Rethinking the effects of performance expectancy and effort expectancy on new technology adoption: Evidence from Moroccan nursing students

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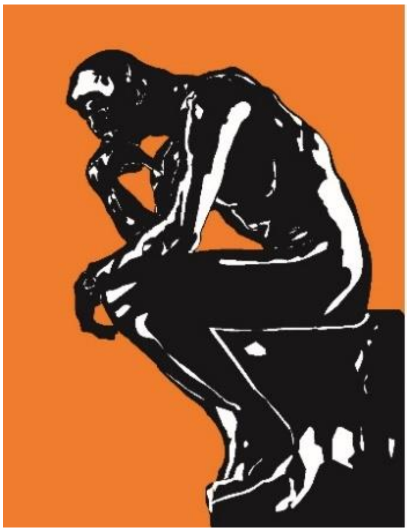

November 28, 2023

Preprint v.1.2

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"Pressing the buttons has gradually become somewhat of a new technological ritual."

In "Innovation"; *The Kingfisher Story Collection (2022)*

Abstract

Clinical practice is a part of the integral learning method in nursing education. The use of information and communication technologies (ICT) in clinical learning is highly encouraged among nursing students to support evidence-based nursing and student-centered learning. Through the information-processing lens of the mindsponge theory, this study views performance expectancy (or perceived usefulness) and effort expectancy (or perceived ease of use) as results of subjective benefit and cost judgments determining the students' ICT using intention for supporting clinical learning, respectively. Therefore, the study examines whether effort expectancy moderates the relationship between performance expectancy and the intention to use ICT among Moroccan nursing students. The Bayesian Mindsponge Framework (BMF) analytics was employed on a dataset of 702 Moroccan nursing students. We found that nursing students' performance expectancy is positively associated with the intention to adopt ICT and social media, while effort expectancy positively moderates this relationship. Moreover, the model with effort expectancy as the moderator was discovered to have a significantly larger weight than the model with effort expectancy as the direct predictor, validating our information-processing reasoning. This study provides a new perspective on the interplay between the benefit and cost perceptions of ICT use to support clinical learning methods in nursing education. Moreover, given the limited education resources, especially in developing countries like Morocco, we recommend nursing education and training prioritize communicating the benefits of ICTs and social media over ease of use. Doing so would help improve the effectiveness and efficiency of nursing education and training while lowering costs.

Keywords: technology acceptance; Unified Theory of Acceptance and Use of Technology; Technology Acceptance Model

1. Introduction

In today's dynamic healthcare context, the integration of Information and Communication Technologies (ICT) has revolutionized healthcare delivery. Lenz and Reichert (2007) assert that ICT plays a fundamental role in transforming various aspects of the healthcare sector, including the education and training of healthcare professionals. This transformation has been underscored by many researchers, such as Haldorai, Murugan, and Ramu (2021), Budhwar (2017), and Uohara, Weinstein, and Rhew (2020). In such a changing landscape, nursing students are at the forefront of adapting to technology-driven healthcare environments (Harerimana & Mtshali, 2019).

The integration of ICT in nursing education underscores the need for an evolving educational setting. Within this framework, nursing students must acquire clinical skills and be able to navigate in a healthcare environment where technology is instrumental in patient care (Paranjape, Schinkel, Panday, Car, & Nanayakkara, 2019). Their educational journeys should integrate with the latest developments in healthcare technology to adequately prepare them for the challenges of modern healthcare (Fawaz, Hamdan-Mansour, & Tassi, 2018).

A growing body of research highlights the potential of ICT in nursing education. It emphasizes the significance of enhancing students' digital proficiency and nursing informatics skills, which include computer skills, information literacy, and nursing informatics knowledge, in the dynamic healthcare environment (Conte, Arrigoni, Magon, Stievano, & Caruso, 2023). Furthermore, ICT usage can bring about meaningful changes in how nurses practice, influencing their approach to planning, delivering, recording, and assessing clinical care (Rouleau et al., 2017).

In addition, integrating nursing informatics into undergraduate nursing programs is on the rise, offering a two-fold benefit. Firstly, it transforms the learning environment and encourages a student-centered teaching approach, as observed by Kala, Isaramalai, and Pohthong (2010). Secondly, it equips students with digital health knowledge and the skills needed to navigate health information systems and technological advancements, enhancing their academic and clinical education (Harerimana, Wicking, Biedermann, & Yates, 2022).

In the ever-evolving healthcare landscape driven by technological advancements, numerous studies aim to comprehend the factors influencing nursing students' adoption or acceptance of ICT (Rouleau et al., 2017). The Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) are the two most well-known models used to define factors influencing an individual's intention to use new technology. While TAM is somewhat referred to as the gold standard in industries other than healthcare (Holden & Karsh, 2010), UTAUT is a widely employed model in healthcare (Kim, Lee, Hwang, & Yoo, 2015). Despite some distinctions, both models share similarities over the influencing roles of perceived usefulness (equivalent to performance expectancy in UTAUT) and perceived ease of use (equivalent to effort expectancy in UTAUT) in affecting individuals' intention to use new technology (Venkatesh, Morris, Davis, & Davis, 2003). As the current study's scope is within healthcare, the two concepts, performance expectancy and effort expectancy, in UTAUT will be used consistently from later on.

