Impacts of social influence, social media usage, and classmate connections on Moroccan nursing students' ICT using intention

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Abstract

The three learning modalities in nursing education are classroom meetings, skill laboratory practices, and clinical practice in hospital or community settings. In clinical internships, the collaborative self-directed learning method is highly encouraged among nursing students. The use of information and communication technologies (ICT) in clinical learning supports the implementation of evidence-based nursing and student-centered learning. The current study examines whether the relationship between social influence and ICT using intention is moderated by the daily duration of use and the number of classmates being friends on social media. The Bayesian Mindsponge Framework (BMF) analytics was employed on a dataset of 702 Moroccan nursing students. We found that social influence was positively associated with nursing students' intention to use ICT for clinical learning during the internship. This positive association was positively moderated by the daily duration of social media usage and negatively moderated by the number of classmates being friends on social media. These findings underscore the potential of using social media platforms to facilitate the incorporation of ICT and social media in nursing education and training. However, the adverse effects of social media on students' mental well-being also need to be acknowledged and managed appropriately.

Keywords: clinical learning; ICT using intention; nursing; social influence; technology acceptance; Mindsponge Theory

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

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

1. Introduction

Information and communication technologies (ICT) encompass any Internet-based technology, infrastructure, or equipment that facilitates communication and delivery between individuals and machines. There is a growing momentum in the widespread application of ICT across various sectors to enhance efficiency. ICT serves as a potent tool to increase access to education, elevate education standards, and contribute to educational transformation and improvement (Fu & ICT, 2013). Within the healthcare sector, the utilization of ICT aids in improving lives and well-being globally, enhancing care quality and information exchange, optimizing the health system, using resources efficiently, educating healthcare professionals, and paving the way for the progressive adoption of universal health coverage (Shao et al., 2022; While & Dewsbury, 2011). Consequently, the integration of ICT in healthcare education holds significance for both instruction and learning.

ICT integration in healthcare education can strengthen flexibility, accessibility, and autonomy (Beri & Gulati, 2022). For instance, students can retrieve learning materials from university websites and utilize online collaboration technologies more efficiently and effectively (Chatterjee & Chakraborty, 2021; Sebbani et al., 2021). The support of ICT transforms the learning environment into a creative and student-centered one, enabling students to be more self-directed and innovative, encouraging active collaboration in learning, and fostering their higher critical thinking skills, thereby enhancing the overall quality of student learning (Fu, 2013; Olatoye et al., 2021). This contributes to the development of students, resulting in the education of more competent healthcare professionals (Ferede et al., 2022). While previous research has highlighted various benefits of using ICT in student learning, there are still challenges to its widespread implementation.

One of the vital challenges in leveraging the benefits mentioned above of ICT depends on the willingness of nursing students to use the ICT system. Therefore, it is important to investigate factors that affect students' willingness to apply ICT in their learning and practice. Chau and Hu (2002) described behavioral intention as an individual likelihood of deciding to accept technology. This likelihood is mostly studied by many investigations under the Unified Theory of Acceptance and Use of Technology (UTAUT) model and its extended UTAUT2 construct proposed by Venkatesh et al. (2003) and Venkatesh et al. (2012), respectively. Jan et al. (2012) and Venkatesh et al. (2016) reported that the UTAUT2 frameworks can explain almost 75% of the variance in assessing people's behavioral intention of new technologies. Results to date indicate variables under the UTAUT2 constructs directly or indirectly influencing people's ICT-related systems using intention, including effort expectancy, performance expectancy, social influence, facilitating condition, additional hedonic motivation, price value, and habit, relating to the areas of education, agriculture, bank and others (Chen et al., 2021; Engotoit et al., 2016; Funmilola et al., 2019; Ghasemzadeh Alishahi et al., 2021).

Among the UTAUT variables, social influence is considered to be a key determinant affecting people's willingness to use ICT. Sociocognitive factors, such as consideration of others' significant beliefs, can forecast participants' behavior (Wilson et al., 2021). Social influence refers to one's perceptions of the resources and support available to perform a behavior (Venkatesh et al., 2003). There is widespread debate examining how social influence influences changes in people's intention to use ICT. Wong et al. (2013) found that the impact of social influence on ICT use intention is insignificant. Teo and Zhou (2014) pointed out indirect effects, which were also presented in the study of Chen et al. (2021). However, the study by Hooda et al. (2022), Raman and Thannimalai (2021), and Zacharis (2020) demonstrated the significant impact of social influence on individual ICT behavioral intention and usage.

Some factors from the remaining 25% variance outside the UTAUT2 model have been found to influence individuals' behavioral intention to use ICT. Shah et al. (2021) combined performance expectancy, effort expectancy, social influence, and facilitating condition to report the significant role of information technology capabilities in shaping teachers' ICT adoption behaviors. Based on the UTAUT2 perspectives, other factors, including content quality and perceived cost, have been identified as key antecedents for the continued use of online course platforms (Chen et al., 2021). Furthermore, assurance, reliability, website design, and customer service were combined with the UTAUT2 variance in determining Internet users' intention to adopt Internet banking (Rahi et al., 2019). Learning value and social isolation also positively impact students' willingness to study using eLearning platforms (Raza et al., 2021; Zacharis & Nikolopoulou, 2022). However, there may be other unidentified elements that require further exploration.

Various factors associated with social influence can impact an individual's intention to use ICT, including friend's influence. Social pressure influences individuals' decision to engage in or abstain from certain activities (Yu, 2012). For instance, Leow et al. (2021) delineated the social influence factor and demonstrated that coercive and normative pressures have a positive influence on behavioral intention. Essentially, an individual's perception of others' approval or disapproval of their inherent characteristics plays a crucial role (Arif et al., 2016). Social influence signifies the influence of others' beliefs on one's behavioral intention (Venkatesh et al., 2003; Venkatesh et al., 2012). These "others" can include friends, family members, or peers who influence the intention to adopt a specific technology (Im et al., 2011; Osman et al., 2013).

