of Retail & Distribution Management, 44*(5), 540-559. doi.org/10.1108/IJRDM-05-2015-0084

Forehand, J. W., Benson, A. D., Chance, K. D., & Armstrong, B. (2021). Exploring factors of mobile device adoption in nursing education. Computers, *Informatics, Nursing, 39*(9), 477-483. doi.org/10.1097/cin.0000000000000751

Hair, J. F. (2014). *A primer on partial least squares structural equation modeling (PLS-SEM).* SAGE Publications.

Izza, S., Firman, A., Rahman, F. F., Gayatri, D., Yetti, K., Boro, M. F. V., et al. (2022). Nursing student reactions in conducting nursing practicum learning using virtual reality simulation. *Universal Journal of Public Health, 10*(6), 563-568. doi.org/10.13189/ujph.2022.100601

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management, 43*(6), 740-755. doi.org/10.1016/j.im.2006.05.003

Koukourikos, K., Tsaloglidou, A., Kourkouta, L., Papathanasiou, I. V., Iliadis, C., Fratzana, A., et al. (2021). Simulation in clinical nursing education. *Acta Informatica Medica, 29*(1), 15-20. doi.org/10.5455/aim.2021.29.15-20

Lateef, F. (2010). Simulation-based learning: Just like the real thing. *Journal of Emergencies, Trauma, and Shock, 3*(4), 348–352. https://doi.org/10.4103/0974-2700.70743

Marangunić, N., & Granić, A. (2015). Technology acceptance model: A literature review from 1986 to 2013. *Universal Access in the Information Society, 14,* 81-95. doi.org/10.1007/s10209-014-03580

Mishra, R., & Trivedi, D. (2023). Simulation-based learning in nursing curriculum-time to prepare quality nurses: A systematic review and meta-analysis. *Heliyon, 9*(5), e16835. doi.org/10.1016/j.heliyon. 2023.e16835

Mubuke, F., Ogenmungu, C., Masaba, A. K., & Andrew, W. (2017). The predictability of perceived enjoyment and its impact on the intention to use mobile learning systems. *Asian Journal of Computer Science and Information Technology, 1*(1), 7.

Narayan, R., Rodriguez, C., Araujo, J., Shaqlaih, A., & Moss, G. (2013). *Constructivism/Constructivist Learning Theory. In Handbook of research on educational technology* (pp. 169-184).

Park, Y., Son, H., & Kim, C. (2012). Investigating the determinants of construction professionals' acceptance of web-based training: An extension of the technology acceptance model. *Automation in Construction, 22*, 377-386. doi.org/10.1016/j.autcon.2011.09.001

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial Least Squares Structural Equation Modeling. In *Handbook of Market Research* (pp. 587-632). Springer. doi.org/10.1007/978-3-030-19576-4_24

Shanmugapriya, K., Seethalakshmi, A., Zayabalaradjane, Z., & Rani, N. R. V. (2023). Mobile technology acceptance among undergraduate nursing students instructed by blended learning at selected educational institutions in South India. *Journal of Education and Health Promotion, 12*(1), 45. doi.org/10.4103/jehp.jehp_91_23

Sun, H., & Zhang, P. (2008). An exploration of affect factors and their role in user technology acceptance: Mediation and causality. *Journal of the American Society for Information Science and Technology, 59*(8), 1252-1263. doi.org/10.1002/asi.20894

Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision Sciences, 27*(3), 451-481. doi.org/10.1111/j.15405915.1996. tb01822.x

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186-204. doi.org/10.1287/mnsc.46.2.186. 11926

Wangpipatwong, S., Chutimaskul, W., & Papasratorn, B. (2008). Understanding citizen's continuance intention to use e-government website: A composite view of technology acceptance model and computer self-efficacy. *Electronic Journal of e-Government, 6*(1), 55-64. doi.org/10. 1037/0898010116678325

Williamson, K. M., & Muckle, J. (2018). Students' perception of technology use in nursing education. CIN: Computers, Informatics, *Nursing, 36*(2), 70-76. doi.org/10.1097/CIN.00000000000 00393.

World Health Organization. (2023). *Patient Safety.* Rerieved November 4, 2025 from https://www.who.int/news-room/fact-sheets/detail /patient-safety.