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Unraveling the Link between Simulation EHR Training and Task Performance: The Mediation Role of Stress

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Abstract:

Past research has explored the link between computer-mediated communication (CMC) and task performance, but it remains unclear how (i.e., under what mechanisms) CMC impacts task performance. Drawing on media naturalness theory and the stimulus-organism-response model as our theoretical framework, we develop a research model and describe how simulation-based EHR training (a type of CMC) can improve EHR-based task performance by mitigating stress. We empirically test the model with a unique experimental dataset from EHR lab assessment and questionnaires that 225 participants completed. The structural equation modeling analysis results show that simulation EHR training helped improve EHR-based task performance (both effectiveness and efficiency) by reducing perceived stress. We discuss theoretical and practical implications, limitations, and future research.

Keywords: Computer-mediated Communication, Electronic Health Records, Simulation, Stress, Efficiency, Media Naturalness Theory, Stimulus-organism-response Model, EHR Task Performance

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1 Introduction

Task performance is an important outcome of information systems (IS) use (Chiasson et al., 2015; DeLone & McLean, 1992, 2003; Goodhue & Thompson, 1995). Extant research in IS has discussed the important influence that technology, task, and user characteristics have on task performance (Burton-Jones & Straub, 2006; Goodhue & Thompson, 1995). For example, task-technology fit theory posits that a fit between task, individual, and technology characteristics can predict IT-enabled task performance (Mehrabian & Russell, 1974). Other research that has studied task performance comes from the computer-mediated communication (CMC) domain. CMC refers to human interaction that occurs via a computer (Monberg, 2005). CMC research includes media theories such as social presence (Short et al., 1976), media richness (Daft & Lengel, 1984; Daft et al., 1987), and media synchronicity (Dennis et al., 2008). These theories help explain technology characteristics (e.g., media), communication tasks, user characteristics, and their role in enabling task performance. However, we know little about the underlying mechanisms through which communication media affect task performance. Accordingly, in this study, we use media naturalness theory (Kock, 2005; Kock et al., 2015) and the stimulus-organism-response model (Mehrabian & Russell, 1974) as lenses to examine how simulation-based EHR training can improve EHR-based task performance. We conceptualize task performance as task efficiency (Schneiderman & Plaisant, 2005)—assessment completion time—and task effectiveness (Motowidlo & Van Scotter, 1994)—assessment score.

Digital electronic health records (EHRs)—electronic health information records that authorized clinical staff can create and manage across more than one healthcare organization (Noblin et al., 2021)—have resulted in important benefits for personalized healthcare (Abul-Husn & Kenny, 2019; Lin et al., 2019; Moqbel et al., 2020). As healthcare organizations have increasingly used EHRs in the last decade, providing quality training to healthcare professionals in using EHRs has become important. Traditional EHR training methods, such as paper-based education, do not incorporate hands-on EHR training and use and, thus, result in inadequate training. Without proper training, users will not be able to take advantage of EHR's many benefits, such as real-time access to patients' information, the ability to identify trends in patient health history, the ability to easily retrieve and share information, helpful reminders and alerts, and the ability to facilitate interaction between providers and patients (Rathert et al., 2019). Recent efforts have highlighted the effectiveness of simulation-based training in several fields, including healthcare (Alinier et al., 2006), aviation (Lee, 2017; Salas et al., 1998), military (Hendrickse et al., 2001), and security (Jensen et al., 2016). However, these studies have largely overlooked the mechanisms through which simulation can improve outcomes. As such, in this study, we use media naturalness theory and stimulus-organism-response model as lenses to investigate simulation-based training (SBT), which can replicate real-world events and replace or supplement existing paper-based training methods and, thus, result in an improved learning experience (Bell et al., 2008; Lateef, 2010).

Based on evolutionary psychology, media naturalness theory focuses on the communicators and the evolutionary characteristics that they have developed over time. This theory contends that humans may prefer richer, more natural communication media, but it notes their compensatory adaptation (i.e., the ability to adapt and overcome the challenges that less natural media may pose), which can result in improved performance) (Kock, 2001, 2009). Hence, based on media naturalness theory and its compensatory adaptation model (Kock, 2001), we posit that using CMC and, specifically, simulation-based EHR training (i.e., high naturalness) impacts task performance in a compensatory manner in that users compensate for communication-related limitations by reducing cognitive efforts (stress) and, thus, augment their task performance.