Consequently, an individual's social interactions with friends and peers often influence their acceptance (Brocke et al., 2009). Specifically, the number of classmates who are friends on social media may influence the impact of social influence on students' intention to use ICT. This correlation exists because social influence is exerted and accepted among peers, while peer influence plays a mediating role in influencing university students' intention to use social media (Trivedi et al., 2022).

Regarding the impact of social influence on one's adoption of ICT, usage time is also identified as one factor. Kelman's (1958, 2017) three processes – compliance, identification, and internalization – are fundamental to social influence, while social interaction and imitation affect decision-making behavior (Karatsoli & Nathanail, 2021). Social influence occurs when attitudes and actions are influenced by social groups (Aronson et al., 2018; Chiu et al., 2013). Students' daily duration or time spent on social media is influenced by their friends. The longer their friends spend on social media, the more time they will allocate to using social media. Students' attitudes towards using ICT platforms, their perceived enjoyment, the value they place on learning efforts, perceived ease of use, and the belief that using relevant platforms enhances learning all contribute to their willingness to use ICT platforms (Hsu & Lin, 2008; Lahrash et al., 2021; Zacharis & Nikolopoulou, 2022). The longer the duration or time of use with regard to accessing social media, the more influential these elements become in specific ICT systems shared by peers. The longer the duration of time results in the automatic performance of the behavior, leading to the formation of a habit. As habits significantly impact students' intention to use e-platforms for learning (Raman & Thannimalai, 2021), their daily duration or time of use when accessing social media will affect their intention to use ICT.

Researchers in Morocco are also investigating factors related to Moroccans' intention to use ICT. Most of the research is based on the UTUAT model. Ghassoub (2023) discovered additional factors influencing school teachers' behavioral intention to accept and use ICT in their teaching practice. These factors include personal self-efficacy, performance expectancy, techno-pedagogical supervision, and facilitating conditions. Elatrachi and Oukarfi (2020) noted that social influence, together with effort expectancy and performance expectancy, are the main factors influencing teachers' willingness to adopt ICT systems in higher education, and they also added the type of institution as a new element. Morchid (2019) highlighted that performance expectancy, effort expectancy, teacher feedback, and compatibility are connected to students' acceptance of mobile-assisted language learning (MALL). Bennani and Oumlil (2014) identified compatibility, perceived usefulness, and perceived ease of use as factors supporting the acceptance of ICT by geriatricians. Satry and Belkadi (2021) revealed significant influences of performance and effort expectancy on citizens' behavioral intentions. Alami and El Idrissi (2022) found that students from business schools significantly depend on their satisfaction, perceived ease of use, and perceived usefulness in accepting e-learning while facilitating conditions do not effectively measure students' attitudes toward e-learning. Little research has addressed variables such as students' daily duration or time of use regarding access to social media and the number of classmates being friends on social media.

To address the gap mentioned above, this research aims to enhance our understanding of whether the relationship between social influence and ICT using intention is moderated by the students' daily duration or time of use regarding access to social media and the number of classmates being friends on social media. The current study has two primary objectives:

1. Examine whether the students' daily duration or time of use regarding the access to social media moderates the relationship between social influence and ICT-using intention.
2. Examine whether the number of classmates being friends on social media moderates the relationship between social influence and ICT-using intention.

2. Method

2.1. Theoretical foundation and proposed hypotheses

This study utilizes the mindsponge theory (MT) as the theoretical foundation (Vuong, 2023). MT uses the human mind's information-processing approach to explain various mental products, like intention and complex human behavior (e.g., ICT use). MT helps explain psychological phenomena in terms of their temporal dimension about the information process associated with the natural renewal of human psychology and society, which can explain and help address complex psychological and behavioral problems (Nguyen et al., 2022). MT views the human mind as an information collection-cum-processor that helps explain how humans think, perceive, believe, behave, and establish social constructs (Vuong, 2023). MT considers the human mind's filtering system of new information/value/idea/technology to be the key factor (Mantello et al., 2023). The Mindsponge mechanism is MT's core, which involves new information/value absorption and ejection processes (Vuong & Napier, 2015).

The Mindsponge Theory suggests that for an intention to emerge in an individual's mind, the information associated with such intention must be present in the mindset. The mindset is a set of core values (e.g., highly-trusted information beliefs) used as a benchmark for the mind's multi-filtering system and shapes the value systems, perceptions, thoughts, feelings, etc. (Vuong, 2023). Information associated with using ICTs and social media for clinical learning must exist in the nursing students' mindsets for the corresponding intention to emerge. For such information to be absorbed and internalized into the students' mindsets, it needs to be deemed beneficial by subjective cost-benefit judgments. The family's and friends' appreciation of students using ICTs and social media for social media can be perceived as beneficial by the students' minds, facilitating the absorption and internalization of ICT and social media usage ideation.

The students' mindsets sometimes do not contain information relevant to the ICTs and social media. In such circumstances, several scenarios will happen:

1) the information will be rejected from the mind;
2) the information will be deemed neutral and held in the buffer zone for later evaluation;
3) the information will accepted into the mindset if there are trust guarantors.

