TECHNOSTRESS AND CONTRIBUTING FACTORS AMONG HOSPITAL NURSES

by

Krista Brandon

A Dissertation Submitted to the Faculty of the

COLLEGE OF NURSING

In Partial Fulfillment of the Requirements

For the Degree of

DOCTOR OF PHILOSOPHY

In the Graduate College

THE UNIVERSITY OF ARIZONA

2 0 2 4

THE UNIVERSITY OF ARIZONA
GRADUATE COLLEGE

As members of the Dissertation Committee, we certify that we have read the dissertation prepared by Krista Brandon, titled Technostress and Contributing Factors Among Hospital Nurses, and recommend that it be accepted as fulfilling the dissertation requirement for the Degree of Doctor of Philosophy.

Sheila Gephart
Date: Nov 17, 2024
Sheila M. Gephart, PhD, RN, FAAN

Kimberly D. Shea
Date: Nov 17, 2024
Kimberly D. Shea, PhD, RN, CHPN

Graciela Emillia Silva Torres (Nov 27, 2024 14:01 MST)
Date: Nov 27, 2024
Graciela E. Silva Torres, PhD, RN, MPH

Final approval and acceptance of this dissertation are contingent upon the candidate's submission of the final copies of the dissertation to the Graduate College.

I hereby certify that I have read this dissertation prepared under my direction and recommend that it be accepted as fulfilling the dissertation requirement.

Sheila Gephart
Date: Nov 17, 2024
Sheila M. Gephart, PhD, RN, FAAN
Dissertation Committee Chair
College of Nursing

ACKNOWLEDGMENTS

To all faculty, staff, and students at the University of Arizona's College of Nursing, thank you for your kindness and support throughout my PhD journey! I would like to express my deepest gratitude to my advisor, Dr. Sheila Gephart, who, despite my repeated attempts to sabotage my own research, remained remarkably supportive and optimistic. Her unwavering belief in my abilities (and willingness to put up with my catastrophizing) was truly inspiring. I would also like to express my deepest gratitude to my statistics professors, Dr. Janet Rothers, Dr. Graciela Silva, and Dr. Helena Morrison. Your ability to explain complex statistical concepts in a way that even I could understand was truly remarkable and gave me the confidence to complete this program. I am deeply grateful to Dr. Cheri Lacasse for her mentorship in developing my leadership skills in education. I would like to also express my sincere gratitude to Dr. Rina Fox and Dr. Jessica Rainbow for their mentorship, which has inspired me to explore the practical applications of mixed-methods research in future endeavors. I am also deeply grateful to Dr. Pamela Reed and Dr. Kimberly Shea for their exceptional ability to describe theoretical concepts, providing me with a lifelong framework for understanding the world. Big thanks to my PhD cohort and other peers for their support in keeping me sane and reminding me that I'm not alone in this journey. I also extend my deepest thanks to all the nurses who chose to participate in this study.

p.s. To anyone reading this acknowledgment section hoping to find their name: If you're not mentioned above, assume you fall under the "et al." of my gratitude. I'd list everyone, but let's be honest, this dissertation is long enough already!

LAND ACKNOWLEDGEMENT

We respectfully acknowledge the University of Arizona is on the land and territories of Indigenous peoples. Today, Arizona is home to 22 federally recognized tribes, with Tucson being home to the O'odham and the Yaqui. Committed to diversity and inclusion, the University strives to build sustainable relationships with sovereign Native Nations and Indigenous communities through education offerings, partnerships, and community service.

DEDICATION

Firstly, I dedicate this work to my family. To my mother, who first taught me the importance of education. To my incredible husband, whose love and encouragement have sustained me through every step of this process. To my son, who selflessly sacrificed some playtimes for my writing, and to my mother-in-law, who generously offered her time to care for him. Without you all, this would not have been possible.

I dedicate this work to those I have lost throughout my PhD journey, Dad, Sookie, Buddy, and Tasha. I love and miss you all.

I also dedicate this work to all the nurses who have touched my life, from my family to my colleagues, and to future nurses caring for me in the hospital and other settings. This dissertation is a tribute to your tireless work and a foundation for future research to make a positive impact on your professional lives.

TABLE OF CONTENTS

LIST OF FIGURES 10
LIST OF TABLES 11
ABSTRACT 12
CHAPTER 1: INTRODUCTION 14
Purpose 14
Background and Significance 14
Usability 15
Impact of Poor Electronic Health Record Usability 16
Documentation Burden 17
Documentation Burden and Nurses 17
Defining Documentation Burden 18
Technostress 19
Theoretical Perspective 19
Nursing Knowledge 20
Nursing Metaparadigm 20
Ontological Worldviews 20
Epistemological Worldview: Intemodernism 21
Emancipatory Knowing 22
Philosophical Integration: Informatics 23
Task-Technology-Fit Theory 23
Technology Acceptance Model 25
Extended Conceptual Model 26
Purpose, Specific Aims, and Research Questions 28
End of Chapter Summary 31
CHAPTER 2: LITERATURE REVIEW 32
Technostress Background 32
Search Strategy 36
Description of Studies on the Topic 37

TABLE OF CONTENTS – Continued

Physician Technostress 37
Nurse Technostress 41
Healthcare Worker Technostress 42
Evidence Synthesis 47
Limitations 49
End of Chapter Summary 49
CHAPTER 3: METHODS 50
Review of Aims and Research Questions 50
Design 53
Human Subjects Protection 54
Data Collection 54
Participants 54
Sample Size 55
Setting and Recruitment Approach 56
Questionnaire and Instruments 58
Demographic Characteristics 58
Usability 59
Cognitive Workload 60
Technostress 61
EHR Unintended Consequences 62
Procedures 63
Data Analysis Strategy 64
End of Chapter Summary 65
CHAPTER 4: RESULTS 66
Survey Screening 66
Potential Fraud Detection 67
Missing Data 68
Description of Sample 69

TABLE OF CONTENTS – Continued

Test of Data Normality 72
Results by Aim 72
Research Aim 1: Describe Technostress Among Hospital Nurses 73
Relationships Between Technostress and Technostress Inhibitors 74
Research Aim 2: Explore Relationships Between Technostress and Work Experience 76
Relationships Between Technostress and Hospital Characteristics 76
Relationships Between Technostress and Current Work Characteristics 77
Relationships Between Technostress and Cumulative Work Experience 79
Research Aim 3: Explore Relationships Between Technostress, EHR Factors, and Workload 80
Relationships Between Technostress and EHR Usability 80
Relationships Between Technostress and Cognitive Workload 81
Relationships Between Technostress and EHR Unintended Consequences (EHR-UC) 82
Overall Model of Factors Associated with Technostress 85
Summary of Results 87
End of Chapter Summary 90
CHAPTER 5: DISCUSSION 91
Restating Study Main Findings 91
Aim 1: Technostress and Inhibitors 91
Aim 2: Technostress and Work Factors 93
Aim 3: Technostress and Technology Factors 94
Overall Interpretation of Results 96
Study Strengths 98
Study Limitations 99
Implications for Practice 100
Implications for Research 102

TABLE OF CONTENTS – Continued

Conclusion 103
APPENDIX A THE UNIVERSITY OF ARIZONA INSTITUTIONAL REVIEW BOARD APPROVAL LETTER.....104
APPENDIX B RESEARCH DISCLOSURE FORM.....107
APPENDIX C RECRUITMENT MATERIALS 110
APPENDIX D INSTRUMENTS AND MEASURES.....114
REFERENCES 125

LIST OF FIGURES

Figure 1 *Task-Technology-Fit Theory*.....25
Figure 2 *Technology Acceptance Model*.....26
Figure 3 *Conceptual Model*.....27
Figure 4 *Participant Flow Chart (n=153)*.....66

LIST OF TABLES

Table 1 *Summary of Missing Data* 68
Table 2 *Participant Demographics (Gender, Highest Level of Education)* 69
Table 3 *Participant Demographics (Age, Years Employed as a Nurse, Years Using EHRs)* 69
Table 4 *Participant Current Work Demographics* 71
Table 5 *Participants' Mean Technostress Creators and Inhibitors* 73
Table 6 *Relationships Between Technostress and Techno-Inhibitors (Correlation)* 74
Table 7 *Linear Regression Predicting Technostress by Techno-Inhibitors* 76
Table 8 *One-Way Analysis of Variance Between Technostress and Hospital Characteristics* 77
Table 9 *One-Way Analysis of Variance Between Technostress and Current Work Characteristics* 78
Table 10 *Relationships Between Technostress and Current Work Characteristics (Correlation)* 79
Table 11 *Relationships Between Technostress and Cumulative Work Experience (Correlation)* 79
Table 12 *Linear Regression Predicting Technostress by EHR Usability* 80
Table 13 *Summary Statistics for Cognitive Workload* 81
Table 14 *Relationships Between Technostress and Cognitive Workload* 82
Table 15 *Summary Statistics for Unintended Consequences of Electronic Health Records* ... 83
Table 16 *Relationships Between Technostress and EHR Unintended Consequences (Correlation)* 84
Table 17 *Multiple Regression Predicting Technostress by EHR Unintended Consequences* . 85
Table 18 *Full Model: Stepwise Linear Regression Predicting Technostress by Candidate Variables* 86
Table 19 *Final Model: Stepwise Linear Regression Predicting Technostress by Candidate Variables* 86

ABSTRACT

Background: Technostress poses a significant challenge to the nursing profession, with far-reaching implications for nurses' health, well-being, and patient care. Despite this, little is known about technostress among hospital nurses working in the United States (US).