The stimulus-organism-response framework posits that an external environmental (e.g., simulation-based training exposure) aspect provokes a person's affective or cognitive condition (e.g., stress), which results in a particular behavioral outcome (e.g., performance) (Mehrabian & Russell, 1974).

Drawing on the media naturalness theory and the stimulus-organism-response model, we propose that using CMC simulation-based EHR training (high naturalness) as compared to past paper-based training (low naturalness) will yield decreased stress (cognitive effort) and increased task performance—task efficiency and task effectiveness. We collected a unique dataset from 225 participants in an EHR laboratory experiment to test our theoretical hypotheses.

With this study, we contribute to the extant literature in several ways. First, based on the media naturalness theory and the stimulus-organism-response model, we investigate the interdependencies among simulation-based EHR training, stress, and task performance. Second, we help research on health IT evolve toward more richly explaining the process by which simulation-based EHR training augments task performance.

We found that simulation-based EHR training influences task performance indirectly by reducing perceived stress. Third, we establish experience as a contextual factor on which task effectiveness depends. Overall, we better explain how simulation-based EHR training affects task performance.

The paper proceeds as follows: In Section 2, we discuss the background that guides this research. In Section 3, we discuss the theoretical development and hypotheses. In Section 4, we report on how we assessed the structural and measurement models. In Section 5, we present our results. In Section 6, we discuss our study's implications for research and practice, its limitations, and opportunities for future efforts. Finally, in Section 7, we conclude the paper

2 Background

2.1 Computer-mediated Communication

The human element represents an important CMC characteristic. CMC refers to using computers to facilitate human interaction (Monberg, 2005). Existing CMC research focuses not only on the technical aspects of communication (such as media richness theory) but also on human-related variables such as performance (Canessa & Riolo, 2006; Taylor, 2006) and the type of communication media (Carlson & Davis, 1998; Markus, 1994). Numerous studies have focused on the effects of CMC on various outcomes when compared to those of more natural communication media (e.g., face-to-face communication). Research shows that individuals who use CMC may face certain limitations that they must compensate for (Bordia, 1997). As such, we believe that simulation-based training, a type of CMC, will affect task performance in a compensatory fashion as the compensatory adaptation model predicts (Kock, 2001). Specifically, we examine the effect that simulation-based EHR training has on performance.

2.2 Electronic Health Records and Simulation-based Training

An EHR system allows medical professionals to store and access patient information electronically and securely across multiple healthcare organizations (Angst & Agarwal, 2006; Dinev et al., 2016; Häyriinen et al., 2008). We can trace early EHR versions back to the 1960s. At that time, different health organizations had begun creating their own systems that lacked intercommunication. By the 1980s, some standards had emerged to ensure adequate communication between systems (Atherton, 2011). However, not until 2009 when the U.S. Government passed the Health Information Technology for Economic and Clinical Health (HITECH) Act did healthcare organizations widely adopt EHRs (Rathert et al., 2019). While EHRs have many recognized benefits, such as real-time patient data availability and easily retrievable and sharable information, researchers have identified several challenges. Rathert et al. (2019) found that EHR users could realize EHR's benefits only if they could use the system correctly. To achieve correct usage, users require adequate training. In 2018, the American Medical Association developed a policy for medical schools and residency programs to incorporate EHR training due to insufficient adequate training in the programs (AMA, 2018). Adequate training can positively affect healthcare providers' self-efficacy and influence how they perceive EHR's importance in improving care quality and patient safety (Vuk et al., 2015). As one challenge in providing adequate training in medical school programs, curriculum and effective teaching methods for EHR training remain in their developmental stage. "Formal pedagogy" has emerged slowly even though healthcare organizations have used EHRs for many years, and significant EHR training gaps in medical education remain (Rajaram et al., 2020; Wald et al., 2014). Rajaram et al. (2020) found few studies have focused on "educational interventions" geared toward EHRs, which has left a significant gap in the literature. In addition, academics in the education field often assume that healthcare organizations will provide medical professionals with training on how to use EHRs due to the many different EHR types that exist; however, these organizations often do not provide such training, which leaves the professionals with little knowledge about how to use these systems when they enter the workforce (Ellis et al., 2020). In this study, we fill the training gap across medical school programs by suggesting that they use simulation-based training to decrease stress due to insufficient training and improve learning and performance when using EHRs.