The trust guarantors are those whom the students trust, so the information provided by those people will be trusted and given a "priority pass" to enter the mindsets without or less

rigorous evaluation of the multi-filtering systems. Thus, if trust guarantors (i.e., colleagues) encourage the students to use ICT and social media for learning, the students will be more likely to have the intention to use ICT and social media platforms for clinical learning. In general, the following Hypothesis (H) was proposed:

H1: Social influence is positively associated with students' probability of having the intention to use ICT and social media platforms for clinical learning

If students are familiar with the utilities of ICT and social media, the encouragement from colleagues and the appreciation of family and friends will be used in combination with the existing information on ICT and social media in the mindset as the benchmarks for the evaluation. Students who have a longer duration of using ICT and social media a day will have more time exposed to information related to ICT and social media, know more utilities of the technologies, and function the technologies better, so their minds will contain more information regarding the technologies and tend to perceive information relevant to ICT and social media more beneficial than those with shorter usage duration. This effect can help amplify the positive association between social influence and ICT usage intention. Thus, the daily usage duration was expected to positively moderate the association between social influence and intention to use ICT and social media platforms for clinical learning.

H2: The association between social influence and students' probability of having the intention to use ICT and social media platforms for clinical learning is positively moderated by the daily usage duration.

Individuals may become information sources for one another. The human interaction involving two-way communications results in back-and-forth influences in the context of social relationships. Communication has a significant role in human interaction, in which non-verbal communication elaborates and clarifies verbal messages, especially in academic conversations between students (Khan & Zeb, 2021). Suppose one nursing student experiences some benefits of using ICT in clinical practice. In that case, there will be a high possibility of communicating these lesson experiences to other students and generating social influences on the intention of other students to use ICT. Thus, the higher number of classmates connected on social media platforms was expected to amplify the association between social influence and intention to use ICT and social media platforms for clinical learning.

H3: The association between social influence and students' probability of having the intention to use ICT and social media platforms for clinical learning is positively moderated by the number of classmates connected on social media.

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 et al., 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 of Arulogun et al. (2020) followed 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. 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:

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

In the current study, four variables were employed for the statistical analysis, namely, *InternshipICTLearningIntention*, *SocialInfluence*, *TimeonSN*, and *ClassmatesonSN* (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 social influence (from nursing colleagues, friends/classmates, and family) on ICT using intention was represented by *SocialInfluence*. *TimeonSN* reflects on how much time was spent daily on a social networking site, while *ClassmatesonSN* reflects on how many classmates were included in the contacts/ friends on the social networking sites.

Table 1. Variable Description

Variable	Description	Data type	Value
TimeonSN	Spending time daily on a social networking site (duration of use)	Numerical	1 = Less than 1 hour 2 = 1 - 6 hours per day 3 = 7 - 12 hours per day 4 = Always online

			1 = Less than 20
ClassmatesonSN	Number of classmates included in the contacts/friends on the social networking sites.	Numerical	2 = 20 - 50
			3 = 51- 100
			4 = Almost everyone
SocialInfluence	Social influence from colleagues, family, and friends on ICT using intention	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 validate the assumptions presented in Subsection 2.1, we constructed the statistical model as presented below:

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

$$\log\left(\frac{\mu_i}{1-\mu_i}\right) = \beta_0 + \beta_1 * SocialInfluence_i + \beta_2 * SocialInfluence_i * TimeonSN_i + \beta_3 * SocialInfluence_i * ClassmatesonSN_i \qquad (1.2)$$

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

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; $SocialInfluence_i$ indicates the agreement level of social influence from colleagues, family, and friends on ICT using intention in clinical learning. The model has an intercept β_0, coefficients of β_1-β_3, 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.

2.2.3. Analysis and Validation

Bayesian Mindsponge Framework (BMF) analytics was employed in the current study for

several reasons (Nguyen et al., 2022; Vuong et al., 2022). First, the analytical method integrates the logical reasoning capabilities of MT 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 et al., 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 like the current study (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 et al., 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). The Pareto-smoothed importance sampling leave-one-out (PSIS-LOO) diagnostics was employed to check the models' goodness-of-fit (Vehtari & Gabry, 2019; Vehtari et al., 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 diagnoses and 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 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/awfn9/

3. Results

Before interpreting the results, evaluating how well Model 1 fits the data is necessary. As can be seen in Figure 1, all estimated k-values are below the 0.5 threshold, indicating a good fit signal between the model and the data.
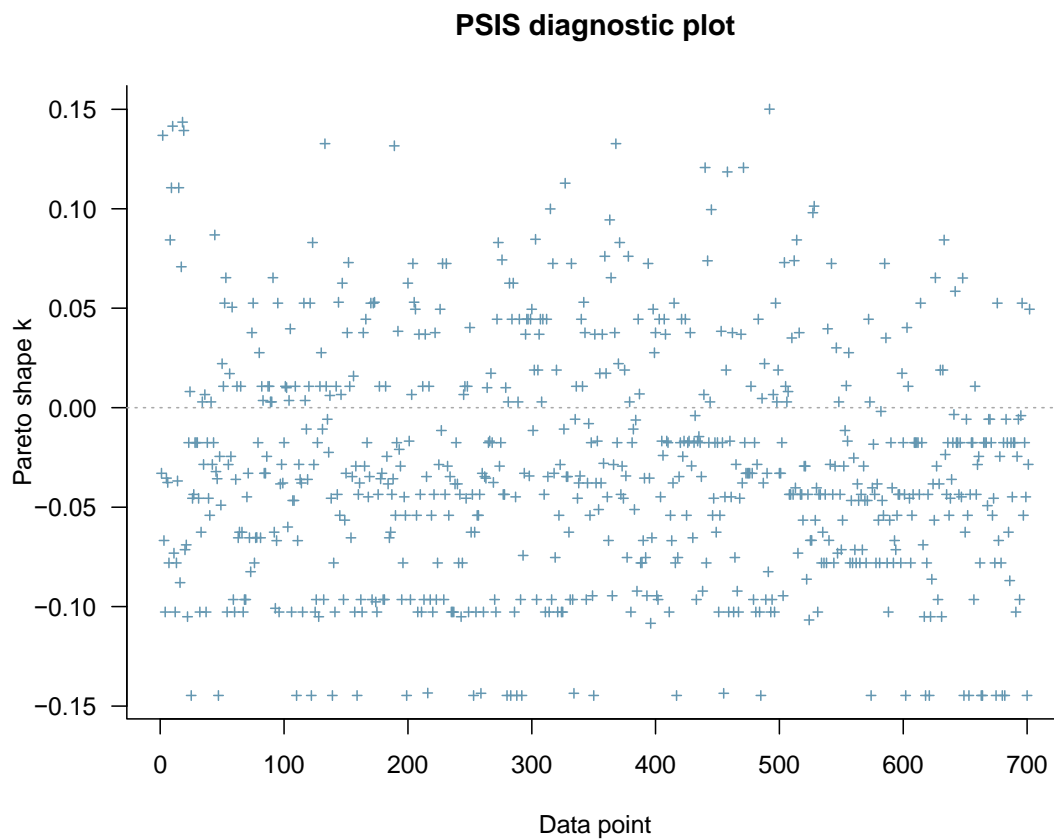