The body of research on students' decisions to incorporate technologies into their academic and professional pursuits consistently highlights performance expectancy and effort expectancy as two main driving factors (Ibrahim & Jaafar, 2011; Vargo-Warran, 2016; Vollmer, Prokosch, Evans, & Kuttler, 2016). Performance expectancy indicates the extent to which individuals believe that using a specific system can improve their work performance. ICT is widely acknowledged as a valuable tool for enhancing academic and professional outcomes in healthcare (Haleem, Javaid, Qadri, & Suman, 2022). This belief in the benefits of ICT consistently corresponds to a higher likelihood of nursing students embracing these technologies (Batucan et al., 2022; Haleem et al., 2022). In contrast, effort expectancy focuses on the perceived ease of using ICT tools and systems (Venkatesh et al., 2003). Research consistently suggests that individuals are more ready to adopt user-friendly and accessible technologies (Chang, Hwang, & Gau, 2022). Effort expectancy directly relates to how easily individuals expect to interact with a system, significantly influencing their intention to use it (Chang et al., 2022; Fleming, Becker, & Newton, 2017).

While existing literature provides valuable insights into the roles of performance and effort expectancy in technology adoption (Ayaz & Yanartaş, 2020; Tubaishat, 2018), their dynamic interaction remains unexplored. In other words, no studies have been conducted to examine if the effect of performance expectancy on technology adoption is conditional on effort expectancy. Moreover, studies about the impact of performance expectancy and effort expectancy in technology adoption within the specific context of Moroccan nursing education are also limited.

In response to this knowledge gap, our research aims to explore the complex interplay between performance expectancy, effort expectancy, and the intention to use ICT among Moroccan nursing students through the information-processing lens. More specifically, our primary objective is to investigate whether effort expectancy moderates the relationship between performance expectancy and the intention to use Information and Communication Technologies (ICT) among Moroccan nursing students. To accomplish this, we employ the Bayesian Mindsponge Framework (BMF) analytics for statistical analysis on a dataset of 702 Moroccan nursing students. The framework combines the mindsponge theory, which explains how the human mind processes information, with Bayesian inference, a powerful statistical method for quantifying intricate relationships (Nguyen, La, Le, & Vuong, 2022).

Notably, Mantello, Ho, Nguyen, and Vuong (2023) have recently used the Mindsponge theory to update the TAM, proposing the Mindsponge Technological Acceptance Model (MTAM) to explain the individual's attitudes toward the harvesting of non-conscious data by AI systems. Besides MTAM, various studies relevant to the adoption of ICT and digital environment have also used mindsponge theory as a theoretical basis or framework for reasoning (Ho et al., 2022; Hswen, Nguemdjo, Yom-Tov, Marcus, & Ventelou, 2022; Kumar et al., 2023; Li, Tang, Zhou, & Wan, 2022; Nguyen et al., 2023; Tran et al., 2020; Vuong et al., 2021; Vuong et al., 2023a, 2023b; Vuong, Le, La, & Nguyen, 2022; J. Wang, Liu, & Cai, 2022; R. Wang, Lin, Ye, Gao, & Liu, 2022). Therefore, it is plausible to employ the mindsponge theory as the theoretical foundation of this study.

This study is dedicated to enriching the educational experiences of Moroccan nursing students and ensuring their readiness to embrace advanced healthcare technologies. It will contribute to the broader conversation about technology adoption in education and healthcare, providing valuable insights for educators, professionals, higher education institution administrators, policymakers, and stakeholders.

2. Method

2.1. Theoretical Foundation

2.1.1. Overview of the mindsponge theory

The current study used the mindsponge theory to conceptualize and construct models. Vuong and Napier (2015) coined the term “mindsponge mechanism” in their research on acculturation and globalization to imply the mind’s dynamic acculturation process by absorbing new values or discarding waning ones. The mindsponge mechanism’s information-processing perspective can be utilized to help elaborate and complement theories, frameworks, and models in sociology and psychology, such as of Abraham Maslow (1943; 1981), Geert Hofstede (1984, 2001), Ikujiro Nonaka and Noboru Konno (1998), Daniel Kahneman and Amos Tversky (2013), Fred D. Davis (1985), etc. The mindsponge mechanism has been recently developed into an information processing theory using evidence from life and neurosciences: mindsponge theory. The theory defines the human mind as an information collection-cum-processor that helps explain how humans think, perceive, believe, behave, and establish social constructs (Vuong, 2023).

Conceptually, the mind is constituted by the mindset, buffer zone, and multi-filtering system (Vuong, Nguyen, & La, 2022). Mindsponge theory defines mindset as a collection of highly trusted information (core values or beliefs) within the human mind. It is a non-empty set of core cultural values or beliefs that are central to individual identity, substantially affecting the information processes of the mind, including filtering systems, thinking, emotions, and behaviors. The buffer zone is a conceptual area in which information is temporarily stored and helps to protect the mindset from external shocks. Moreover, the zone is also where the multi-filtering system kicks in to filter and evaluate new information or values in terms of appropriateness, usefulness, benefit-risk, etc., when new information initially enters the mind.

The mindsponge theory has two main spectrums: the mind and the environment (Vuong, 2023). Environment, or the infosphere, is conceptually a broader information processing system that consists of physical and social systems surrounding the human mind. The human mindset is not a static information collection but is continuously updated through information exchange with the environment (e.g., sensory systems and behaviors). This process has influenced the mindset’s content by the availability of information and accessibility in the environment. When new information enters the human mind, it will be integrated into the mindset or differentiated for the cost-benefit judgment, determining whether this new information is accepted or rejected. Only the information successfully passing the multi-filtering system will be accepted to enter the mindset, becoming a component of the collection of highly-trusted information (core values or beliefs) stored in the mindset. In some scenarios, if the perceived benefits of new information greatly surpass the existing core values based on the subjective cost-benefit judgment, it will replace the existing core values. Subsequently, the new mindset will affect human thinking processes, filtering systems, and behaviors.