Purpose/Aims: The purpose of this study was to examine technostress among hospital nurses and its relationships with hospital characteristics (magnet status, type of EHR used, and if the location is a teaching hospital), current work characteristics (hospital department, weekly hours worked, frequency of floating departments, and years of experience at current hospital), cumulative work experience (years of experience as a nurse and years of experience using EHRs), EHR usability, cognitive workload, and EHR unintended consequences (EHR-UC).

Methods: This study used a cross-sectional descriptive design. Participants (n=153) were recruited online via social media and recruitment platforms over a period of 10 weeks. Data were collected using an online Qualtrics survey containing a demographic questionnaire and validated instruments to measure technostress, EHR usability, cognitive workload, and EHR-UC. Data analysis was conducted in Stata 16.1 using one-way analysis of variance, Spearman correlations, and multiple linear regression.

Findings: The average level of overall technostress was moderate (M= 2.54; SD = 0.61), on a scale of 1 to 5. Only one technostress inhibitor (technical support provision) showed a significant, small negative correlation with technostress, r (153) = -.21, p = .01. The frequency of floating between departments was the only work characteristic significantly associated with technostress (F= 3.41, p= .04). No significant relationships were found between technostress and other hospital characteristics or cumulative work experience. Significant predictors of

technostress included EHR usability, cognitive workload, and EHR-UC. The final regression model showed that EHR usability, cognitive workload, and EHR-UC collectively explained 41% of the variance in technostress, F (3,128) = 31.84, p <.001, Adjusted R^2=0.41.

Conclusions/Implications: These findings highlight the complex relationships between technostress and various organizational and technological factors in hospital environments. By understanding the factors contributing to technostress and implementing strategies to mitigate its effects, nursing organizations and individuals can create healthier and more supportive work environments for nurses. Future research is needed to explore this important issue.

CHAPTER 1: INTRODUCTION

Purpose

Over 20 years have passed since electronic health records (EHRs) began their widespread adoption, and promised benefits have not been fully realized (Bates & Singh, 2018; Tsai et al., 2020). Issues with EHR usability and an increasing amount of documentation demands have negatively impacted clinician well-being, leading to moral distress, burnout, poor work satisfaction, and issues with communication, safety, inefficiency, and quality of care (McBride et al., 2023). Despite an increase in research surrounding clinician experiences with EHRs, there is still a lack of attention to registered nurses, particularly nurses' perspectives regarding EHR use and workplace experiences (Melnick et al., 2020; Wu et al., 2021) and the unintended consequences of using EHR technology (Harmon et al., 2023). This dissertation aimed to examine the unintended consequences of EHR use among nurses working in hospitals, with particular attention to technology-related stress and ongoing usability concerns. This chapter will describe the background and significance of poor EHR user experience, describe this dissertation's theoretical underpinnings, and state the specific aims of this dissertation.

Background and Significance

In 1999, The Institute of Medicine (IOM; currently known as the National Academy of Medicine) released a landmark report, *To Err is Human: Building a Safer Health System* (IOM, 2000). The report stated that medical errors (often preventable) were a top problem in the United States healthcare system and offered insights on error prevention and mitigation to promote patient safety. In the past 20 years, many solutions have been developed to improve patient safety using technology, such as electronic health records (EHRs), clinical decision support

systems, and barcoding of patient medications. However, EHRs also brought new issues affecting patient safety, including problems with usability (Bates & Singh, 2018). For nurses specifically, some unintended consequences of EHR use include frequent changes to workflow and difficulty accessing relevant patient information (Gephart et al., 2015). Such issues have made the EHR a large source of stress and burnout for hospital clinicians (Alobayli et al., 2023). The following sections will discuss several factors influencing the user experience of the EHR, including usability, documentation burden, and technostress.

Usability

Various definitions of *usability* are used in healthcare literature, along with several important related concepts. The International Organization for Standardization (ISO; 2018) defines usability as how well a system achieves specific goals with efficiency (level of resources needed to perform a task), effectiveness (the ability of the user to complete a task and the quality of the task's output), and satisfaction in the context of a user's needs. Human-computer interaction researcher Jakob Nielsen (2012) defines a product's usefulness by two equally important concepts: how easy the product is to use (usability) and if the product provides features needed by its users (utility). Nielsen's concept of usability is further described by five aspects: learnability (ease of accomplishing tasks the first time a user encounters the product), efficiency (how quickly experienced users can perform tasks using the product), memorability (ease of reestablishing proficiency after a period of time not using a product), errors (how many errors a user makes while using the product, including severity and how they recover from errors), and satisfaction (how pleasant the product's design is to users). A conceptual analysis by Shultz and Hand (2015) analyzed these usability definitions, among others, in the context of

nursing informatics and suggested usability be defined as “the degree to which the user perceives acceptable learnability, efficiency, and satisfaction when using the technology” (p. 66).

Impact of Poor Electronic Health Record Usability

Poor EHR usability is a significant issue in healthcare (National Academies of Science, Engineering, and Medicine, 2019; Office of the Surgeon General, 2022) and has been linked to clinician burnout (Harris et al., 2018; Kroth et al., 2019; Melnick et al., 2020, Shanafelt et al., 2016), higher odds of inpatient mortality (Kutney-Lee et al., 2021), and errors leading to patient harm (Howe et al., 2018; Kim et al., 2017; Ratwani et al., 2018). These implications are associated with higher strains on healthcare systems, including billions of dollars lost to nursing burnout (Office of the Surgeon General, 2022) and medical errors (Rodziewicz et al., 2022).

In addition to improving usability, there is an overwhelming demand by clinicians to decrease the cognitive demand for EHRs. Common issues threatening cognitive work in the EHR include information overload, ambiguity, and complexity (Koon, 2021). For example, data in the EHR is often displayed overwhelmingly, making it harder to find relevant information (Colicchio et al., 2019). Data fragmentation places a high cognitive demand on clinicians and can lead to errors (Roman et al., 2017). Increasing EHR data complexity and documentation responsibilities have resulted in unique challenges in healthcare. Recent studies have indicated that this documentation burden is a contributing factor to clinician burnout (Alexander & Staggers, 2009; Dyrbye et al., 2020) and a drastic need for additional research and interventions to reduce EHR documentation burden for clinicians (Koon, 2021; Nguyen et al., 2021a; Nguyen et al., 2021b; Yan et al., 2021).

Documentation Burden

Several other issues, such as documentation burden, contribute to poor user experience with work-related technology. *Documentation burden*, or a feeling of being overwhelmed by documentation expectations, has been identified as a problem in the nursing profession since before widespread electronic health record (EHR) implementation (Congdon & Magilvy, 1995), and early studies showed promise that switching from paper documentation to EHRs may save nurses time (Minda & Brundage, 1994). However, documentation burden remains an understudied concept in nursing, with most research focused on physicians and advanced practice providers (Gesner et al., 2022; McBride et al., 2023).

Documentation Burden and Nurses

While much of the literature focuses on the overwhelming burden physicians face with EHR documentation, it does not focus nearly enough on nurses' unique challenges. Nurses use a variety of ways to document patient care in the EHR, and physicians do not routinely use some of those functions. Functions routinely used by nurses in the EHR include patient problem lists and demographics, ordering, notes, test result access, decision support, communication, and patient support materials (DesRoches et al., 2008). Nurses also use assessment flowsheets in the EHR to document patient care in hospitals. A recent workflow redesign study (Lindsay & Lytle, 2022) showed that nurses ranked flowsheet optimization as their biggest need for EHR optimization.

Researchers have attempted to quantify how much time nurses spend documenting in the EHR, finding that 19 - 41% of nurses’ time is spent documenting care overall (Hendrich et al., 2008; Higgins et al., 2017; Momenipour et al., 2019; O’Brien et al., 2015; Perpetua et al., 2023;

Schenk et al., 2017; Tan et al., 2019; Westbrook et al., 2011; Yee et al., 2012; Yen et al., 2018). During a typical 12-hour shift, ICU nurses manually document 633-689 flowsheet entries, and acute care nurses document an average of 631-875 entries (Collins et al., 2018).

Qualitative inquiry has provided additional perspectives on how nurses view the current state of care documentation. Bøgeskov and Grimshaw-Aagaard (2018) found nurses in Denmark were torn between viewing their documentation work as either essential or a meaningless burden that distracts from real patient care. In another study in Tehran, all participants stated that documentation was one of the biggest obstacles to being present with the patient (Atashzadeh-Shoorideh et al., 2021). Viewing the EHR as an obstacle or entity that distracts from "real" patient care seems to be an international phenomenon and may be one aspect of documentation burden. However, this is difficult to ascertain since there is still no consensus on how to best define documentation burden.

Defining Documentation Burden

There is still no consensus on how to best define the documentation burden in the healthcare space. This paper previously used the definition of "feeling of being overwhelmed by documentation expectations", but the phenomenon includes more than subjective elements, such as increased effort and time spent documenting in the EHR (Moy et al., 2021a). Future research should explore this, including a thorough concept analysis of the term, similar to past work, to develop a comprehensive understanding of the nursing workload (Alghamdi, 2016; Swiger et al., 2016). This work could help distinguish documentation burden from other phenomena, such as technostress (Bondanini et al., 2020) and information overload (Hall & Walton, 2004). This could also further investigate how documentation burden links conceptually to usability,

situational awareness (Savoy et al., 2023), data fragmentation (Moy et al., 2021b; Roman et al., 2017), and mental and cognitive workload (Colligan et al., 2015; Dias et al., 2018; Galy et al., 2012; Kremer et al., 2019; Young et al., 2015). Additionally, experiences of documentation burden should be explored in settings other than the hospital, such as community health (De Groot et al., 2022), for a more holistic understanding of the phenomenon. Additional research into documentation burden could also contribute to the development of tools to measure the phenomenon among nurses, such as the Burden of Documentation for Nurses and Midwives (BurDoNsaM) survey, developed by Brown and colleagues (2020) to measure documentation burden among nurses and midwives formally. To date, this survey has only been used in one pre-post intervention study (Cooper et al., 2023).