Figure 1. Model 1's PSIS-LOO diagnosis

The posterior distribution statistics of Model 1 are shown in Table 2. All *n_eff* values are greater than 1000, and *Rhat* values are equal to 1, so Model 1's Markov chains are deemed well-convergent. The convergence of Markov chains is also reflected in the trace plots of Figure 2. In particular, after the 2000th iteration, all chains' values fluctuate around the central equilibrium.

Table 2: Estimated results of Model 1

Parameters	Mean	SD	n_eff	Rhat

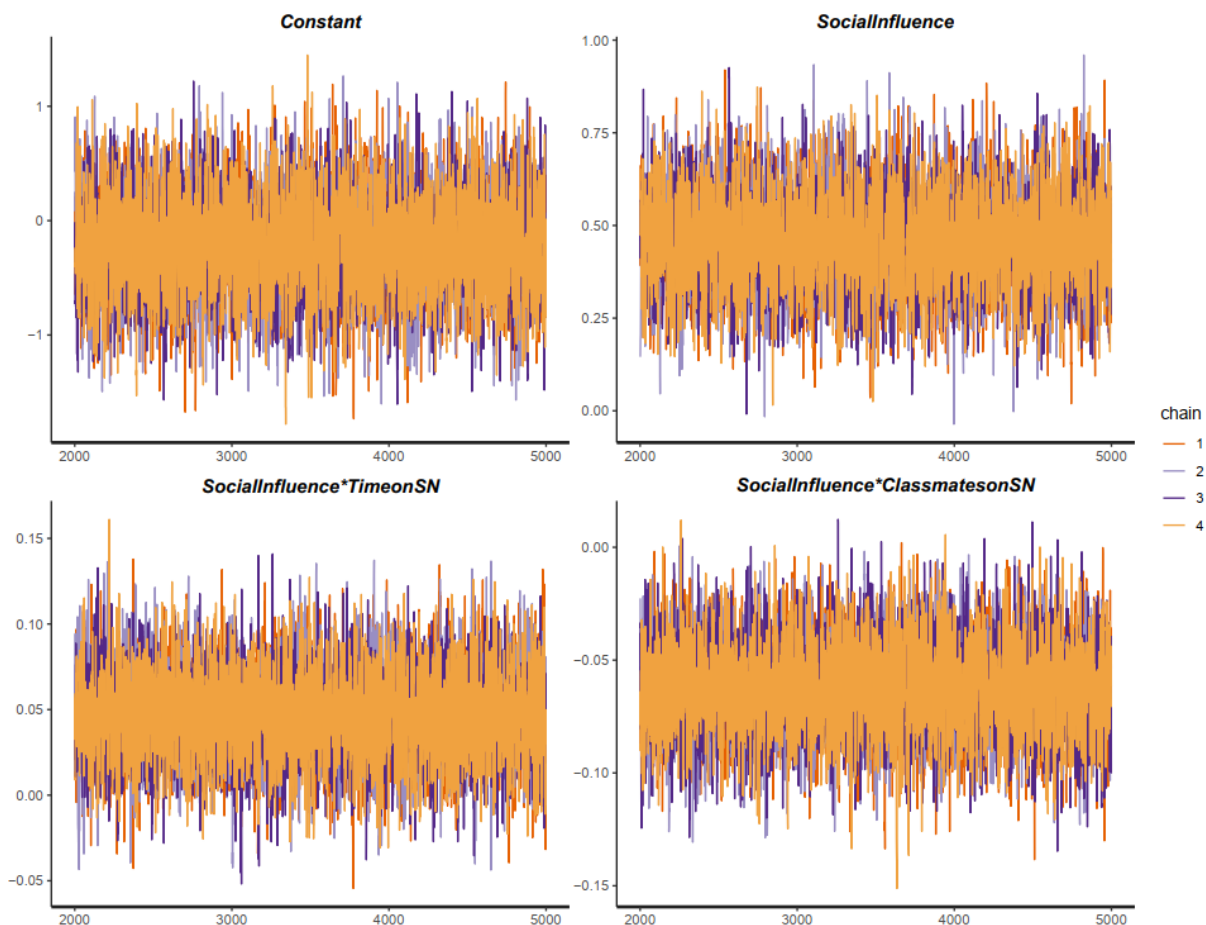|				
Constant	-0.21	0.44	5729	1
SocialInfluence	0.46	0.13	5679	1
*SocialInfluence*TimeonSN*	0.05	0.03	7611	1
*SocialInfluence*ClassmateonSN*	-0.06	0.02	7595	1