Simulation-based training (SBT) replaces typical instruction with tasks that replicate real-world events or settings and manage an individual's experience in an "artificial" environment (Bell et al., 2008; Lateef, 2010; Salas et al., 2009). Researchers have studied such training in numerous fields, and it has particular value in healthcare because it allows trainees to "engage in dynamic practice in contextualized task environments" that mimic real-world scenarios (Rosen et al., 2008, p. 34). Most available research on SBT use in

healthcare focuses on medical procedure training. However, we need additional quantitative research that examines how one can use SBT to train medical students to use EHRs.

We can classify SBT into different types of simulations: role-playing, physically based, and computer-based simulations (Salas et al., 2009). In a pilot study of a computer-based simulation to train participants on how to use an electronic medical record (EMR) system (a system that only one healthcare organization can use as compared to EHR systems, which many organizations can use), Shachak et al. (2015) observed that participants found the simulation useful in learning how to use the system. The authors found participants preferred interactive scenarios that mimicked the real system and recommended integrating SBT with an EHR system when one uses it for training purposes (Shachak et al., 2015). In this study, we focus on computer-based simulations and their effect on EHR-related task performance.

Because SBT imitates real-life scenarios (Salas et al., 2009), we use media naturalness theory (Kock, 2005; Kock et al., 2015) and the stimulus-organism-response model (Mehrabian & Russell, 1974) as lenses to examine how computer-based SBT provides a task-related experience that can benefit participants by reducing stress, which, in turn, increases task performance (which we measure in this study with task effectiveness and task efficiency).

3 Theoretical Development and Hypotheses

3.1 Research Model

Figure 1 shows our research model.

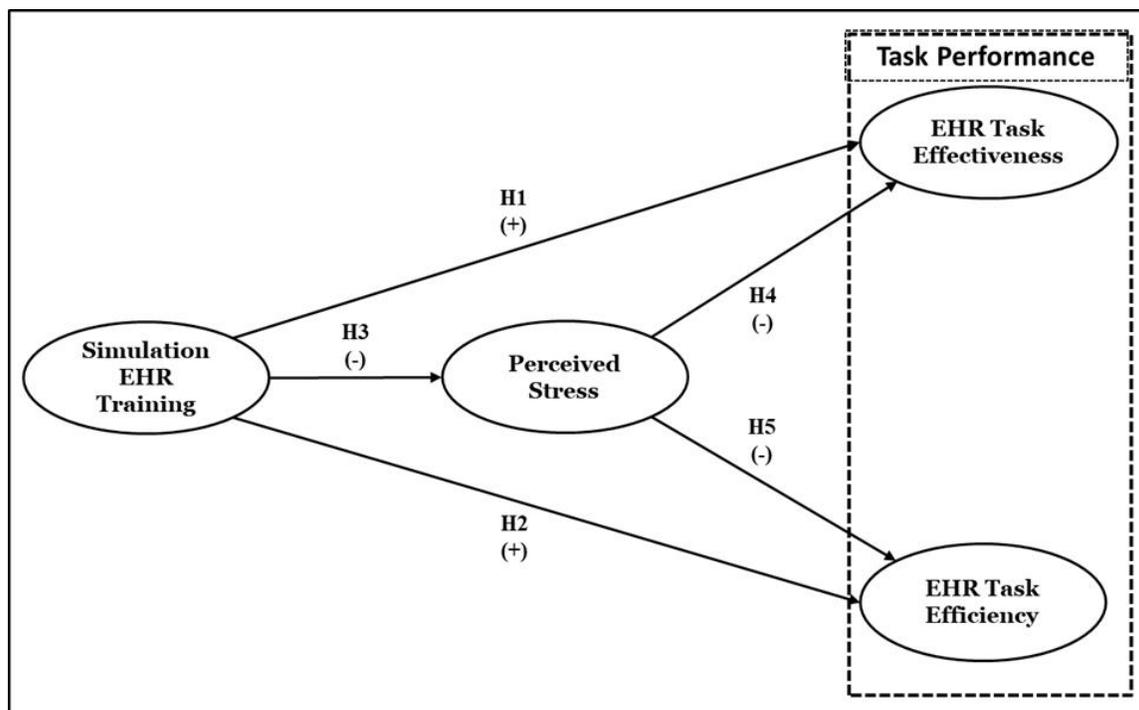


Figure 1. Research Model with Hypotheses

3.2 Stimulus-Organism-Response Model

The stimulus-organism-response model (Mehrabian & Russell, 1974) theorizes that an external stimulus leads to cognitive or emotive reactions (i.e., internal states), which, in turn, induce responses. The model emphasizes the reactions or outcomes when an organism and response encounter a stimulus (e.g., computer/simulation-based vs. paper-based training). In the stimulus-organism-response model, a stimulus refers to a thing external to the individual, such as a training method in university. The organism denotes an internal cognitive state or process that intervenes between the stimuli and response. The response refers to the outcomes or consequences of the organism and stimulus (Kamboj et al., 2018), such as users'

behavior or performance. As such, the model suggests that an internal cognitive state (e.g., stress) intervenes or mediates the impact that a stimulus has on a response.