Conversely, if the new information is considered inappropriate, unuseful, high risk, false/wrong, and has discrepancies with the existing core values in any way, it will likely be dismissed. When cost-benefit judgment results are ambiguous, the new information will be temporarily stored in a buffer zone until sufficient data is available for re-evaluation (Vuong, Nguyen, et al., 2022). Mindsponge theory suggests that the outcome of information processes will be used as input for the subsequent information processes (Vuong, 2023).

2.1.2. Model conceptualization

Based on the mindsponge information process above, it can be deemed that for the intention or willingness to use various ICT and social media platforms for clinical learning to emerge in the nursing students' minds, the information associated with using ICT and social media needs to be integrated into the mindset. For this to happen, two primary conditions must be satisfied (Nguyen & Jones, 2022; Nguyen, Le, Ho, Nguyen, & Vuong, 2021). First, the information associated with using ICT and social media platforms for clinical learning must be available and accessible in the surrounding environment. Second, the information must be justified as beneficial by the mind to be absorbed and integrated into the mindset. The performance expectancy and effort expectancy in the UTAUT corresponds well with this second condition (Venkatesh et al., 2003). In the current study, we mainly focus on the second condition.

The subjective cost-benefit evaluation of new information greatly depends on the existing highly-trusted information, core values, or beliefs in the mindset, as the mindset's content is used as the benchmark for new information assessment. The performance expectation can be considered equivalent to the information associated with the perceived benefits of using ICT in the students' minds. The higher the performance expectancy is, the likelier the benefit-related information exists in the mindset and influences the multi-filtering system. The effort expectancy can be considered equivalent to the information associated with the perceived cost of using ICT in students' minds. The higher the effort expectancy is, the less likely the cost-related information exists in the mindset and influences the multi-filtering system.

In both UTAUT and TAM, the perceived benefits (i.e., performance expectancy or perceived usefulness) and perceived costs (i.e., effort expectancy or perceived ease of use) of technologies are viewed to have direct linear effects on technology adoption intention. However, from the dynamic perspective of information processing of mindsponge theory, we think this view should be adjusted: the perceived costs (i.e., effort expectancy or perceived ease of use) should be viewed as a moderator for the relationship between perceived benefits (i.e., performance expectancy or perceived usefulness) and the technology adoption intention. However, why should the benefit perception not be the moderator?

Theoretically, for information to enter the mindset, it must be deemed beneficial; in other words, such information's perceived net value must be positive. Assuming that there are only perceived benefits in the mindset, the information associated with using the ICT will have a positive net value, thus integrated into the mindset. In contrast, assuming that there are only perceived costs in the mindset, the information associated with using the ICT will have a negative net value, thus highly likely being rejected from the mindset. Even if the perceived cost is extremely low, almost 0 (or the perceived ease of use is extremely high), it can only make the information associated with using the ICT have a neutral net value at best. Therefore, cost perception of using ICT should be viewed as a moderator of the relationship between benefit perception and ICT adoption intention rather than a direct predictor.

To test our thinking, we analyzed three different models (see Subsection 2.2.2) and then compared the model's goodness of fit with the data. If the model with cost perception (or effort expectancy) as moderator has greater weight than the model with cost perception being a normal direct predictor, our thinking can be deemed plausible.

2.2. Model Construction

2.2.1. Variable selection and rationale

This study used secondary data from a dataset of 702 nursing students from 23 Institute of Nursing and Health Technology (ISPITS) across Morocco (Bahri, El Mlili, Akande, Kerkeb, & Madrane, 2021). The dataset is about Moroccan nursing students' intention to use ICT and social media platforms for learning in this COVID-19 era, which is constructed with five major categories, namely: 1) performance expectancy, 2) effort expectancy, 3) social influence, 4) facilitating conditions, and 5) voluntariness of use.

Respondents were composed of 66% females. The age range was 17-24 years old. Smartphones and laptops were the two major devices used to access the internet, accounting for 97.3% and 53.7%, respectively. The frequently used social media platforms were Facebook, WhatsApp, YouTube, and Instagram, with the combination of Facebook and WhatsApp being the widely used combination of social media platforms (98%). Google Classroom, Zoom, Facebook Live and mobile learning via mobile applications were the most widely used ICT platforms for learning.

The questionnaire design was adopted from Arulogun, Akande, Akindele, and Badmus (2020) following the UTAUT structure. It was available in English and French. This questionnaire assessed nursing students' readiness and willingness to accept and use ICT and social media platforms for learning and discharging their duties during and after this COVID-19 era. The questionnaire was distributed to nursing students through an online Google form. Before undertaking the survey, respondents were instructed to read the contents and objectives and provide their agreement to the consent form afterward. The questionnaire was administered among Moroccan nursing students only, and all the questionnaire items were made compulsory for the respondents to avoid missing items. The responses were obtained in spreadsheet (excel) format. The dataset was peer-reviewed before it was published in Data in Brief with address:

- https://www.sciencedirect.com/science/article/pii/S235234092100514X

In the current study, three variables were employed for the statistical analysis: *InternshipICTLearningIntention*, *PerformanceExpectancy*, and *EffortExpectancy* (see Table 1). To measure the ICT-using intention, we employed the *InternshipICTLearningIntention* variable, which reflects the respondents' intention to use ICT during clinical practice. The *PerformanceExpectancy* variable is the composite variable generated by averaging three variables reflecting the performance expectancy of the nursing students, with 0.83 of Cronbach alpha. The *EffortExpectancy* variable is the composite variable generated by averaging three variables reflecting the effort expectancy of the nursing students, with 0.84 of Cronbach alpha.