Figure 2. Model 1's trace plots

The Gelman-Rubin-Brooks and autocorrelation plots also show that the Markov chains have good convergence. Gelman-Rubin-Brooks plots are used to evaluate the ratio between the variance between Markov chains and the variance within chains. The y-axis demonstrates the shrinkage factor (or Gelman-Rubin factor), while the x-axis illustrates the iteration order of the simulation. In Figure 3, the shrinkage factors of all parameters rapidly decrease to 1 before the 2000th iteration (the warm-up period). This manifestation indicates that there are no divergences between Markov chains.
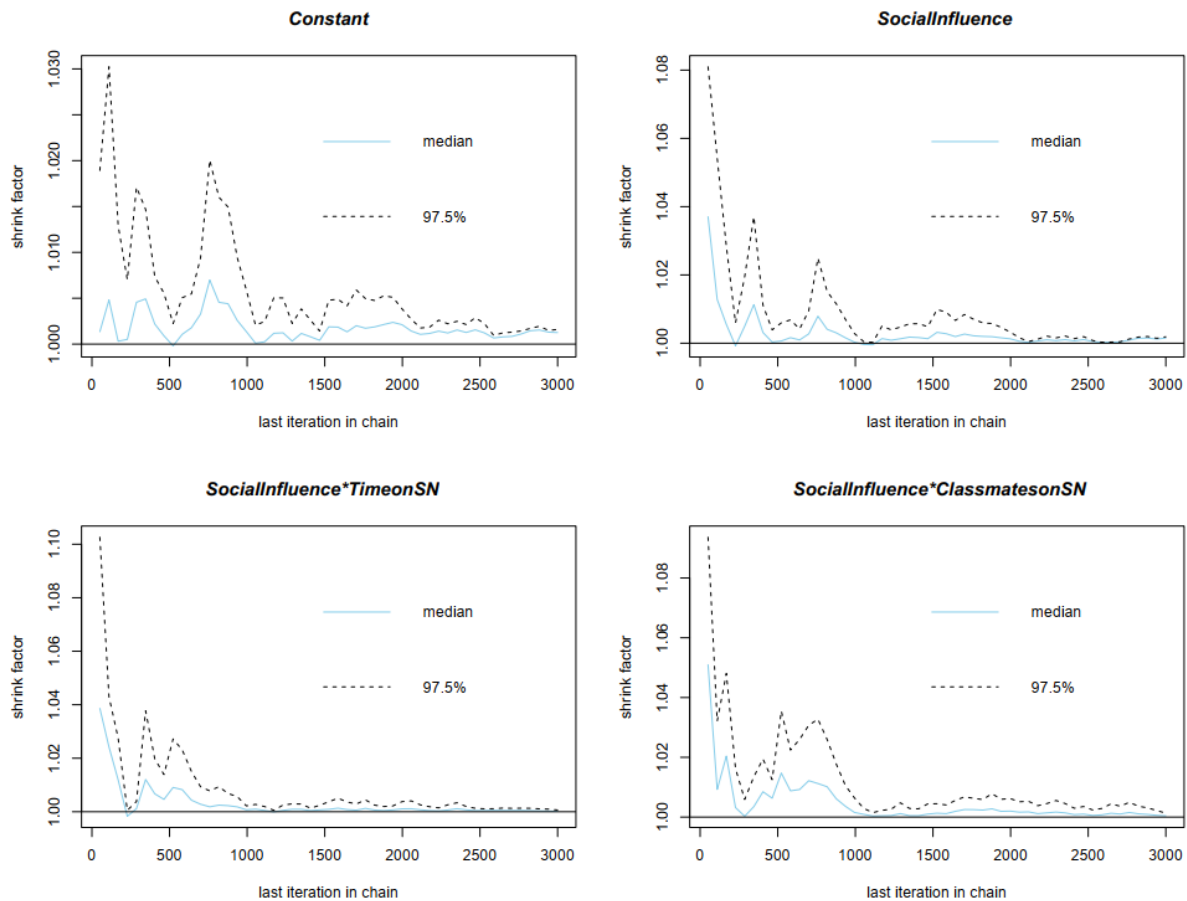
Figure 3. Model 1's Gelman-Rubin-Brooks plots