We leverage the stimulus-organism-response model as a theoretical framework to explain trainee cognitive reactions that result from exposure to two different training approaches and their effect on task performance. In this research, simulation-based training exposure constitutes the stimulus, stress (a cognitive state) the organism, and EHR task performance (efficiency and effectiveness) the response.

3.3 Media Naturalness Theory

Kock (2001) developed media naturalness theory based on theories rooted in the evolutionary psychology discipline. This discipline holds that, to comprehend the human mind, one must delve into humankind's evolution throughout time. Media naturalness theory proposes that humans have developed certain characteristics throughout evolution that have made them better suited for face-to-face communication. As a result, they have adapted better to the "natural" media they have become accustomed to throughout time (namely, face-to-face communication and all the non-verbal cues that come along with it). The theory posits that communication does not simply exhibit or lack naturalness; rather, it views naturalness as a scale, spectrum, or continuum. According to media naturalness theory, when a communication medium's naturalness decreases, communicators will experience higher cognitive effort, more ambiguity, and lower physiological arousal or excitement (DeRosa et al., 2004; Kock, 2001, 2004, 2005, 2009). Hence, the theory implies that, when communicating using a natural medium (i.e., simulation), communicators will experience less cognitive effort (e.g., stress), which will enhance their performance. While the cognitive effort construct has multiple facets, studies have operationalized it by using several proxies, such as stress, mental effort, and time pressure, and others (Longo & Barrett, 2010). In this study, we use perceived stress to measure cognitive effort.

Based on media naturalness theory, we argue that simulation-based (high naturalness) EHR training will influence task performance (i.e., task efficiency and effectiveness) when compared to traditional paper-based (low naturalness) training. According to media naturalness theory, the closer a communication medium to face-to-face communication, the easier a person will find it to communicate with more naturalness. In this study's context, we argue that CMC simulation-based training is more natural than paper-based training. Thus, based on media naturalness theory, we hypothesize that simulation EHR training participants will perform better than participants in a less natural medium:

H1: Simulation EHR training has a positive relationship with EHR task effectiveness.

H2: Simulation EHR training has a positive relationship with EHR task efficiency.

Although we theorize that CMC simulation-based training directly impacts task performance, we posit that it also impacts task performance in a compensatory manner in which users compensate for limitations and, thereby perform better.

In particular, drawing on media naturalness theory, we argue that users adapt to the naturalness capabilities of the simulation technology, thereby, experiencing less stress. According to media naturalness theory, when a communication medium's naturalness increases, communicators experience lower cognitive effort (DeRosa et al., 2004; Kock, 2001, 2009). Similarly, we argue that one will experience lower cognitive stress (a proxy for cognitive effort) when faced with more natural communication, such as CMC simulation-based EHR training. Thus, we hypothesize that simulation-based EHR training will help reduce the stress that participants perceive while using an EHR system to perform tasks.

H3: Simulation EHR training has a negative relationship with perceived stress.

Based on the stimulus-organism-response model, we posit that, because stress hinders cognitive abilities necessary to perform tasks, trainees will exhibit decreased task performance (Bong et al., 2016; Brosnan, 1998; Gilroy & Desai, 1986; Kock et al., 2018; Struthers et al., 2000). Thus, we hypothesize that participants who exhibit higher stress levels will perform less effectively and efficiently in EHR tasks.

H4: Perceived stress has a negative relationship with EHR task effectiveness.

H5: Perceived stress has a negative relationship with EHR task efficiency.