Table 1. Variable Description

Variable	Description	Data type	Value
PerformanceExpectancy	Expectancy on benefits of using the ICT and social media platforms in clinical learning	Numerical	Likert scale: from 1 (strongly disagree) to 5 (strongly agree)
EffortExpectancy	Expectancy on the ease of using the ICT and social media platforms in clinical learning	Numerical	Likert scale: from 1 (strongly disagree) to 5 (strongly agree)
InternshipICTLearningIntention	Intention and willingness to use various ICT and social media platforms in clinical learning during the COVID-19 period and beyond	Binary	1 (Yes) and 0 (No)

2.2.2. Statistical Model

To test our thinking, we built three models. The first model demonstrates performance expectancy and effort expectancy as the direct predictors of the intention to adopt ICT for learning. The second model presents effort expectancy as the moderator of the relationship between performance expectancy and intention to adopt ICT for learning. The third model shows the double roles of effort expectancy as the direct predictor and moderator in the relationship between performance expectancy and the use of ICT.

The first model is constructed as follows:

$$InternshipICTLearningIntention \sim \text{normal}\left(\log\left(\frac{\mu_i}{1-\mu_i}\right), \sigma\right) \quad (1.1)$$

$$\log\left(\frac{\mu_i}{1-\mu_i}\right) = \beta_0 + \beta_1 * PerformanceExpectancy_i + \beta_2 * EffortExpectancy_i \quad (1.2)$$

$$\beta \sim normal(M, S) \quad (1.3)$$

The probability around the mean $\log\left(\frac{\mu_i}{1-\mu_i}\right)$ is determined by the shape of the normal distribution, where the width of the distribution is specified by the standard deviation σ. μ_i indicates the probability that nursing student i' has the intention to adopt ICT and social media for clinical learning; $PerformanceExpectancy_i$ indicates the level of benefits of using ICT and social media in clinical learning that the nursing student i expected; $EffortExpectancy_i$ indicates the level of ease of use regarding ICT and social media in clinical learning that the nursing student i expected. The model has an intercept β_0, coefficients of β_1 and β_2, and the standard deviation of the "noise", σ. The coefficient values are distributed as a normal distribution around the mean denoted M with the standard deviation denoted S.

The second model demonstrating *EffortExpectancy* as a moderator is constructed as follows:

$$InternshipICTLearningIntention \sim \text{normal}\left(\log\left(\frac{\mu_i}{1-\mu_i}\right), \sigma\right) \quad (2.1)$$

$$\log\left(\frac{\mu_i}{1-\mu_i}\right) = \beta_0 + \beta_1 * PerformanceExpectancy_i + \beta_2 * PerformanceExpectancy_i * EffortExpectancy_i \quad (2.2)$$

$$\beta \sim normal(M, S) \quad (2.3)$$

β_2 in Model 2 indicates the coefficient of the non-additive effect of $PerformanceExpectancy_i$ and $PerformanceExpectancy_i$ on $InternshipICTLearningIntention$. If the coefficient β_2's distribution is significant, and the association between the performance expectancy and ICT adoption intention is conditional on, or moderated by, the effort expectancy.

The third model demonstrating *EffortExpectancy* as both a moderator and direct predictor is constructed as follows:

$$InternshipICTLearningIntention \sim \text{normal}\left(\log\left(\frac{\mu_i}{1-\mu_i}\right), \sigma\right) \quad (2.1)$$

$$\log\left(\frac{\mu_i}{1-\mu_i}\right) = \beta_0 + \beta_1 * PerformanceExpectancy_i + \beta_2 * EffortExpectancy_i + \beta_3 * PerformanceExpectancy_i * EffortExpectancy_i \quad (2.2)$$

$$\beta \sim normal(M, S) \quad (2.3)$$

If Model 2 has the best goodness of fit, our reasoning in Subsection 2.1 can be considered validated.

2.3. Analysis and Validation

Bayesian Mindsponge Framework (BMF) analytics was employed in the current study for several reasons (Nguyen et al., 2022; Vuong, Nguyen, et al., 2022). First, the analytical method integrates the logical reasoning capabilities of mindsponge theory with the inferential advantages of Bayesian analysis, exhibiting a high degree of compatibility (Nguyen et al., 2022). Second, Bayesian inference is a statistical approach that treats all the properties (including the known and unknown ones) probabilistically (Csilléry, Blum, Gaggiotti, & François, 2010; Gill, 2014), enabling reliable prediction of parsimonious models. Nevertheless, utilizing the Markov chain Monte Carlo (MCMC) technique still allows Bayesian analysis to deal effectively with various intricate models, such as multilevel and nonlinear regression frameworks (Dunson, 2001). Third, Bayesian inference has various advantages in comparison to the frequentist approach. One notable advantage is the ability to utilize credible intervals for result interpretation instead of relying solely on the dichotomous decision based on *p*-values (Halsey, Curran-Everett, Vowler, & Drummond, 2015; Wagenmakers et al., 2018).

In Bayesian analysis, selecting the appropriate prior is required during the model construction process. Due to the exploratory nature of this study, uninformative priors or a flat prior distribution were used to provide as little prior information as possible for model estimation (Diaconis & Ylvisaker, 1985).