Technostress

The concept of *technostress* can be used to further examine the stress that can result from workplace technology and may uncover additional knowledge regarding clinicians and EHR use. Technostress can be defined as "stress that individuals experience due to their use of information systems" (p.6; Tarafdar et al., 2019). Chapter 2 of this dissertation will discuss technostress in more detail.

Theoretical Perspective

Nursing theories play a critical role in aligning philosophy and practice, serving as a foundation for inquiry (Butts & Rich, 2018). Nursing is a diverse practice encompassing various cultures, lifespans, settings, and beliefs. To best support this practice, nurses can adopt a perspective that allows for multiple worldviews, theories, and pragmatic strategies. This section will describe important guiding frameworks underlying this dissertation.

Nursing Knowledge

Nursing knowledge can be broadly categorized into three categories: the metaparadigm, worldviews, and theories. The nursing metaparadigm, the broadest category, is an overall representation of the meaning of nursing science and practice (ontology); worldviews further explain nursing practice or the nature of knowledge; and theories clarify and translate these ideas into pragmatic tools for practice and research (Reed, 2020a). These items shape and support the discipline of nursing. The following subsections describe philosophical perspectives that shape my worldview of human health and nursing informatics.

Nursing Metaparadigm

The nursing metaparadigm represents the identity of nursing using four elements: human beings, environment, health, and nursing practice (Butts & Rich, 2018). These elements can be made relevant to any nursing practice, specialty, or venue. When examining the metaparadigm from a nurse informaticist's perspective, technology can serve as an environment and other elements as subsystems that continuously interact and influence each other. This is a helpful construct to examine how health can be influenced by the technological environment and how nurse informaticists can enhance health using technology. Nurse informaticists can use the metaparadigm to not only guide inquiry, but also to ensure the use of technology does not undermine fundamental nursing values (Francis, 2017).

Ontological Worldviews

A worldview is a set of beliefs that conceptualize how one views reality, the world, and life (Reed, 2020a). Worldviews ground our assumptions and can help us understand differing viewpoints. Ontological worldviews further explain nursing science and practice (Reed, 2020a).

The complex nursing practice involves a continuous and interdependent relationship between nurses, patients, and their environments to realize individual health outcomes fully. Several worldviews support the idea of continuous change through dynamic relationships between humans and the environment, including philosopher Stephen Pepper's (1948) contextual-developmental worldview, nurse theorist Margaret Newman's (1992) unitary transformative worldview, nurse theorist Rosemarie Parse's (1987) simultaneity paradigm, and nurse theorist Jacqueline Fawcett's (1993) simultaneous action worldview. These four ontological worldviews offer unique but congruent perspectives (Reed, 2020a) that shaped this author's worldview and contributed as a foundation to this dissertation.

Epistemological Worldview: Intermodernism

A contemporary philosophical perspective, intermodernism, offers a balanced epistemological worldview of modern and post-modern concepts relevant to the nursing profession. The intermodern perspective supports the dual nature of nursing as a science and a profession, with emphasis on both modern science's epistemic, empirical values and non-epistemic values (Reed, 2019). Including non-epistemic values (such as moral, social, political, emotional, or cultural) in science is now generally considered good practice, although there is often debate surrounding the classification and definitions of these values (Reydon & Ereshefsky, 2022). The intermodernism view emphasizes the importance of critical thinking and an awareness of factors that influence one's reality, such as social, biological, cultural, and cognitive understandings (Reed, 2020b).

The practice of nursing, where knowledge and experience work in tandem, can operate in a philosophical middle ground that includes multiple diverse viewpoints; this approach could

help prevent harmful binary or exclusionary thinking (Sakamoto, 2018). This section has discussed how the nursing metaparadigm and specific worldviews (ontological and epistemological) have provided a philosophical foundation for this dissertation. This philosophy supports a holistic view of nursing that includes an individual's needs, empirical scientific findings, and other influences, such as social, cultural, or political elements that may impact health.

Emancipatory Knowing

Several theories and models can serve as lenses to illuminate or expand upon non-epistemic elements mentioned in intermodernism. *Critical theory* offers a lens to reveal hidden oppressions and offers a philosophical framework that includes instrumental, practical, and emancipatory methods of reasoning; some key practices of critical theory include self-reflection, deconstruction, and critique of social structures and power relations that can oppress humankind (Reed & Shearer, 2017). As one builds their philosophy of practice, it is equally important to deconstruct perspectives to develop a more inclusive philosophy to enhance care for an increasingly diverse society.

In 1978, nursing scholar Barbara Carper developed four distinct but related *patterns of knowing* to describe nursing knowledge development: empirical (science of nursing), aesthetic (art of nursing), personal (knowledge and actualization of oneself), and ethical (moral knowledge). In 2008, a fifth pattern was added by Drs. Peggy Chinn and Maeona Kramer to represent emancipatory knowing (Chinn et al., 2022). *Emancipatory knowing* in nursing is philosophically inspired by critical social theory and includes both knowing (epistemological) and doing (ontological) dimensions of nursing practice (Butts & Rich, 2018). Awareness of the

nature of nursing knowledge can serve as a blueprint for conceptualizing or rethinking problems faced in the nursing profession. For example, a common issue in the informatics field is poor electronic health record (EHR) usability, where nurses describe they are overwhelmed and confused by the EHR's user interface and how information is displayed. This issue is certainly impacted by all patterns of knowing, including emancipatory, ethics, personal, aesthetics, and empirics. To fully appreciate this issue from a nursing perspective, all dimensions can be critically and creatively pondered, leading to actions and then practice integration (Chinn et al., 2022). Reflective action, informed by emancipatory knowing, is one way to achieve nursing praxis, bridging the gap between theory and practice. This can lead us closer to realizing health equity and social justice (Peart & MacKinnon, 2018).

Philosophical Integration: Informatics

Philosophical views inform a researcher's choice of mid-range theories, and research models. In nursing informatics, one overall goal is to improve health using technology. The following sections will describe some technology-related theories and how they were used to develop this dissertation's conceptual model.

Task-Technology-Fit Theory

Middle-range theory can be characterized as a set of related ideas that are focused on a limited view of practice, with ideas applicable to nursing, using models to describe relationships among concepts (Smith & Liehr, 2018). Middle-range theories are much narrower in scope than grand theories and can offer more specific guidance for research by including empirically measurable variables. A recent scoping view identified eight nursing theories related to digital nursing practice in the current research, but most theories had little to no empirical evidence

supporting them (Wynn et al., 2023). Theories from other disciplines can inform the development of nursing middle range theory, but only if their groundwork is congruent with the nursing discipline and nursing perspectives are clearly articulated in the new model (Liehr & Smith, 2017). Simply borrowing theories from other disciplines, without modifications to address the unique perspectives of the nursing profession, can be detrimental to nursing practice. Nursing theory-guided practice enables nurses to fully articulate their unique work contributions (Younas & Quennell, 2019). This is especially important in nursing informatics research, where theory is commonly borrowed without revisions or not included at all (Iduye, 2023). To support this dissertation, middle-range theories and related concepts were selected that were conceptually congruent to the theoretical foundations described previously.

The task-technology-fit (TTF) theory was developed by Goodhue and Thompson (1995) to describe technology use by examining how key factors (task, technology, and individual user characteristics) influence the success of technology fit into practice and, ultimately, user performance. In other words, when technology accurately fits the task characteristics it aims to support, users should report improved performance. A major assumption of TTF is that technology use can lead to improved performance only if the technology matches the individual's specific task requirements. Figure 1 displays the key concepts and relationships outlined in TTF. Goodhue and Thompson (1995) proposed three assumptions of TTF: (1) individual perceptions of TTF are affected by both task and technology characteristics, (2) individual perceptions of TTF influence their utilization of technology systems, and (3) individual perceptions of TTF will predict perceived performance impacts, beyond what utilization can predict alone. The TTF is a useful model to outline specific characteristics that

shape a user's experience with technology, particularly in the context of their work. However, another model was also chosen for this dissertation that illustrates additional usability concepts.

Figure 1

Task-Technology-Fit Theory

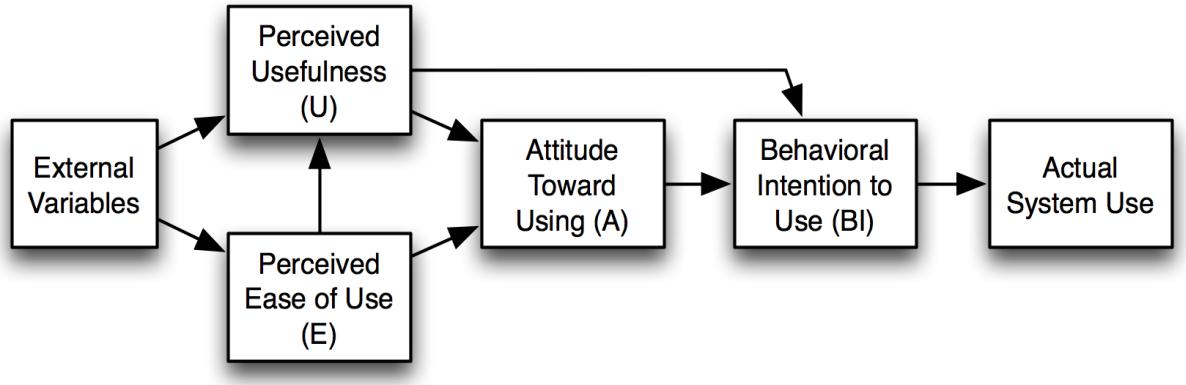
(Adapted from Goodhue and Thompson, 1995)

Technology Acceptance Model

The technology acceptance model (TAM; Davis, 1986) posits that acceptance of technological products relies on a user's perceptions of several variables, including perceived usefulness (how well the system enhances job performance), perceived ease of use (how easy the system is to use), a user's attitude towards using the technology (positive or negative), and a user's behavioral intention to use the technology (if they actually use the system). Figure 2 shows the original TAM, as envisioned by Davis (1986).