The Markov property refers to the memory-less property of a stochastic process. In other words, iteration values are not auto-correlated with the past iteration values. Autocorrelation plots are used to evaluate the level of autocorrelation between iteration values. The plots in Figure 4 show the average autocorrelation of each Markov chain along the y-axis and the delay of these chains along the x-axis. Visually, after several delays (before 5), the autocorrelation levels of all Markov chains swiftly drop to 0, indicating that the Markov properties are preserved and the Markov chains converge well.
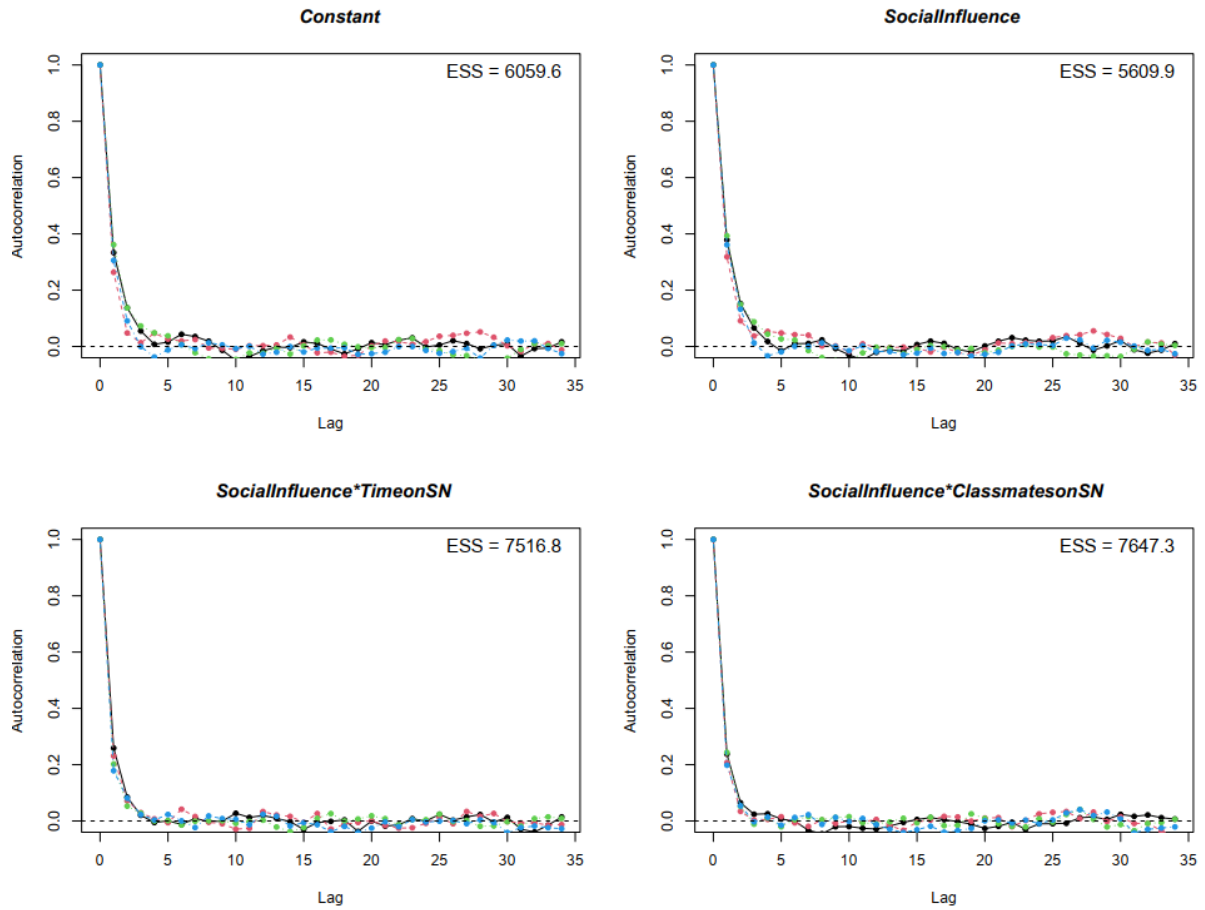
Figure 4. Model 1's autocorrelation plots

Since all the diagnostics confirm the convergence of Markov chains, the simulated results are eligible for interpretation. The estimated results of Model 1 show that social influence is positively associated with nursing students' intention to use ICT during their clinical internship to learn ($M_{SocialInfluence} = 0.46$ and $S_{SocialInfluence} = 0.13$). The association is positively moderated by students' daily duration of using social media ($M_{SocialInfluence*TimeonSN} = 0.05$ and $S_{SocialInfluence*TimeonSN} = 0.03$) and negatively moderated by the number of classmates being friends on social media ($M_{SocialInfluence*ClassmateonSN} = -0.06$ and $S_{SocialInfluence*ClassmateonSN} = 0.02$).

The posterior distributions of three coefficients are shown in Figure 5, with the thick line representing Highest Posterior Density Intervals at 89%. As can be seen, all the distributions lie entirely on the negative or positive side of the x-axis, indicating the high reliability of the results.
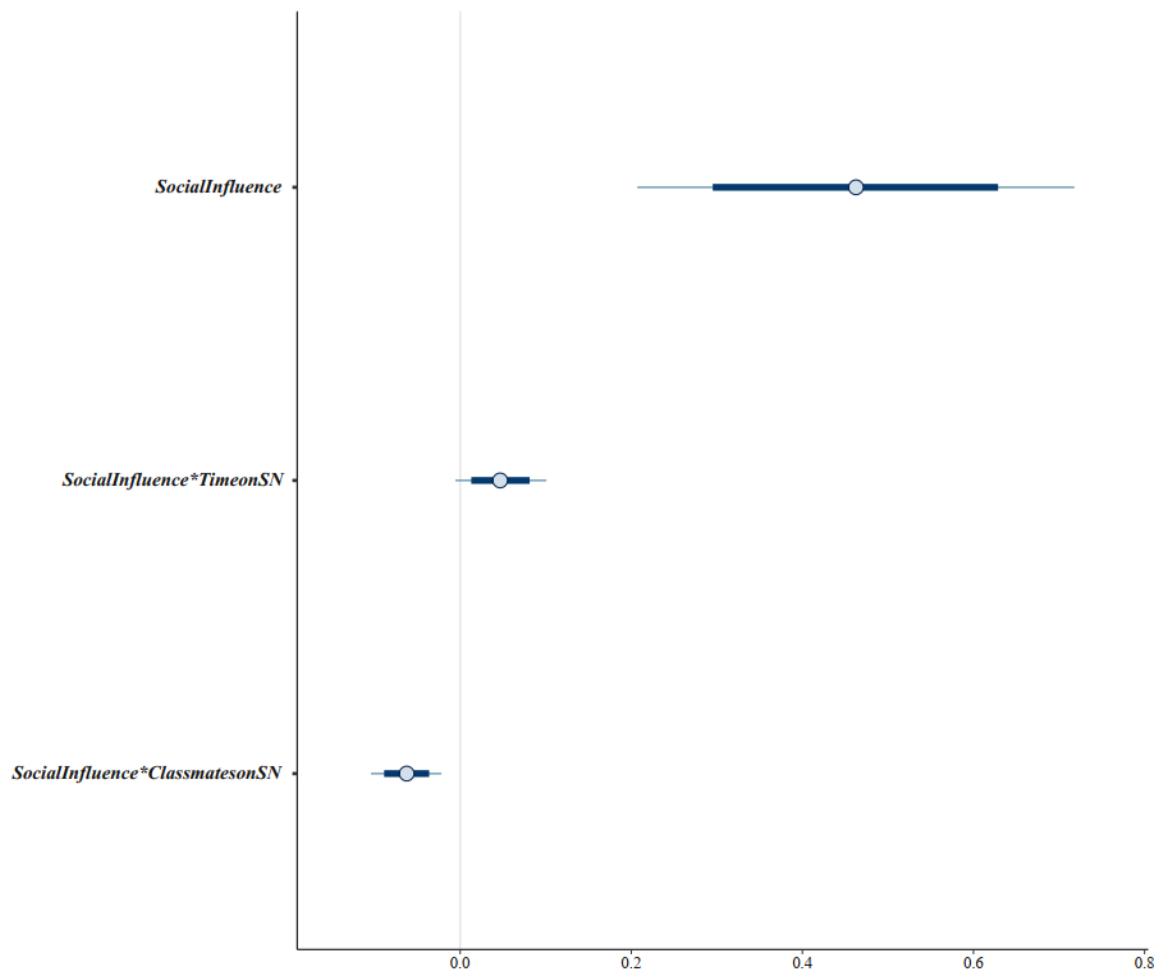
Figure 5. Model 1's posterior distributions