After the model was fitted, we calculated and compared the weight of three models in terms of Watanabe-Akaike information criterion (WAIC), Pseudo-BMA without Bayesian bootstrap, Pseudo-BMA with Bayesian bootstrap, and Bayesian stacking. We adopted the Akaike weight to standardize all weights, which divides the entire weight of 1 across the models under consideration, making it easier to assess their relative prediction accuracy (McElreath, 2018). Each model's weight will be a number ranging from 0 to 1, and the weights will always add up to 1. Therefore, the model with the greater value has higher prediction accuracy. The model with the best fit with the data will be used for result interpretation.

In addition to that, we also employed the Pareto-smoothed importance sampling leave-one-out (PSIS-LOO) diagnostics to check the models' goodness-of-fit (Vehtari & Gabry, 2019; Vehtari, Gelman, & Gabry, 2017). LOO is computed as follows:

$$LOO = -2LPPD_{loo} = -2\sum_{i=1}^{n} \log \int p(y_i|\theta) p_{post(-i)}(\theta) d\theta$$

$p_{post(-i)}(\theta)$ is the posterior distribution calculated through the data minus data point i. The k-Pareto values are used in the PSIS method for computing the LOO cross-validation in the R **loo** package. Observations with k-Pareto values greater than 0.7 are often considered influential and problematic for accurately estimating LOO cross-validation. When a model's k values are less than 0.5, it is typically regarded as being fit.

If the model fits well with the data, we will proceed with the convergence diagnosesand result interpretation. In the current study, we validated the convergence of Markov chains using statistical values and visual illustrations. Statistically, the effective sample size (*n_eff*) and the Gelman–Rubin shrink factor (*Rhat*) can be used to assess the convergence. The n_eff value represents the number of iterative samples that are not auto-correlated during stochastic simulation, while the *Rhat* value is referred to as the potential scale reduction factor (Brooks & Gelman, 1998). If *n_eff* is larger than 1000, it is generally considered that the Markov chains are convergent, and the effective samples are sufficient for reliable inference (McElreath, 2018). As for the *Rhat* value, if the value exceeds 1.1, the model does not converge. The model is considered convergent if $Rhat = 1$. Visually, the Markov chains' convergence was also validated using trace plots, Gelman–Rubin–Brooks plots, and autocorrelation plots.

The Bayesian analysis was performed on R using the **bayesvl** open-access package, which provides good visualization capabilities (La & Vuong, 2019). Considering the issues of data transparency and the cost of reproduction, all data and code snippets of this study were deposited onto an Open Science Framework (OSF) server (Vuong, 2018): https://osf.io/73pwj/.

3. Results

Initially, we compared the weights of WAIC, Pseudo-BMA without Bayesian bootstrap, Pseudo-BMA with Bayesian bootstrap, and Bayesian stacking to determine which model had the most predictive weight. Table 2 shows that Model 2 weighs best in almost all categories except for the pseudo-BMA with the Bayesian bootstrap category. However, in general, it is plausible to say that Model 2 fits the data best, even when compared with Model 3, which has a higher number of variables. Moreover, the predictive weight of Model 1 demonstrating effort expectancy as a direct predictor of ICT adoption intention had the lowest weight in all categories. These details suggest that our reasoning using the information-processing lens of mindsponge theory is validated, and effort expectancy should be viewed as a moderator for the relationship between performance expectancy and ICT adoption intention rather than a direct predictor.

Table 2. Model comparison and weight ranking

Weights	WAIC	Pseudo-BMA without Bayesian bootstrap	Pseudo-BMA with Bayesian bootstrap	Bayesian stacking
Model 1	0.249	0.249	0.249	0.120
Model 2	0.405	0.405	0.369	0.128
Model 3	0.346	0.346	0.382	0.752

Most predictive model	Model 2	Model 2	Model 3	Model 2

As Model 2 is the model that fits the data best, the result interpretation of Model 2 is shown in the main text. The estimated results of Model 1 and Model 3 are displayed in Tables S1 and S2 in the Supplementary.

The PSIS-LOO diagnostics test was conducted on Model 2; its results are illustrated in Figure 1. Visually, all *k* values are below the threshold of 0.5, indicating that the constructed model fits well with the data.