Figure 2

Technology Acceptance Model



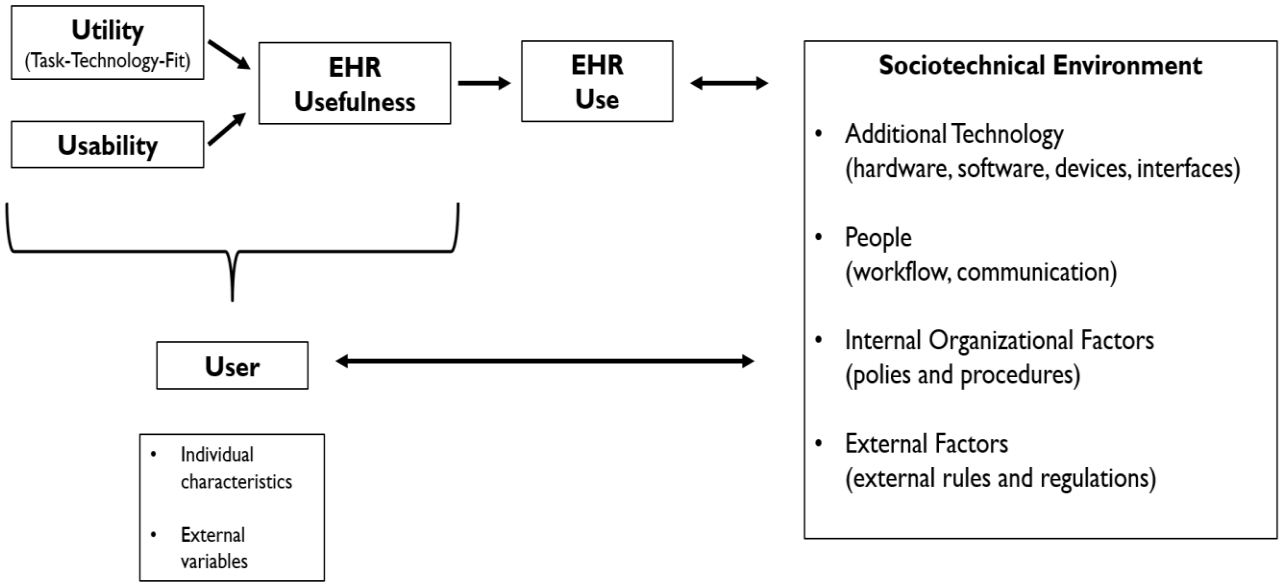
(Adapted from Davis, 1986)

Extended Conceptual Model

Both TTF and TAM models are widely used in informatics research, and both models contribute unique perspectives on potential variables influencing technology use. For this dissertation, both models were integrated into a conceptual framework to guide research from a usability perspective. One popular definition of *usability* was coined by Jakob Nielsen (2012), who posited that a product's usefulness was determined by two equally important concepts: how easy the product is to use (usability) and if the product provides features needed by its users (utility). The TTF provides insight into how well the technology fits into an individual's work and if it provides features needed by its users (utility), according to characteristics of the work task, the technology, and its users. The TAM illustrates how other elements impacting usability (perceived usefulness and perceived ease of use) can influence one's technology use. Figure 3 shows an extension of these concepts into a new model used for this dissertation.

Figure 3

Conceptual Model



In this model, the task-technology-fit of the EHR is described as its *utility*, and the EHR's ease of use is described as its *usability*. Together, utility and usability contribute to the EHR's *usefulness* and inform the overall *use* of the EHR. However, EHR technology use is also informed by its sociotechnical environment, including additional technologies, people, and internal/external organizational factors. Sociotechnical systems theory (STS) addresses the complexity of human and technology coexistence (McBride & Tietze, 2019) and emphasizes interactions between people, tools, and technologies with the optimization of safety, worker satisfaction, and productivity (Waterson et al., 2015). STS was used as the foundation for Sittig and Singh's (2010) eight-dimensional model for healthcare technology. The eight-dimensional model is a framework to analyze and evaluate health information technology interventions in the context of eight dimensions: hardware/software, clinical content, human-computer interface,

people, workflow/communication, organizational policies/procedures, external factors, and system measurement/monitoring. These concepts contributed to the *Sociotechnical Environment* section of this conceptual model. This model also shows the relationship between EHR use and its sociotechnical environment is bidirectional, with both having the potential to influence each other.

This dissertation's conceptual model also addresses the user individually. A user's perceptions and experiences define the EHR's utility, usability, and usefulness, which contributes to the EHR's overall use. For example, an EHR's utility and usability can vary dramatically from user to user within an organization, depending on individual characteristics such as their role, experience, and level of EHR training. This model also shows the bidirectional relationship between the user and their sociotechnical environment, both having the potential to influence each other.

Purpose, Specific Aims, and Research Questions

This dissertation aimed to examine the unintended consequences of EHR use among nurses working in hospital environments, with particular attention to technology-related stress and ongoing EHR usability concerns. Since little is known about nurses and technostress, this dissertation aimed to describe technostress among the sample of working hospital nurses and identify factors significantly related to technostress. Knowledge from this study can guide future research efforts, including optimization efforts to decrease technostress among hospital nurses. The specific aims of this dissertation, along with associated research questions, are discussed below. An in-depth discussion of measures and variables will be covered in Chapter 3.

1. Aim 1: Describe technostress among nurses working in hospital environments across the United States

   Associated research questions:

   a. Among the sample of hospital nurses, what is the average level of overall technostress?
   b. Among the sample of hospital nurses, what are the average levels of technostress creators (techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty)?
   c. Among the sample of hospital nurses, what are the average levels of technostress inhibitors (literacy facilitation, technical support provision, and involvement facilitation)?
   d. Among the sample of hospital nurses, what are the average organizational outcomes related to technostress, including job satisfaction, organizational commitment, and continuance commitment?

2. Aim 2: Explore relationships between nurses' technostress, hospital characteristics (magnet status, type of EHR used, and if the location is a teaching hospital), current work characteristics (hospital department, weekly hours worked, frequency of floating departments, and years of experience at current hospital), and cumulative work experience (years of experience as a nurse and years of experience using EHRs)

   Associated research questions:

   a. Are there significant relationships between nurses' technostress and hospital characteristics (magnet status, type of EHR used, and if the location is a teaching hospital)?
   b. Are there significant relationships between nurses' technostress and current work characteristics (hospital department, weekly hours worked, frequency of floating departments, and years of experience at the current hospital)?
   c. Are there significant relationships between nurses' technostress and cumulative work experience (years of experience as a nurse and years of experience using EHRs)?

3. Aim 3: Explore relationships between technostress, EHR usability, cognitive workload, and EHR unintended consequences (workload issues, patient safety, sociotechnical impact, workarounds, system design, technological barriers)

   Associated research questions:

   a. Are there significant relationships between nurses' technostress and EHR usability?
   b. Are there significant relationships between nurses' technostress and cognitive workload?
   c. Are there significant relationships between nurses' technostress and unintended EHR consequences (workload issues, patient safety, sociotechnical impact, workarounds, system design, technological barriers)?

End of Chapter Summary

To summarize the previous sections, some major unintended consequences of EHR use have persisted since the technology was implemented decades ago. Such issues include problems with EHR usability that can overwhelm clinicians, leading to a high cognitive demand, documentation burden, information overload, data fragmentation, ambiguity, and complexity. These issues are linked to stress and burnout among clinicians, along with negative outcomes for patients. Technostress, a concept relatively new to healthcare, was used to measure technology-related stress that occurs with clinicians using EHRs and other workplace technology. Obtaining a wider understanding of technostress and its related factors can potentially improve not only EHR technology but also the sociotechnical environment supporting workplace technology. The next chapter will discuss technostress in more detail.

CHAPTER 2: LITERATURE REVIEW

As discussed in the first chapter, there have been large efforts over the years to investigate the negative unintended consequences of EHR use. A recent systematic review (Alobayli et al., 2023) investigated associations between EHR use and clinician stress and found that the largest contributors were poor usability and time spent documenting in the EHR. However, little is known about the overall state of technology-related stress among healthcare workers, which is often measured as *technostress* in other fields. This chapter provides an overview of current literature relating to technostress and research done in the healthcare space.