4 Methodology

4.1 Measurement Instrument

To test our proposed model, we conducted an experiment in a training lab and collected data using a survey and an EHR proficiency assessment. We developed the survey based on previously tested instruments to ensure its validity, and we modified some existing measurements to make them more suitable for the current research context. We measured perceived stress based on a four-item construct from Kock et al. (2018). We operationalized the simulation EHR training variable as a binary variable (1 = the treatment group who went through simulation EHR training and 0 = the control group who did not go through the simulation EHR training). The control group did not have formal exposure to the EHR and instead received the legacy approach that comprised paper-based training prior to when their clinical clerkships began. We measured EHR task efficiency as performance speed (i.e., how much time it took participants to complete the assessment tasks). A lower assessment completion time indicated a participant who performed more efficiently (Schneiderman & Plaisant, 2005). We measured EHR task effectiveness as how many correct hands-on tasks the participants performed using an interactive assessment through Adobe Captivate.

4.2 Data Collection

After completing the hands-on EHR lab assessment, participants filled out a survey. The participants included two student cohorts who participated in third-year orientation in medicine. After their formal EHR training, medicine faculty members invited them to participate in the lab's EHR assessment. We provided the respondents with consent information that informed them that they participated in the assessment and survey on a voluntary basis. Furthermore, we collected anonymous data and used it only for research purposes in aggregate format.

Table 1. Descriptive Statistics and Demographic Characteristics

	Category	N	[%]	Mean	SD
EHR assessment task performance score				64.35	13.38
EHR experience	No Experience	122	54.71		
	Some Experience	101	45.29		
Cohort	Simulation	107	47.6		
	Non-simulation	118	52.4		
GPA	< 3.0	12	5.4		
	≥ 3.0	209	94.6		
Age	21 - 24	124	55.11		
	25 - 27	68	30.22		
	28 - 31	23	10.22		
	32+	10	4.44		
Gender	Female	116	51.56		
	Male	109	48.44		
Race	American Indian or Alaska Native	0	0		
	Asian	25	11.11		
	Black or African American	10	4.44		
	Hispanic or Latino	12	5.33		
	Native Hawaiian or Other Pacific Islander	0	0		
	White	178	79.11		

In total, 225 respondents participated in the EHR lab assessment and completed the questionnaire. We show the results in Table 1. Most respondents (79.11%) were White. More than half (55.11%) were 21 to 24 years old. The sample had a balance in gender (48.44% males and 51.56% females). Around 95 percent of the participants had a 3.0 GPA or above. While 118 participants (52.4%) represented the non-simulation EHR training cohort, 107 (47.6%) represented the cohort that went through simulation EHR training. More than half (55%) of the participants had no EHR use experience. It took participants 3.83 (SD = 3.9) minutes to complete the EHR assessment. Their average EHR assessment task performance score was 64.35 (SD = 13.8).

5 Results

5.1 Measurement Model Evaluation

To test our research model, we used partial least square (PLS), a second-generation variance-based structural equation modeling (SEM) technique (Chin, 1998; Haenlein & Kaplan, 2004; Kock, 2010), because it can assess a measurement model and structural model simultaneously. Researchers prefer PLS over covariance-based SEM when data does not meet multivariate normality (Gefen & Straub, 2005; Hair et al., 2010) and they need to explain complex relationships (Hair et al., 2010). We employed WarpPLS 7.0 to produce estimates for the measurement instrument's validity and reliability and the structural equation modeling analysis (Kock, 2010).

Before we assessed our hypotheses, we evaluated the latent construct's reliability and validity using composite reliability (CR), Cronbach's alpha, and convergent and discriminant validity. As Table 2 shows, the CR and Cronbach's reliability coefficients exceeded the suggested threshold of 0.70 (Fornell & Larcker, 1981; Nunnally & Bernstein, 1994), which indicates that the measurement instrument had acceptable reliability.

Table 2. Descriptive Statistics, Convergent Validity, and Reliability for Constructs

Construct	ID	Mean (SD)	Loadings	CR	ALPHA	FVIF	NORMAL
Perceived stress	Stress1	3.06 (1.13)	(0.935)	0.961	0.945	1.134	NO
	Stress2	2.73 (1.06)	(0.842)				
	Stress3	2.97 (1.15)	(0.964)				
	Stress4	2.91 (1.14)	(0.965)				

Note: all loadings were significant at $p < 0.001$.

CR = composite reliability, alpha = Cronbach's alpha, FVIF = full collinearity variance information factor, normal = multivariate normal distribution (Jarque-Bera), perceived stress = perceived stress experienced while completing the EHR task assessment.