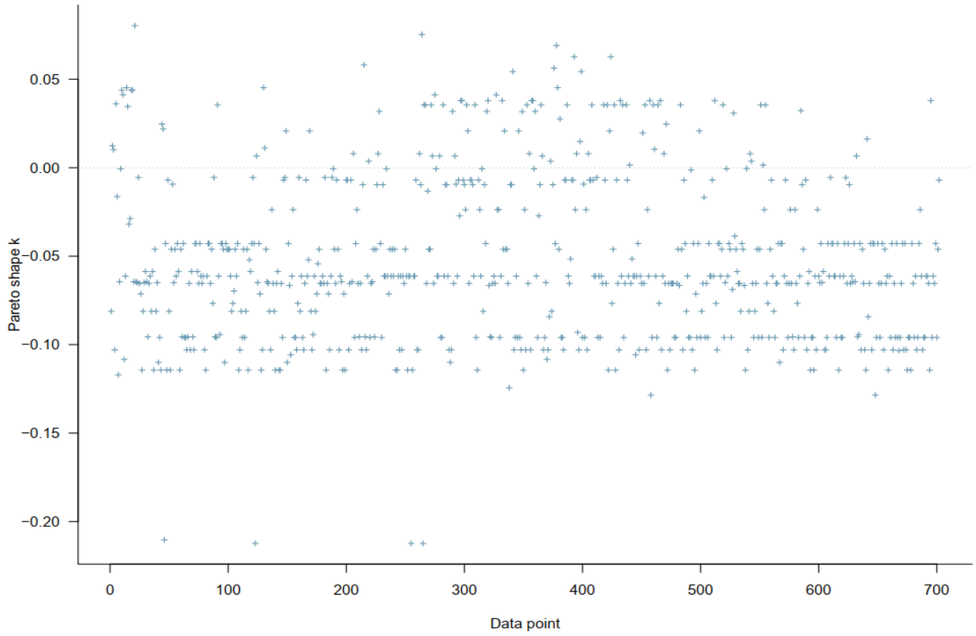

Figure 1. PSIS-LOO diagnostic plot for the model

Table 3 shows the estimated posteriors of Model 2's parameters. All *n_eff* values are above 1000, and all *Rhat* values equal 1, which shows that the model is well convergent. The convergence of the Markov chains is also validated through the trace plots (see Figure 2), which show that the chains fluctuate around central equilibriums after the warm-up period (after the 2,000th iteration).

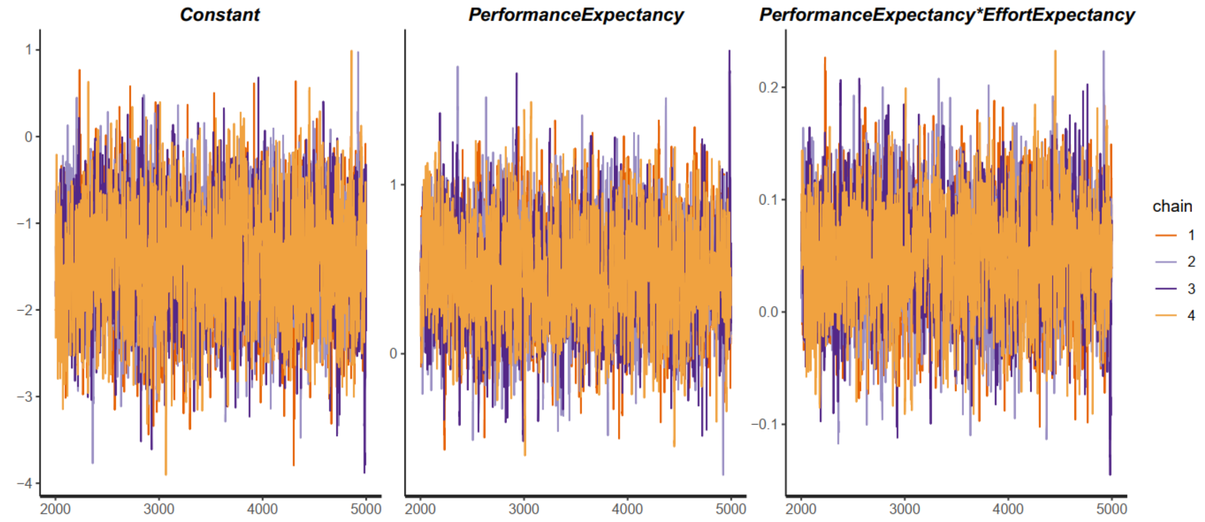

Figure 2. Trace plots for the model

The Gelman-Rubin-Brooks plots in Figure 3 show that *Rhat* values drop to 1 during the warm-up period, while the autocorrelation plots in Figure 4 show that the autocorrelation level is eliminated after a finite number of lags. These are also good signals of Markov chain convergence.