Technostress Background

.The term technostress was first introduced in a 1984 book. Silicon Valley industrial psychologist Craig Brod used the term to describe an evolving phenomenon he witnessed with some of his patients. He described technostress as "a modern disease of adaptation caused by an inability to cope with the new computer technologies in a healthy manner" (p.16). Brod posited that the stress of adopting new computer technology can lead to negative consequences based on one's underlying personality traits and relationship with technology. People afraid of computers exhibited symptoms of technoanxiety, such as fatigue, headaches, irritability, and other cognitive and physical symptoms. The technoanxious were resistant to learning about computers and adopting new technology. Interestingly, one of Brod's technoanxious examples was an intensive-care unit nurse, Janice, struggling with adopting a new computerized system for documentation. She reported wanting to avoid using the computer at work and having nightmares of a machine swallowing her whole. At the other end of the spectrum, some were described by Brod as technocentered, or highly motivated individuals eager to adopt computer technology and even

mirror its characteristics. Brod described highly technocentered individuals as having increased perfectionistic tendencies, difficulty relating to others empathetically, and loss of creativity. Brod's book had mixed reviews. Some reviewers agreed that technostress was an interesting phenomenon that needed more research, but the book lacked supporting evidence outside of anecdotal stories and lacked acknowledgment of the complex social context of computer use (Meehan, 1985; Roth, 1986).

Now, some 40 years after the release of Brod's book, this phenomenon has evolved with scholarly pursuits to measure and report technostress in the workplace. Stress from ever-evolving technology can lead to negative outcomes for people in an organization, such as decreased work satisfaction (Tarafdar et al., 2007). This type of stress is typically observed in employees heavily dependent on computers for their work, with cognitive symptoms including mental fatigue, headache, restlessness, irritation, moodiness, and difficulty concentrating (Arnetz & Wiholm, 1997).

In their seminal work, Ragu-Nathan and colleagues (2008) developed a conceptual framework of technostress and an empirically validated instrument to measure technostress creators and inhibitors. While there were other models of organizational stress at that time, authors felt that no existing model fully addressed the expanding role of information and communication technologies (ICTs) in the workplace. This technostress model was rooted in sociotechnical systems theory (STS; Tarafdar et al., 2007), the transaction-based model of stress and coping (TSC; Lazarus, 1966; Lazarus and Folkman, 1984) and organizational stress research that followed (Cooper et al., 2001). TSC proposed that a person's ability to cope with stress depends on how the stressor is perceived, either as a threat (potential harm) or a challenge

(positive growth). One's level of resources influences whether one perceives a stressor as a challenge or a threat, and unmanageable stressors result in *strain* or distress (Cooper et al., 2001). For example, nurses may see a major technology implementation as a *challenge* or potential for positive growth if they feel they have adequate support staff to answer questions, help with workflow, or assist with patient care while they learn the new technology. Nurses may instead view a new technology as a *threat* if they feel support is inadequate. How nurses cope with this technology depends on how it is perceived (challenge or threat).

Based on TSC and STS concepts, Ragu-Nathan and colleagues (2008) described technostress as "stress experienced by end users in organizations as a result of their use of ICTs" (p. 417-418) and defined conditions that create technostress as *stressors*. These stressors were categorized as technostress creators and organized into five categories:

- *Techno-overload*, in which the technology forces users to work longer and faster
- *Techno-invasion*, in which users feel constantly connected to the technology, disrupting boundaries between work and personal life
- *Techno-complexity*, in which the technology demands increased time and effort from users to understand how to use ICTs
- *Techno-insecurity*, in which users feel threatened about losing their jobs from either automation or people with better knowledge of ICTs
- *Techno-uncertainty*, in which the fast-paced evolution of technology requires continuous changes, requiring users to constantly re-learn ICT functionality and processes

Technostressors can be measured using the Technostress Creators Inventory (TCI; Ragu-Nathan et al., 2008) alone, or with the full Technostress Questionnaire, which includes technostress

creators, technostress inhibitors, and outcomes (job satisfaction, organizational commitment, and continuance commitment). *Technostress inhibitors* are described as organizational factors that reduce technology-related stress. These factors include literacy facilitation (ICT knowledge-sharing processes across the organization), technical support provision (end-user help desk activities supporting ICT functionality and processes), and involvement facilitation (organizational methods that encourage adoption of new ICT, including involvement of end-users). Outcomes in the model include job satisfaction, organizational commitment (user's commitment to the organization), and continuance commitment (user's intention to remain at their current job). Individual differences (age, gender, education, computer confidence) were also explored.

Authors used a variety of methods to test the reliability and validity of all eleven constructs (techno-overload, techno-invasion, techno-uncertainty, techno-insecurity, techno-complexity, literacy facilitation, technical support provision, involvement facilitation, job satisfaction, organizational commitment, and continuance commitment) and their relationships with three outcomes (job satisfaction, organizational commitment, and continuance commitment. Cronbach's alpha values for all eleven constructs ranged from 0.91 to 0.71, demonstrating acceptable construct reliability. The authors also ran first-order correlated measurement models to affirm discriminant and convergent validities. They found no significant error correlations among any items, and values of model-fit indices all exceeded recommended values. Structural equation modeling (SEM) analysis results showed satisfactory fit. Results indicated that technostress creators decreased job satisfaction, and technostress inhibitors increased job satisfaction and both organizational and continuance commitment.

The TCI portion of the technostress questionnaire is one of the most commonly used self-assessment measurements in technostress research across various industries (Marsh et al., 2022). This technostress model and questionnaire could help provide valuable insights into EHR documentation research in the post-EHR implementation world. The complex sociotechnical ecosystem of an organization involves not only EHRs but also people, processes, and technologies working together and influencing how work is done. It is unknown how much technostress research has been performed in the healthcare space. As part of this dissertation, a literature review was performed to examine the prevalence of technostress in healthcare literature and review how it is commonly measured in healthcare research.

Search Strategy

A literature search was performed in the National Library of Medicine's MEDLINE-PubMed and CINAHL databases to answer the following clinical questions: What is the state of the science regarding technostress among clinicians working in hospital and/or clinic environments? How is technostress measured in these studies? The key term used for the search was “technostress”, and the search was limited to the English language and peer-reviewed articles from the past 20 years (2004-2024), up until March 10, 2024. Articles were eligible for inclusion if they discussed technostress among healthcare workers in hospital or clinic settings, including physicians and nurses. All articles were screened by title and abstract. Articles that did not have healthcare workers as the main population were excluded. Articles that only included telework or remote work were excluded, as this review focused on healthcare workers from clinic or hospital environments. The initial search resulted in 184 articles. After removing duplicate and irrelevant studies, 20 relevant papers were identified.

Description of Studies on the Topic

Technostress is a relatively new term in healthcare. Despite this literature search from 2004, most articles included in this review (18 of 20) were published in 2020 or later. Of the 20 articles, nine were physician-focused, four were nursing-focused, and seven included multiple healthcare professions (physicians, nurses, and others). The following sections describe each article in more detail about technostress.

Physician Technostress

Most of the studies reviewed and examined physician experiences with technostress. Attipoe and colleagues (2023) used the technostress model (Tarafdar et al., 2019) to shape their qualitative inquiry - a thematic analysis of semi structured physician interviews regarding their experiences with using the EHR outside clinic work hours. Their research included both positives and negatives of EHR use outside work hours. Positives included flexibility with work-life balance and improvements in their documentation quality. Negatives included increased documentation burden and working more outside work hours on the EHR. Most physicians discussed positive coping mechanisms for their EHR-related stress, including setting clear boundaries for their work-life balance. These physicians voiced that improvements to EHR usability are needed, and technology updates can contribute to their stress.

Bahr et al. (2023) surveyed 403 physicians across a variety of settings and specialties in Canada, using the Maslach burnout inventory (MBI) and the physician technology usage scale (PTUS) to examine if work-related technology use outside of work hours contributed to burnout. Authors discovered that technology use outside of working hours was significantly associated with physician burnout (r = 0.212, 95% CI [0.116,0.303], p <.01). Interestingly, the number of

years in practice was negatively correlated with technology use and burnout levels, and authors stated that more research is needed to explain this relationship.

Bail et al. (2023) examined the relationships between technostress, burnout, work engagement, and job satisfaction among 116 German urology physicians and found technostress was significantly positively associated with burnout ($\beta = 0.293$; $p < 0.001$) and negatively associated with work engagement ($\beta = -0.175$; $p < 0.001$) and job satisfaction ($\beta = -0.206$; $p < 0.001$). ICT advantages and disadvantages were also well-described from their analysis of free-text survey questions and coping strategies for dealing with technostress. Physicians in this study reported moderate levels of technostress overall ($M = 2.67$, $SD = 0.69$). The authors also found that physicians' reported levels for techno-complexity and techno-uncertainty were lower than scores from other industries.

Bernburg et al. (2024) surveyed 204 physicians working in German emergency medicine departments to examine relationships between technostress creators, technostress inhibitors, job satisfaction, and work engagement. Physicians in this study reported medium levels of technostress overall ($M = 3.18$, $SD = 0.69$), medium levels of exhaustion symptoms, and high levels of work engagement and job satisfaction. Of the three technostress categories studied (techno-overload, techno-complexity, and techno-uncertainty), techno-overload had the highest mean ($M = 3.52$, $SD = 0.81$). More than half of physicians reported frequent stress associated with double documentation tasks. A low to moderate level of technostress inhibitors (or positive resources) was reported ($M = 2.71$, $SD = 0.82$). The authors also found that low levels of EHR technology acceptance were significantly associated with higher levels of technostress, with

moderately negative correlations for both perceived usefulness (r = -0.347; p=.01) and perceived ease of use (r = -0.473; p=.01).