We tested the measure's convergent validity by assessing factor loadings. All indicators exceeded the recommended 0.50 (Hair et al., 2010), which indicates the measurement instrument had acceptable convergent validity. Since survey methods may be subject to common method variance (CMV), we followed Kock's (2015) approach and calculated full collinearity to test for CMV. As Table 2 shows, the full collinearity variance inflation factor (FVIF) score was less than the recommended 3.3, suggesting that multicollinearity and CMV did not likely pose a concern for the study.

5.2 Hypothesis Testing

Figure 2 depicts the results we obtained from testing our model, which includes the path coefficient estimates that denote the magnitude of the relationships between the variables. The R^2 values refer to the variance that exogenous variables explained. The research model explained 12 percent of the variance in EHR task effectiveness, four percent of the variance in perceived stress, and eight percent of the variance in EHR task efficiency.

Simulation EHR training, although in the expected direction, did not significantly increase EHR task effectiveness ($\beta = 0.03$, $p > 0.05$). Thus, we did not find support for H1. In contrast, simulation EHR training significantly reduced perceived stress ($\beta = -0.20$, $p < 0.001$) and significantly increased EHR task efficiency ($\beta = 0.20$, $p < 0.001$), which supports H2 and H3, respectively. Perceived stress significantly reduced EHR task effectiveness ($\beta = -0.21$, $p < 0.001$), which supports H4. Perceived stress significantly reduced EHR

task efficiency ($\beta = -0.13$, $p < 0.05$), which supports H5. Table 3 summarizes the support we found for the hypotheses. We elaborate on these results in the subsequent sections.

Table 3. Hypothesis Testing Results

Hypothesized relationship	Support?
H1: Simulation EHR training has a positive relationship with EHR task effectiveness.	No
H2: Simulation EHR training has a positive relationship with EHR task efficiency.	Yes
H3: Simulation EHR training has a negative relationship with perceived stress.	Yes
H4: Perceived stress has a negative relationship with EHR task effectiveness.	Yes
H5: Perceived stress has a negative relationship with EHR task efficiency.	Yes