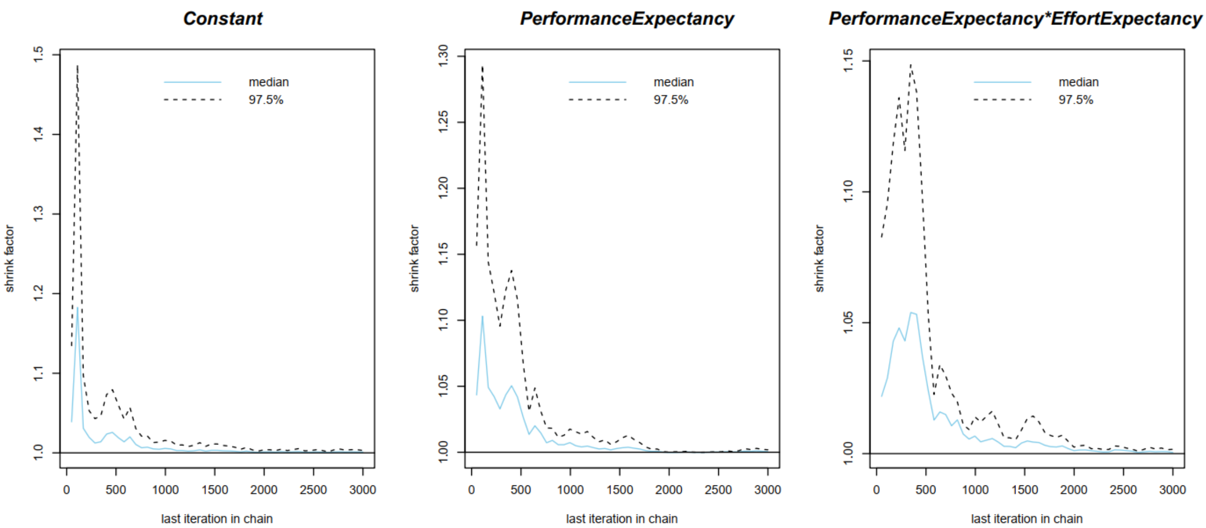

Figure 3. Gelman-Rubin-Brooks plots for the model

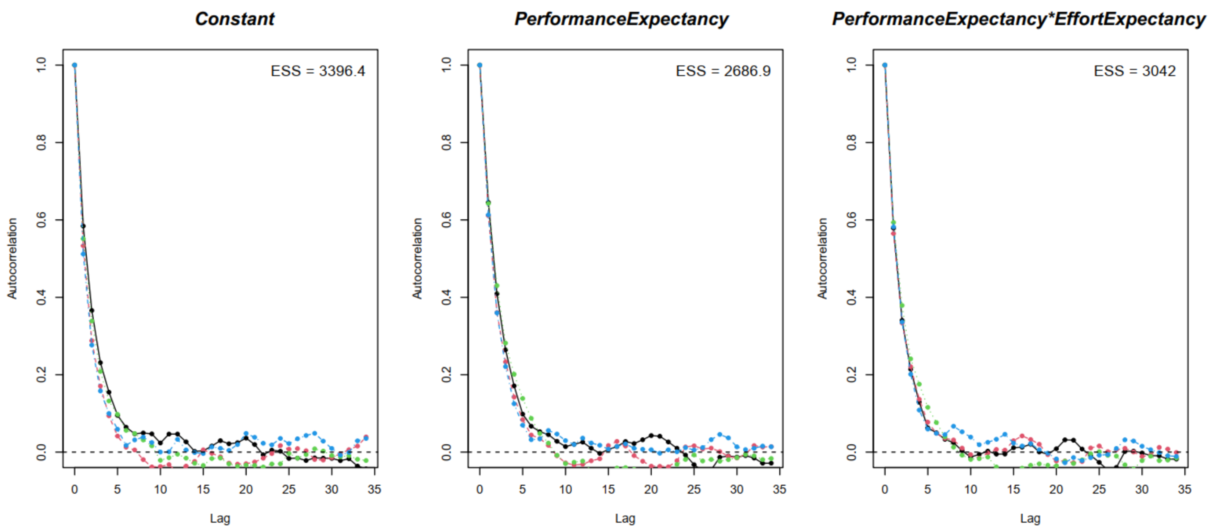

Figure 4. Autocorrelation plots for the model

As the Markov chains are well-convergent, all the technical requirements of the simulation are met. Therefore, estimated results are eligible for interpretation. The results shown in Table 3 imply that *PerformanceExpectancy* is positively associated with *InternshipICTLearningIntention* ($M_{PerformanceExpectancy} =$ 0.46 and $S_{PerformanceExpectancy} = 0.31$); meanwhile, *EffortExpectancy* positively moderates the relationship between *PerformanceExpectancy* and *InternshipICTLearningIntention* ($M_{PerformanceExpectancy*EffortExpectancy} =$ 0.05 and $S_{PerformanceExpectancy*EffortExpectancy} = 0.05$).

Table 3. Estimated posteriors

Parameters	Mean	SD	n_eff	Rhat
Constant	-1.42	0.64	3287	1
PerformanceExpectancy	0.46	0.31	2639	1
PerformanceExpectancy EffortExpectancy*	0.05	0.05	2811	1

Figure 5 shows Model 2's posterior distributions with their Highest Posterior Density Intervals (HPDI) at 89%. For the posterior distribution of *PerformanceExpectancy*, the HPDI is located entirely on the positive side of the *x*-axis, suggesting there is more than 89% possibility that *PerformanceExpectancy* positively affects nursing students' ICT adoption intention. Meanwhile, a portion of *PerformanceExpectancy* EffortExpectancy*'s HPDI is still on the negative side of the *x*-axis, so the positive moderation effect of *EffortExpectancy* can only be deemed moderately reliable.