Deng et al. (2023) used a mixed methods design to identify and measure factors influencing medical practitioners' intention to use Internet hospitals in China. Authors defined an internet hospital as "a wide range of portals, applications, or platforms that extend beyond traditional web-based health, mobile health, or telemedicine services" (p. 2), including services such as appointment scheduling, treatment, and dispensing. In the first phase, authors conducted interviews with 16 experts to assess barriers and facilitators to using Internet hospitals. A conceptual model was built with this information, and in the second phase, a cross-sectional survey was completed by 593 physicians for analysis. For this study, the authors used a technostress model by Ayyagari et al. (2011). They included four main concepts to guide their research: work overload, invasion of privacy, role ambiguity, and work-family conflict.

Liu et al. (2019) developed a model and questionnaire to assess factors influencing physicians' technostress using mobile electronic medical records (MEMR). This work was based on the technostress framework (Ragu-Nathan et al., 2008; Tarafdar et al., 2007). Overall, responses showed high physician approval for MEMR's perceived usefulness and perceived reliability (M > 3.6), but low approval for its mobile self-efficacy, perceived complexity, and technology dependence (M< 2.9). This initial questionnaire validation study found adequate reliability and validity, with Cronbach's α for all constructs greater than 0.8 and composite reliability (CR) of all constructs exceeding the suggested cut-off value of 0.6.

Tell and colleagues (2023) surveyed 114 neuro and vascular surgery physicians to identify their digital technology-related stressors, examine their influence on health-related

outcomes, and identify potential preventive measures for technostress. For the technostress portion of their survey, authors used an adapted version of the technostress scale by Ragu-Nathan et al. (2008), including the three technostress creators of techno-overload, techno-complexity, and techno-uncertainty (14 survey items). Two technostress inhibitor constructs (literacy facilitation and involvement facilitation) were also used. Overall, participating physicians reported medium levels of technostress (M = 2.8, *SD* = 0.65), with techno-overload scoring the highest of all technostress constructs (M = 3.09, *SD* = 0.86). Double documentation was the most frequently reported stressful side effect of technology use, followed by technical errors, health insurance control tools, and lack of computer workstations. Physicians reported low to medium technostress inhibitors (levels of persisting resources; M = 2.51, *SD* = 0.85), low levels of burnout symptoms (M = 2.92, *SD* = 0.97), and were mostly satisfied with their job (M = 4.05, *SD* = 0.63).

Two of the physician articles were narrative or editorial reviews. In an article about continuous glucose monitoring, Goldman (2022) briefly discussed the possibility of technostress among healthcare providers that access EHR-integrated patient-generated data and outlined some mitigation strategies. Ye (2021) discussed how interactions with EHR-integrated patient-generated health data (PGHD) might contribute to overall clinician burnout and identified specific factors that may contribute to burnout, including technostress, time pressure, and workflow-related issues. Technostress creators were discussed, in the context of EHR-integrated PGHD systems, with specific examples of how physicians and other healthcare workers could be impacted. Some strategies to reduce technostress were also discussed, such as training, improvements to EHR usability and usefulness, developing standards for the use of PGHD in

EHRs, and using artificial intelligence (AI), automation, and other approaches to optimize workflows and reduce the amount of irrelevant or duplicate data that clinicians see in the EHR-integrated system.

Nurse Technostress

Four articles discussed technostress from a nursing perspective: one scoping review, one concept analysis, one narrative editorial, and one original research study. Lucena and colleagues (2021) performed a scoping review to discover nurses' strategies to prevent or decrease work-related technostress. A total of 880 potential studies were analyzed, but none fully met their inclusion criteria. The authors confirmed that technostress remains understudied in healthcare, and no known research exists that explores how nurses cope with work-related technostress. Tacy (2016) conducted a concept analysis on technostress in nursing, citing literature from business, education, and mass media literature. Related concepts are also discussed, such as computer-related stress, technophobia, and technology overload. Instruments used to measure technostress and related phenomena were discussed, such as the computer technology hassles scale (Hudiburg, 1995) and the nurse educator technostress scale (Burke, 2009). The technostress model and questionnaire by Ragu-Nathan et al. (2008) were not discussed. The author concludes with recommendations, including a call to increase awareness of technostress in nursing education. Smith and Palesy (2020) wrote a brief review of the technology-related stress with perioperative nursing roles. One major concern cited was perioperative nurses' concerns that increased dependence on technology reduces the human element of nursing altogether, leading to additional responsibilities of technological troubleshooters and technicians. Perioperative nurses work within the unique sociotechnical environment of the operating room, a highly complex

environment where technology is ever-evolving and adequate training is sometimes lacking. This article does not specifically discuss technostress or the technostress framework (Ragu-Nathan et al., 2008; Tarafdar et al., 2007), but it reviews former publications related to technology-related stress and perioperative nurses.

Of the four nursing articles, there was one original research study. Su and Chao (2022) developed and tested a model for predicting the key factors affecting nurses' behavioral intention to use mobile learning (mlearning) in Taiwanese hospitals, based on the extended unified theory of acceptance and use of technology (UTAUT) model, technostress, and other concepts. In their cross-sectional questionnaire, authors included questions about technostress, information quality, system quality, satisfaction, performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention to use. For technostress specifically, five questions were included, using adapted scales from technostress literature (Tarafdar et al., 2007; Lee et al., 2016). The authors found that technostress ($\beta = -0.253$) negatively influenced effort expectancy, supporting their hypothesis that an increase in nurses' technostress will decrease effort expectancy (how easy mlearning is to use). Technostress did not significantly impact performance expectancy (how useful the user perceives mlearning). The authors stated that this was the first known study to examine technostress in the context of behavioral intention to use mlearning.

Healthcare Worker Technostress

Seven articles focused on technostress among multiple healthcare professions (physicians, nurses, and others). Bakhai et al. (2022) explored relationships between communication, work-life balance, and COVID-19 among the United Kingdom's National

Health Service (NHS) staff. This study included 3047 healthcare workers in 32 various work roles, including nursing and medical staff, across a variety of work settings. Staff reported increased difficulties with email and other technologies during COVID-19. For example, 48% reported that after COVID-19, their personal time was invaded by work-related communications (compared to 23% before the pandemic). While technostress was cited as a concern related to this research, it was not measured as a variable.

Chen and Hsiao (2021) developed a new model and instrument to measure factors impacting EHR infusion at the individual level, based on previous research examining postadoption stages of technology (Cooper & Zmud, 1990), task-technology fit model (Goodhue, & Thompson, 1995), and mHealth infusion model (O'Connor et al., 2013). Authors adapted previous information systems work (Cooper & Zmud, 1990) to define *infusion* as "the exploratory, integrative, and future use of [electronic medical records]" (p. 16-17). In other words, optimal EHR infusion could represent an ideal post-implementation state of EHR adoption, where the system is part of routine use and utilized to its full potential within an organization. Their model assesses antecedents of EHR infusion, including technological characteristics determining EHR technology usability (accessibility, maturity, portability), task characteristics (time criticality, interdependence, mobility), and individual user characteristics (personal innovativeness, technostress, habit). A survey instrument was developed based on this model and tested with 211 healthcare professionals (150 from nursing departments and 61 from medical departments) at a teaching hospital in Taiwan. This initial validation study of the questionnaire found adequate reliability and validity, exceeding recommended values for all constructs (Cronbach alpha >.798, composite reliability >.734, average variance extracted >

.604). Results also revealed that EHR infusion was mostly affected by user habits (β=.411), portability (β=.217), personal innovativeness (β=.198), technostress (β=.169), and time criticality (β=.168). When considering the task-technology-fit model, these results indicate that user characteristics impact EHR infusion more than technology or task characteristics.

Golz and colleagues (2021a) surveyed health professionals working in Swiss psychiatric hospitals to examine associations between digital competence and technostress, as well as associations between technostress and long-term consequences for health professionals (intention to leave the organization or the profession, burnout symptoms, job satisfaction, general health status, quality of sleep, headaches, and workability). The 493 participants were comprised of nurses (60%), psychologists (12.3%), social workers (11.1%), physicians (8.7%), and medical-therapeutic professionals (7.7%). For this study, a technostress questionnaire by Gimpel et al. (2019) was used, along with others developed by authors to measure digital competence and long-term consequences. Overall, participants rated their technostress as moderate (M=1.30, *SD* = 0.55) and their digital competence as high (M= 2.89, *SD* = 0.73). Nursing staff and physicians reported the highest technostress scores (both with M = 1.41, *SD* = 0.54). Nurses (M = 2.71, *SD* = 0.78) and physicians (M = 2.82, *SD* = 0.66) reported the lowest digital competence levels. Age (β=.004; *p*=.03) and profession were significantly associated with both digital competence and technostress. Authors found that technostress was a relevant predictor of several long-term consequences, including burnout symptoms (β=10.32; *p* <.001), job satisfaction (β=−6.08; *p* <.001), intention to leave the profession (β=4.53; *p* =.002), intention to leave the organization (β=7.68; *p* <.001), general health status (β=−4.47; *p* <.001), quality of sleep (β=−5.87; *p* <.001), headaches (β=6.58; *p* <.001), and workability (β=−1.40; *p* <.001).

In another study, Golz and colleagues (2021b) performed secondary data analysis from a previous large-scale study in Switzerland to discover the prevalence of technostress among health professionals and investigate potential influencing factors. 8,112 health professionals from 163 health organizations in Switzerland were included in this study, including nurses and midwives (75% of participants) and physicians (7%). Participants worked across a variety of settings in Switzerland, including acute care and rehabilitation hospitals, psychiatric hospitals, nursing homes, and home care organizations. Technostress was measured using a single item developed and tested by the authors: "How often do you feel stressed by the use of technologies at your workplace, e.g. electronic patient record?" It was rated using a scale ranging from "0" (never/almost never), "25" (rarely), "50" (sometimes), "75" (often), and "100" (always). Overall, health professionals reported a mean technostress score of 39.23 (*SD* = 32.54), and scores varied significantly across settings. Acute care and psychiatric hospitals scored the highest levels of technostress (M = 46.38, *SD* = 31.95). Physicians reported the highest levels of technostress, followed by nurses. Authors also found that technostress increased with an individual's education level, and higher levels of social support resulted in decreased technostress.