To aid result interpretation, we calculated the students' probability of intending to use various ICT and social media platforms in clinical learning by applying the mean values shown in Table 2 to Model 1. The calculated probabilities are illustrated in Figures 6 and 7. For clarity, the value of *ClassmateonSN* in Figure 6 was set as 1 (corresponding to 'less than 20'), while the value of *TimeonSN* in Figure 7 was set as 1 (corresponding to 'less than 1 hour').
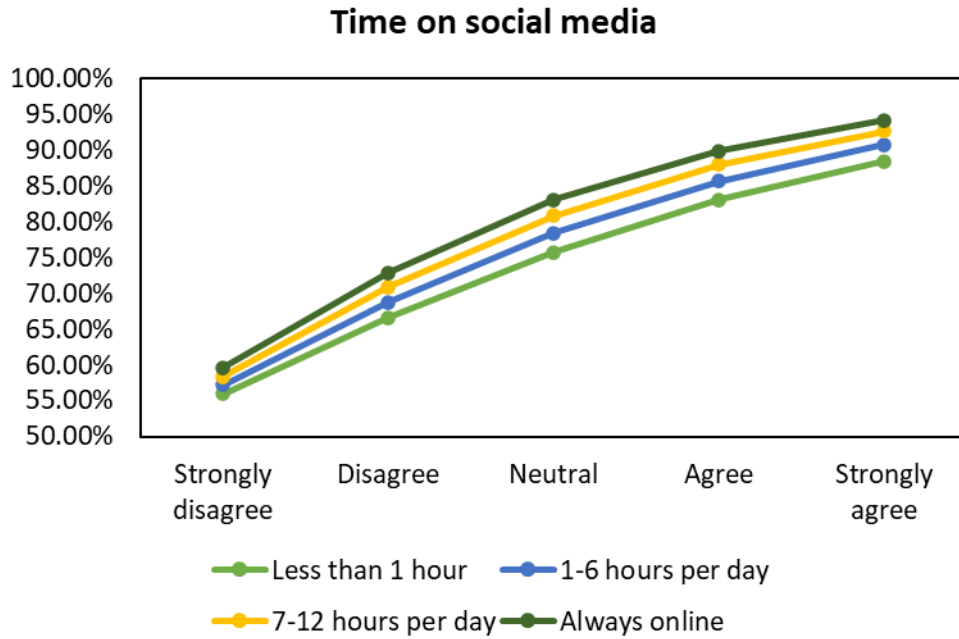
Time on social media

Figure 6: Estimated probability of having intention to use ICT according to the social influence level and the duration of use (the number of classmates was set as 'less than 20')
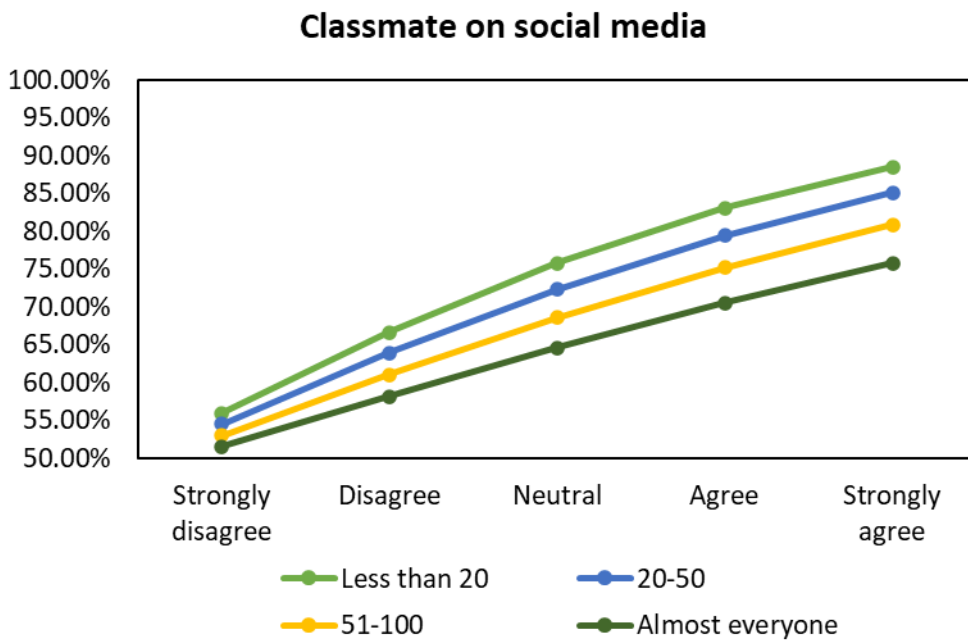
Classmate on social media

Figure 7: Estimated probability of having the intention to use ICT according to the social influence level and the number of classmates (the duration of use was set as 'less than 1 hour')

Based on Figures 6 and 7, we can see that the nursing students' probability of having the intention to use ICT increases according to the rising level of social influence. While the

positive effect of social influence on ICT usage intention is amplified by the students' duration of using social media, it is lessened by the number of classmates connected on social media.