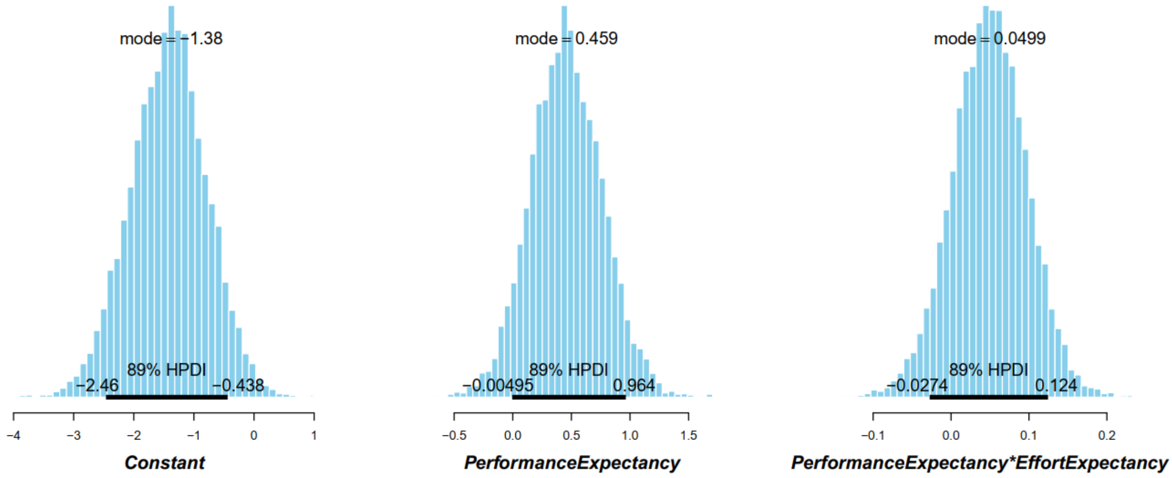

Figure 5. Coefficients' posterior distributions of Model 2 with HPDI at 89%

4. Discussion

Using the Bayesian Mindsponge Framework (BMF) analytics on a dataset of 702 Moroccan nursing students, the current study found that students' performance expectancy is positively associated with the ICT and social media adoption intention, while the effort expectancy positively moderates that relationship. These findings corroborate previous studies that performance expectancy and effort expectancy play a significant role in people's behavioral intentions of ICT utilization (Attuquayefio & Addo, 2014; Sitthipon, Siripipatthanakul, Phayaphrom, Siripipattanakul, & Limna, 2022). Besides that, they also add novelty to the existing literature on UTAUT and TAM by showing a new perspective on the interplay between the benefit and cost perceptions.

Specifically, the results validate our thinking from the dynamic perspective of information processing of mindsponge theory: the cost perception (i.e., effort expectancy or perceived ease of use) should be viewed as a moderator for the relationship between benefit perception (i.e., performance expectancy or perceived usefulness) and the technology adoption intention. The study not only provides a novel information-processing viewpoint on the emergence of technology adoption intention in the human mind but also complements UTAUT and TAM on how their two core components (i.e., performance expectancy – effort expectancy and perceived usefulness – perceived ease of use) interplay dynamically. However, to further validate the thinking, studies should continue to be conducted among different groups of end-users with other types of technologies and in contexts with different socio-cultural characteristics.

The current findings also help us identify the information type we should prioritize. To elaborate, although both performance expectancy and effort expectancy positively influence the intention to adopt ICT and social media, performance expectancy has a more fundamental role than effort expectancy since effort expectancy can only moderate the relationship between performance expectancy and ICT and social media adoption intention. Given the limited education resources, especially in developing countries like Morocco, educators or preceptors, universities, and healthcare providers or professional organizations should prioritize communicating with nursing students about the benefits of ICTs and social media for their future clinical practice more than information associated with ease of use. Doing so will help improve the effectiveness and efficiency of nursing education and training while lowering costs.

ICT usage in clinical learning catalyzes the application of evidence-based practice (EBP) in nursing. There are at least four major pathways identified in which nursing students intend to use ICT during clinical practice period in order to implement EBP in nursing, namely: 1) ICT use for finding more information related to the patient's disease (definition, risk factor, etiology, classification, pathophysiology, transmission, clinical manifestation, complication, diagnostic test, prevention, management, and nursing care plan), 2) ICT use for finding more information related to medical therapy (types, indication, contra-indication, dosage, side effects, short-term and long-term effects, alternatives/ adjustment, etc.), 3) ICT use for finding more information related to laboratory-radiology results' interpretation (types, components, normal range, interpretation methods, etc.), and 4) ICT use for finding more information to address patient's needs or problem solving (disease concept, prognosis, therapies, alternatives, life style modification, administrative matters, financial resources, etc.). Therefore, in the nursing students' clinical practice, their intention to use ICT may impact their nursing care delivery to the patients.

To improve the practice of using ICT in clinical learning, we would like to make several recommendations on further boosting nursing students' behavioral intention to use ICT for clinical learning during the internship. For effectively developing nursing students' intention to use ICT for their clinical learning, academic-clinical preceptors, universities, healthcare providers, and professional organizations can help to create more opportunities for them to access and interact with trusted and clinically relevant ICT and social media platforms. Exposure to various ICT system environments during classroom meetings, laboratory and clinical practices can be beneficial for developing nursing students' higher level of understanding and mastering those tools and systems, raising their belief in the ease of ICT use and the effectiveness of its utilization in learning performance enhancement. Policymakers must ensure policies are in place to encourage third-party developers to deliver software products and solutions that benefit nursing students and enable them to modernize their clinical ICT practices (Engotoit, Kituyi, & Moya, 2016). At the same time, the ICT products and solutions developed by these telecommunication companies need to be as user-friendly as possible, giving nursing students a good and pleasant user experience to promote their behavioral intention to use ICT for clinical learning (Chen et al., 2021). Furthermore, the government must focus on planning and funding nursing schools, providing nursing students with the necessary infrastructure and capabilities to enhance their ICT skills and perform better (Shah, Khan, Khan, Khan, & Xuehe, 2021).

The current study has several limitations reported here for transparency (Vuong, 2020). Because the dataset only contains Moroccan samples, extending the results to other areas and nations should be done with caution. In addition, the responses of Moroccan nursing students about their behavioral intention to use ICT and social media platforms are self-reported, which may create subjective bias. Future studies applying more objective measurements should be implemented. Moreover, the current study is based on survey data, so it exhibits some limitations in reflecting the dynamic interplay effect of performance and effort expectancy on technology adoption. Experimental studies should be conducted to address these limitations.

Supplementary

Table S1. The estimated results of Model 1

Parameters	Mean	SD	n_eff	Rhat
Constant	-1.83	0.58	5026	1
PerformanceExpectancy	0.67	0.20	4379	1
EffortExpectancy	0.10	0.17	4735	1

Table S2. The estimated results of Model 3

Parameters	Mean	SD	n_eff	Rhat
Constant	0.07	1.36	1840	1
PerformanceExpectancy	0.04	0.45	1925	1
EffortExpectancy	-0.62	0.50	1982	1
PerformanceExpectancy EffortExpectancy*	0.21	0.14	1872	1

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