Kaltenegger et al. (2023) surveyed 167 university hospital employees to assess associations of technostressors with low-grade inflammation and burnout symptoms. Participants included nurses (27.5%), physicians (19.8%), research staff (18%), medical-technical personnel, administrative staff, and others (33.6%). Self-report questionnaires were used to assess general psychosocial working conditions (work overload, job control, social climate), burnout symptoms, and other sociodemographic and health-related characteristics. Technostress was measured with German translations based on work by Ragu-Nathan et al. (2008), including four constructs of

techno-overload, techno-complexity, techno-uncertainty, and techno-insecurity. Other scales were included to measure technostressors, such as work interruptions, multitasking, and information overload. Challenge technostressors were also measured using several scales for reliability, usefulness, involvement, and technical support provision. In addition to self-report surveys, capillary blood samples were obtained to test C-reactive protein levels as an inflammatory biomarker. Authors found techno-overload, techno-complexity, interruptions, and multitasking were positively associated with core symptoms of burnout (exhaustion, mental distance). Techno-overload and techno-complexity were also associated with secondary burnout symptoms (psychosomatic complaints). No significant associations were found between challenge technostressors and outcomes or technostressors and low-grade inflammation (C-reactive protein levels).

In another study, Kaltenegger et al. (2024) performed a prospective cohort study of 238 hospital employees to evaluate associations between technostress, burnout symptoms, general work stress, hair cortisol levels, and chronic low-grade inflammation. Nurses comprised 28.2% of the participants, followed by physicians (22.3%). Standardized questionnaires were used to assess general job strain (job demand-control ratio), technostressors (work interruptions, multitasking, and information overload), burnout symptoms (exhaustion, mental distance), and other covariates. Participants also provided capillary blood samples to measure C-reactive protein (CRP) and hair strands to measure hair cortisol concentration (HCC). This time, scales by Ragu-Nathan et al. (2008) were not used to measure technostress. Authors found that technostress was negatively associated with HCC ($\beta = -0.16$, $p = .003$), but not burnout and CRP. General work stress was not significantly associated with HCC, CRP, or burnout.

Stadin et al. (2020) interviewed 20 healthcare managers from four hospitals in Sweden. These managers included physicians (5), nurses (4), occupational therapists (2), social workers (2), and others (7). Authors analyzed data from semi-structured interviews to discover main themes relating to participant experiences with technostress, including technostress creators and actions to handle technostress. Healthcare managers' experiences of technostress were categorized as related to three main themes of potential technostressors: negative aspects of digital communication (high workload, invasion of private life, negative feelings); poor user experience of ICT systems (time-consuming ICT); and a need to improve organizational resources (facilitating digital literacy and user influence, redistribution of work and ICT). Participants' methods of handling technostress included three categories: taking action related to culture, norms, and social support (good email culture, co-worker support); organizational resources (support and assistance), and individual resources (strategies and competence).

Evidence Synthesis

This review contained multiple types of literature on technostress experiences among healthcare professionals. Two articles used qualitative methods (Attipoe et al., 2023; Stadin et al., 2020), and one used a mixed methods design (Deng et al., 2023). Five articles were reviews and editorials (Goldman, 2022; Lucena et al., 2021; Smith & Palesy, 2020; Tacy, 2016; Ye, 2021). Two studies collected biomarkers from blood samples, along with cross-sectional survey data (Kaltenegger et al., 2023; Kaltenegger et al., 2024). One study performed secondary data analysis (Golz et al., 2021b). Nine studies used cross-sectional surveys to collect technostress data (Bahr et al., 2023; Bail et al., 2023; Bakhai et al., 2022; Bernburg et al., 2024; Chen & Hsiao, 2021; Golz et al., 2021a; Liu et al., 2019; Su & Chao, 2022; Tell et al., 2023).

This review included research articles from a variety of locations. Most of the research was located in Germany (Bail et al., 2023; Bernburg et al., 2024; Kaltenegger et al., 2023; Kaltenegger et al., 2024; Tell et al., 2023). Other locations included Canada (Bahr et al., 2023), China (Deng et al., 2023), Sweden (Stadin et al., 2020), Switzerland (Golz et al., 2021a; Golz et al., 2021b), Taiwan (Chen & Hsiao, 2021; Liu et al., 2019; Su & Chao, 2022), and the United Kingdom (Bakhai et al., 2022). Only one article examined technostress in the United States (Attipoe et al., 2023).

As discussed previously, nine articles examined physician experiences with technostress, seven articles included multiple healthcare professions (physicians, nurses, and others), and four articles were nursing-focused. Among the nursing articles, there was only one original research study, located in Taiwan. In this review, no articles examined technostress among nurses in the United States.

Many articles used classic technostress research to develop their research models, hypotheses, and instruments. Many studies utilized a classic technostress questionnaire by Ragu-Nathan et al. (2008) or Tarafdar et al. (2007), either in full or adapted, as part of their cross-sectional survey research (Bail et al., 2023; Bernburg et al., 2024; Chen & Hsiao, 2021; Kaltenegger et al., 2023; Liu et al., 2019; Stadin et al., 2020; Su & Chao, 2022; Tell et al., 2023). One study (Deng et al., 2023) used a different model of technostress (Ayyagari et al., 2011) to develop their conceptual model. Two studies used different technostress instruments: Tacy (2016) used the nurse educator technostress scale (Burke, 2009), and Golz et al. (2021a) used a technostress questionnaire created by Gimpel et al. (2019). One study (Golz et al., 2021b) measured technostress with a single item developed by authors. Another study (Kaltenegger et

al., 2024) measured technostress by calculating an overall mean score based on three scales (information overload, work interruptions, and multitasking).

Limitations

This literature review has some limitations. “Technostress” was used as the only search term for this review to capture articles related to the technostress phenomena cited from psychology and technology literature (Ragu-Nathan et al., 2008). However, this term is not well known in healthcare, so similar phenomena are likely discussed instead in relation to technology use, such as documentation burden, information overload, technophobia (Sherril et al., 2022), digital stress (Fischer et al., 2021), and information system stress (Kaihlanen et al., 2021). However, this review aimed to review only healthcare articles related to the technostress phenomenon as described by Ragu-Nathan et al. (2008) and others (Tarafdar et al., 2007, 2010, 2019). Future research should investigate similarities and differences between technostress and other phenomena mentioned. In addition, only English-language full-text articles were analyzed, so this review may be missing some key relevant works from other countries.

End of Chapter Summary

This literature review illustrates the gap in technostress literature, particularly among nurses and other healthcare professionals in the United States. Although technostress is a relatively new concept in healthcare literature, the validated technostress questionnaire (Ragu-Nathan et al., 2008; Tarafdar et al., 2007) has been used in many studies to investigate this phenomenon. This dissertation aimed to explore technostress among nurses and discuss relationships between technostress and other more well-known phenomena. The next chapter will discuss the methods to achieve specific aims and associated research questions.

CHAPTER 3: METHODS

The purpose of this dissertation was to examine the unintended consequences of EHR use among nurses working in hospital environments, with particular attention to technology-related stress and ongoing EHR usability concerns. Since little is known about nurses and technostress, this dissertation aimed to both describe technostress among the sample of working hospital nurses and identify factors significantly related to technostress. Knowledge from this study can guide future research efforts, including optimization efforts targeted to decrease technostress among hospital nurses. This chapter will review the aims of this dissertation and outline its methods, including design, sample, setting, recruitment approach, and data analysis. Procedures to ensure rigor and protection of human subjects will also be discussed.

Review of Aims and Research Questions

The specific aims of this dissertation, along with associated research questions and hypotheses, are discussed below. An in-depth discussion of measures and variables is covered later in this chapter.

1. Aim 1: Describe technostress among nurses working in hospital environments across the United States

   Associated research questions:

   a. Among the sample of hospital nurses, what is the average level of overall technostress?

   b. Among the sample of hospital nurses, what are the average levels of technostress creators (techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty)?

c. Among the sample of hospital nurses, what are the average levels of technostress inhibitors (literacy facilitation, technical support provision, and involvement facilitation)?

d. Among the sample of hospital nurses, what are the average levels of organizational outcomes related to technostress, including job satisfaction, organizational commitment, and continuance commitment?

The technostress questionnaire by Ragu-Nathan and colleagues (2008) was used to measure overall technostress, technostress creators (techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty), technostress inhibitors (literacy facilitation, technical support provision, and involvement facilitation), and organizational outcomes related to technostress (job satisfaction, organizational commitment, and continuance commitment). Items on the technostress questionnaire range from 1 (strongly disagree) to 5 (strongly agree). An overall technostress composite score was calculated by averaging the scores of each of the five technostress creator dimensions. Mean scores range from 1 to 5. A higher composite score indicates higher technostress overall. We hypothesized that the average technostress score differs according to the levels of technostress inhibitors.