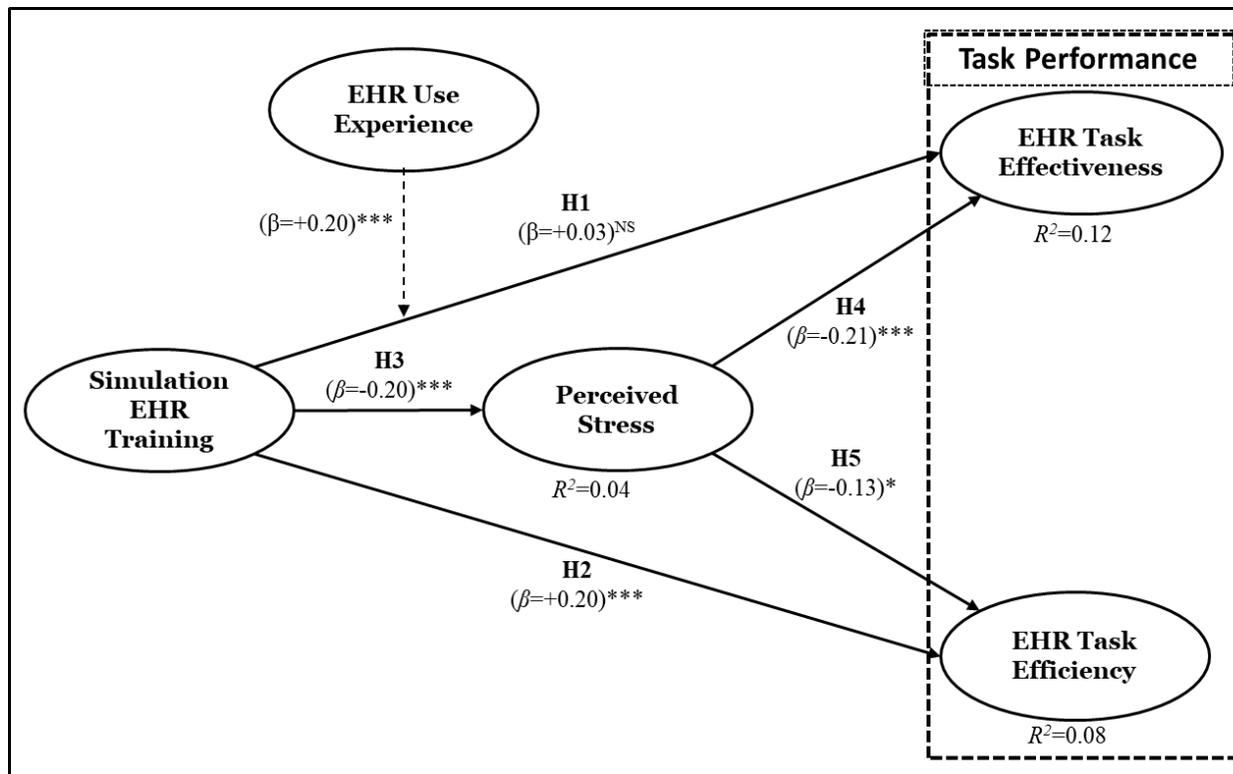


Figure 2. Research Model with Results¹

5.3 Post Hoc Moderation Analyses

In this section, we discuss the results that we obtained from conducting additional exploration analyses to understand the main relationships in a more nuanced manner. First, we focused on understanding the results we obtained for H1, which we failed to find support for. We conducted exploratory moderation analyses to understand under what conditions the original hypothesis held.

5.3.1 Age-experience Framework

The age-experience framework (AE Framework) (Kock et al., 2018) states that, as individuals grow older, they involuntarily acquire “mental schemas” through various life experiences (Kock et al., 2018). These schemas result in task-related preparation, which impacts how competent they feel when completing a task

¹ Note: ** $P < 0.001$; NS: not significant

such that individuals who have task-related experience will exhibit more effective task performance (in our case, EHR task performance).

Based on this framework, we infer that individuals trained using simulation EHR, combined with additional practice and experience, perform better than individuals trained using the legacy training method. We found that EHR user experience positively moderated the relationship between simulation EHR training and EHR task effectiveness ($\beta = 0.20$, $p < .001$) and, thereby, strengthened the positive relationship between simulation EHR training and EHR task effectiveness. In other words, the relationship between simulation EHR training and EHR task effectiveness in our model was only significant when individuals combined their simulation training with EHR use experience. While one would expect additional practice and experience to improve efficacy and performance, our study results show that experience becomes more significant when combined with EHR simulation training. This finding demonstrates value in our intervention in which we leveraged the existing curriculum module (and, thus, did not take significant time away from all the respondents' other needs).

6 Discussion

In this paper, we examine the mechanisms under which CMC simulation-based EHR training can help medical students improve task performance (task efficiency and task effectiveness). We found that, compared to traditional training, simulation EHR training results in decreased participant stress levels, improved task efficiency, and improved task effectiveness. The results suggest that stress level negatively influences task performance. Thus, in the EHR context, the communication training mode plays a pivotal role in determining task performance.

We found support for all of our hypotheses except for the first one (which posits a direct relationship between the simulation EHR training and task effectiveness). In other words, we found no significant difference between simulation- and traditional-based training in terms of task effectiveness. This result could suggest that the simulation learning model complements traditional training in medicine. However, we also found that EHR experience moderated the relationship between training mode (simulation vs. traditional) and task effectiveness. In particular, the moderation result shows that when one combines simulation training with EHR experience, it significantly improves task effectiveness. This finding supports previous literature that posits that simulation allows individuals to develop experience prior to performance (DeVita et al., 2005; Gupta et al., 2008), which helps augment performance.

6.1 Contributions to Theory

While research has found that technology, task, and user characteristics influence task performance, they have paid little attention to understanding the underlying mechanisms through which communication media affect task performance. In this study, we expand the systems use notion in the technology-mediated communication context to underscore the important role that users' interaction with simulation technology has in determining task performance. Thus, we contribute to the media naturalness theory by specifically identifying the cognitive state stress as a key mechanism under which the simulation communication mode impacts task performance. While we identified the underlying mechanism explaining the relationship between simulation and task performance in the EHR training context, our approach may generalize to examining system performance outcomes in general. We suggest that we also need to identify relevant underlying mechanisms in different contexts.

By employing media naturalness theory, we enrich conventional media theories such as media richness to explain how using near-natural and rich technology-mediated communication can still result in improved task performance.