4. Discussion

The development and integration of ICT into nursing education and practice, especially health information technology, create significant changes in the nursing world, which is associated with low intention to use ICT. Meanwhile, intention directly predicts actual ICT usage (Ibrahim et al., 2019). E-learning is the most significant change to occur in nursing education, which is influenced by the differences in computer and information literacy between students and educators, and nursing informatics is a great support in needs (Button et al., 2014). Nursing students are the future professional nurses who will be more exposed to advancing health information technologies in practice. Concerning their intention to use ICT during clinical practice as early as possible is crucial because they will be a part of the largest group of regulated healthcare providers and the biggest user group of health information technology in practice in the future. Using the BMF analytics on a dataset of 702 Moroccan nursing students, the current study found that social influence is positively associated with nursing students' intention to use ICT for clinical learning during the internship.

This finding confirms Hypothesis 1 and aligns with previous studies that found that social influence is positively associated with ICT use in clinical placement among Israeli nursing students. The previous model could predict 28% variances in ICT usage in this population (Warshawski, 2020). This study's finding is also consistent with the study of Pan and Gao (2021), which discovered that social influence demonstrated a significant association with behavioral intention to use ICT, which can explain 70.2% variances of ICT using intention. Social influence was proven to significantly impact ICT adoption, in which behavioral intention is the mediator (Nassar et al., 2019). In addition, the extended social influence factor (coercive, normative, and mimetic pressures) can influence the intention to use ICT (Leow et al., 2021).

This study identified the social influence factor from three sources that supply students with information regarding ICTs and social media usage for clinical learning: family, friends, and colleagues. Specifically, nursing colleagues can transmit their thoughts on the benefits of using ICT to empower the students to use ICT during the internship period. Simultaneously, the appreciation coming from students' family and friends for using ICT for clinical learning can be deemed motivation (or perceived benefits) for them to think of using ICT for clinical learning. However, based on MT reasoning, it should be noted that the effect of social influence on ICT usage intention is conditional on the weight (importance) and trustworthiness of the information sources (i.e., family, friends, and colleagues) towards the students. Empirically, a study on 1,562 nursing students confirmed that trust positively

correlates with the behavioral intention to use ICT, e.g., mobile learning applications to support learning activities (Chao, 2019).

Study findings also add novelty to the existing literature by showing that the duration of daily use of social media can amplify the positive association between social influence and students' intention to use ICT and social media in clinical learning, which confirms the second Hypothesis. The result highlights the potential of using social media platforms to facilitate the incorporation of ICT and social media in nursing education and training.

The pedagogical use of social networking technology in education is of growing interest to academics as a potential teaching-learning tool. Social media plays a role in nursing students' face-to-face and distance learning activities (Giroux & Moreau, 2022). It creates a space for nursing students to form learning communities. It can also be utilized for supportive, professional, and social learning in nursing education (Ferguson et al., 2016). A study on 533 nursing students confirmed that social media platforms enhanced the students' learning self-efficacy and helped promote peer learning between nursing classmates and engaging with academics (Tower et al., 2014). Another study on 654 nursing students showed that most students believed that social media positively influenced self-directed learning, so they suggested that it is essential to develop a social media and professionalism course for nursing students (Zhu et al., 2021). Social media facilitates peer-to-peer learning and support, augmenting online-offline social relationships and building professional identity as a nurse among nursing students (Ferguson et al., 2016).

The learning activities on social media platforms are centered on the platforms' interactive nature, allowing information to be dynamically shared and discussed in real time (O'Connor et al., 2017). Two-way communication in social media forums may facilitate information-exchanging activities between nursing interns (e.g., digital academic content related to health information). A study on 121 nursing students showed that social media is an engaging way to promote discussion and share information between nursing classmates (Price et al., 2018).

However, the current study also found that the number of nursing classmates included in the contact or friends' list of social media accounts was a negative moderator in the relationship between social influence and ICT-using intention in this population. The result contradicts the third Hypothesis, which assumes positive moderation. The explanation for this contradiction might come from the costs of having too many connections on social media. More connections mean more information sources and a higher need to track and manage the information. If the information cannot be tracked or managed appropriately, it might lead to the fear of missing out and worry about their peers' responses and feelings (Qutishat & Sharour, 2019; Weinstein & James, 2022). Such fear and worries can lead to mental illness and degrading well-being (Gupta & Sharma, 2021; Orben et al., 2022). These negative mental conditions might be the factors lessening the effects of social influence (i.e., from colleagues, friends, and family) on the intention to use ICT and social media for clinical

learning. Therefore, although social media platforms are beneficial for nursing education and learning, their adverse impacts on students' mental well-being need to be acknowledged and managed appropriately. Further studies are also suggested to explore the negative moderation effect of the number of classmates connected on social media on the relationship between social influence and the intention to use ICT and social media in clinical learning.

The current study has several limitations reported here for transparency (Vuong, 2020). Because the dataset came from samples of Moroccan nursing students, extending the results to other fields of discipline and nations should be done with caution. The social influence and intention to use ICT reported here are the subjective perceptions of nursing students who filled out the self-reported questionnaire, which may contain information biases. The online learning platforms identified here were diverse, involving non-specific-building-for-learning-purposed social media platforms. Future studies applying more objective measurements that involve more specific and reliable online learning platforms are highly encouraged. In addition, the current study is based on survey data, so it exhibits some limitations in reflecting the dynamic interplay effect of social influence and intention to use ICT or technology adoption. Experimental studies should be conducted to address these limitations.

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