6.2 Contributions to Practice

This study makes several key practical contributions. First, our research emphasizes that simulation-based training can help improve users' EHR performance. In any effort to implement a system, user training represents one important success pillar. For CMC technology such as EHR, information exchange represents a key factor; hence, training geared toward improving this information exchange skill via CMC simulation technology will likely lead to better performance. Medical students receive much training about how to handle encounters with patients; however, they might find that they require EHR training as well, such as how to electronically enter, update, and retrieve patient data, prescribe medicine, refer patients to

other specialists, check if a patient is allergic to certain ingredients, conduct patient admission and patient discharge processes, and so on. Conducting these tasks by properly using EHRs will help reduce medical errors responsible for more than 250,000 deaths per year in the USA alone (Makary & Daniel, 2016). Second, our study helps health IT research evolve toward more richly explaining the process via which simulation-based EHR training augments task performance. We found that simulation-based EHR training indirectly influences task effectiveness by reducing perceived stress and directly and indirectly improving task efficiency. Third, to the best of our knowledge, this research represents the first study to incorporate the moderating role that EHR user experience has on the impact that simulation-based EHR training has on task effectiveness. It establishes experience as a contextual factor on which task effectiveness depends. Overall, our research better explains how CMC simulation-based EHR training affects task performance. It contributes important practical implications by presenting an improved method of training for future physicians in using EHRs, which will allow them to experience reduced stress and, in turn, provide better care to patients.

6.3 Limitations and Future Research

While we focus on the CMC training method in this study, we derived the results based on medical students rather than physicians. While this sample population may limit our study's generalization, we found it adequate given the EHR technology's relevance to their future daily career tasks. Future research could replicate this study using physicians. Furthermore, our respondents comprised medical students on the cusp of entering the workforce from a medical school in the United States. Thus, results from our study may not generalize to other nation's medical student sample. Research on using SBT for EHR use remains relatively new, and room for growth in this area exists. Specific characteristics or learning styles may make certain individuals better suited for SBT. Future efforts would benefit from collecting data regarding student characteristics such as personality traits and learning styles that can affect the relationship between SBT and performance (Chang et al., 2008).

The extant literature in SBT shows that feedback constitutes an integral part of the learning process. While the training system that we used in this study can handle the feedback and re-test cycle, we did not use it. In the future, a longitudinal study that provides opportunities for feedback after the initial measurement and repeats the training could shed additional light on what processes can yield the best performance (Rosen et al., 2008; Shapiro et al., 2008). In addition, while we identified stress as an underlying mechanism through which CMC impacts performance, future efforts could explore other intervening factors. Finally, our research model explained 12 percent of the variance in EHR task effectiveness and eight percent of the variance in EHR task efficiency—a relatively small effect). Hence, future efforts should extend our research model by exploring other variables that could improve the model's explanatory power.

7 Conclusion

Since extant research on task performance largely has overlooked the mechanisms through which CMC impacts performance, we focus on filling that void in this study. Leveraging media naturalness and stimulus-organism-response model, we found that CMC impacted task performance by reducing stress. In particular, we analyzed simulation-based EHR training on task efficiency and task effectiveness and found that this effect also occurred via reducing stress levels. We found that simulation-based training resulted in decreased perceived participant stress and increased task efficiency and effectiveness. Also, an increase in perceived participant stress resulted in decreased task effectiveness and task efficiency. Although perceived stress directly affected task effectiveness, simulation-based training did not have a significant direct effect on task effectiveness. In a post hoc analysis, we found that experience had an important moderation effect on the relationship between the training type and task effectiveness. These results have important practical significance because they demonstrate that, through a decrease in stress levels, simulation-based training results in improved task performance. The type of EHR training that we present in this study can benefit not only medical students but also healthcare professionals and, thus, result in improved patient care.

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Appendix A: Measure Instrument

We used the questions and question statements below to collect data in addition to demographic questions. Participants answered the questions on perceived stress on a five-point Likert-type scale with the anchors “strongly disagree” (1) to “strongly agree” (5).

Perceived stress

Stress1: I felt stressed while completing this EHR assessment

Stress2: I felt nervous while completing this EHR assessment

Stress3: This EHR assessment made me feel stressed

Stress4: Completing this EHR assessment was stressful

EHR task performance

We measured EHR task performance based on a hands-on lab-based assessment that used EPIC electronic health record system to perform physician tasks. We conducted the assessment using Adobe Captivate.

EHR task efficiency

We measured EHR task efficiency as the reverse time it took a participant to complete the EHR task assessment.

Simulation EHR training

We measured simulation EHR training as a binary variable (1 = the treatment group who went through simulation EHR training and 0 = the control group who did not go through the simulation EHR training).

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