2. Aim 2: Explore relationships between nurses' technostress, hospital characteristics (magnet status, type of EHR used, and if the location is a teaching hospital), current work characteristics (hospital department, weekly hours worked, frequency of floating departments, and years of experience at current hospital), and cumulative work experience (years of experience as a nurse and years of experience using EHRs) Associated research questions:

a. Are there significant relationships between nurses' technostress and hospital characteristics (magnet status, type of EHR used, and if the location is a teaching hospital)?
b. Are there significant relationships between nurses' technostress and current work characteristics (hospital department, weekly hours worked, frequency of floating departments, and years of experience at the current hospital)?
c. Are there significant relationships between nurses' technostress and cumulative work experience (years of experience as a nurse and years of experience using EHRs)?

A demographics questionnaire developed by the PhD candidate and dissertation committee was used to measure demographic characteristics (age, gender, and level of education), hospital characteristics (magnet status, type of EHR used, and if the location is a teaching hospital), current work characteristics (hospital department, weekly hours worked, frequency of floating departments, and years of experience at current hospital), and cumulative work experience (years of experience as a nurse and years of experience using EHRs). We hypothesized that hospital characteristics, current work characteristics, and cumulative work experience predict technostress.

3. Aim 3: Explore relationships between technostress, EHR usability, cognitive workload, and EHR unintended consequences (workload issues, patient safety, sociotechnical impact, workarounds, system design, technological barriers)

   Associated research questions:

a. Are there significant relationships between nurses' technostress and EHR usability?
b. Are there significant relationships between nurses' technostress and cognitive workload?
c. Are there significant relationships between nurses' technostress and unintended EHR consequences (workload issues, patient safety, sociotechnical impact, workarounds, system design, technological barriers)?

Usability was measured using the System Usability Scale (SUS; Brooke, 1996). The cognitive workload was calculated using the National Aeronautics and Space Administration Task Load Index (NASA-TLX; Hart & Staveland, 1988). EHR unintended consequences (EHR-UC; workload issues, patient safety, sociotechnical impact, workarounds, system design, technological barriers) were measured using the Carrington-Gephart Unintended Consequences of EHR Questionnaire (CG-UCE-Q; Carrington et al., 2015; Gephart et al., 2016). We hypothesized that EHR usability, cognitive workload, and unintended consequences of EHRs predict technostress.

Design

A descriptive, correlational, and cross-sectional quantitative study design was used to describe technostress among hospital nurses and examine relationships between technostress and other variables of interest. With correlational study designs, variables are not manipulated but examined in relation to each other to explain associations, not causations (Kazdin, 2022). Descriptive correlational designs are appropriate when little is known about a phenomenon and when researchers seek to describe naturally occurring relationships between variables (Sousa et

al., 2007). This design was chosen due to the limited knowledge of technostress among nurses and to match this dissertation's purpose, aims, and research questions.

Human Subjects Protection

This study was reviewed and approved by the Institutional Review Board of the University of Arizona. Letters of Approval are in Appendix A. At the beginning of the study, participants were provided information regarding their consent to the study and privacy and confidentiality measures. It was also stressed to participants that participation is voluntary. Access to study data was limited only to the PhD candidate and three dissertation committee members. The research disclosure form information is in Appendix B.

Data Collection

This study collected cross-sectional data from participants who completed online self-report questionnaires to describe and identify factors significantly related to technostress among nurses. Cross-sectional designs allow for comparisons between groups at a single point in time (Kazdin, 2022) and can help generate hypotheses for future studies (Wang & Cheng, 2020). The following sections will describe the study's participants, setting, recruitment approach, and instruments used for questionnaire items.

Participants

This study used convenience sampling to recruit nurses who worked in hospital settings in the United States. Inclusion criteria included registered nurses (RNs) or licensed practical nurses (LPNs) working in hospitals (part-time or full-time), 18 years of age or older, living in the United States, fluent in the English language, with greater than 6 months of experience using the EHR as part of their current work. Nurses were excluded from this study if they: do not work in

the United States, work in non-hospital settings (such as ambulatory clinics or skilled nursing facilities), do not use an EHR, or have less than 6 months experience using the EHR as part of their current work. Nurses' level of education, hours worked in the hospital, and other details were collected as part of a demographic questionnaire, discussed later in this chapter.

Sample Size

An a priori analysis of statistical power was performed to determine adequate sample sizes using G*Power software (version 3.1.9.7), a recommended approach for calculating sample size and power for a study (Faul et al., 2009; Kang, 2021). A study's power is dependent on the level of significance set by the researcher (alpha, or the probability of type I error), sample size, and effect size (or the probability of type II error; Kazdin, 2022). For this study, the alpha (α) was set at .05, a widely acceptable measure that indicates the probability of falsely rejecting the null hypothesis, or making a type 1 error (Howell, 2016).

For Aims 2 and 3, an a priori power analysis was conducted using G*Power version 3.1.9.7 (Faul et al., 2007) to determine the minimum sample size required to test hypotheses using correlation. Analysis was set with parameters at two-tailed, alpha of .05, 80% power, to detect at least a moderate effect size of .30 (Cohen, 1988). Bivariate correlations/ correlation coefficients (r, ranging from –1.00 to +1.00) will be used to examine relationships between variables. Based on these calculations, G*Power suggested a minimum group size of 84 participants.

For Aims 2 and 3, an a priori power analysis was conducted to determine the minimum sample size required to test the hypothesis using linear multiple regression with up to 11

predictors. Results indicated the required sample size to achieve 80% power for detecting a medium effect ($f^2 = 0.15$; Cohen, 1988), at a significance criterion of $\alpha = .05$, was N = 123. Based on all calculations, a sample size goal of 150 participants was proposed to allow for attrition and missing data.

Setting and Recruitment Approach

This study's setting was limited to the Internet. The PhD candidate recruited participants from across the United States over a period of 10 weeks using social media sites and a crowdsourcing research platform, Prolific (https://www.prolific.com/). For social media recruitment, the PhD candidate shared information regarding the study on Facebook (https://www.facebook.com/), Reddit (https://www.reddit.com/), and LinkedIn (https://www.linkedin.com/). When applicable, appropriate permission was obtained before posting on privately moderated groups, and comments features were turned off to prevent participants from accidentally identifying themselves. Recruitment posts included a poster that detailed the study's inclusion and exclusion criteria and a link to the study consent form and questionnaire. Appendix C contains the recruitment information poster and wording used in social media posts.

An online participant research platform, Prolific (https://www.prolific.com/), was also used to recruit study participants. Crowdsourcing sites such as Prolific and Amazon Mechanical Turk (MTurk) have become commonplace in behavioral health research and offer a convenient way for researchers to recruit participants and pay them for their time, such as the time completing online surveys (Chandler & Shapiro, 2016). Mortensen and Hughes (2018) reviewed 35 peer-reviewed health and medical research studies and found that MTurk was a reliable tool

for participant recruitment (Mortensen & Hughs, 2018). Prolific, a newer crowdsourcing recruitment site, was created in 2014 by academic researchers and is used by over 35,000 researchers today (Prolific, 2024). Prolific maintains a pool of over 200,000 active participants globally that are verified with bank-grade ID checks and routine screenings (Prolific, 2024). The use of the Prolific platform for health research is also gaining traction as a convenient and efficient recruitment method (Myers et al., 2022; Stanton et al., 2022; Turner et al., 2021). Research suggests that the Prolific platform produces better data quality than its competitor MTurk (Albert & Smilek, 2023; Adams et al., 2020; Douglas et al, 2023; Peer et al., 2022). For crowdsourcing recruitment, the PhD candidate invited participants from a selection of the Prolific database matching this study's inclusion criteria. Participants recruited via Prolific were paid $4.00 for their participation in completing the online survey.

Qualtrics (http://qualtrics.arizona.edu) was used to create the online survey, capture electronic signatures for consent, and house and export study data. Prior to the study's start date, the PhD candidate performed quality control testing of the online survey to ensure accurate scoring and capture of included items. A codebook described each variable in the data set and related notes. The study's questionnaire was reviewed by two nurses outside the dissertation committee to determine its legibility and estimated time to complete the full survey. Both nurses reviewing the survey estimated times of less than 20 minutes to complete the survey, so a time of "30 minutes or less" was included in the social media recruitment information poster to describe participant burden for social media participants. Initial social media data was analyzed and updated for crowdsource participants to include an estimated completion time of "15 minutes"

for all surveys. Appendix B contains consent information for both social media participants and crowdsourced participants (Prolific). Appendix C contains additional recruitment information.

Questionnaire and Instruments

The full survey was developed using one demographic questionnaire and several psychometrically validated instruments. Variables of interest include EHR usability, cognitive workload, technostress, and unintended consequences. The full survey was reviewed by the dissertation committee experts to determine face and content validity.

One threat to web-based survey research is the possibility of bots, or computer programs that enter the survey and complete results with random responses (Xu et al., 2022). Some procedures can be followed to prevent bot interference in web-based survey research, such as preventing multiple submissions in the survey, including CAPTCHA (Completely Automated Public Turing test to tell Computers and Humans Apart) prompts inside the survey, or including attention checks, where the participant is prompted by the survey to select an explicit response. CAPTCHA and internal Qualtrics measures were used to mitigate bot interference in the survey. Survey completion time was also monitored to ensure completions were not under 3 minutes. Participants recruited via Prolific had some additional measures to combat bot interference and measure participant response and attention, such as attention check questions, comparing users' unique Prolific ID and IP addresses, and other internal measures in Prolific.

Demographic Characteristics

Individual factors, such as age, specialty, and work environment can influence EHR-related stress (Alobayli et al., 2023). An initial demographic questionnaire was developed by the PhD Candidate and dissertation committee members to evaluate covariates or potential

confounders, including nurses' demographic characteristics (age, gender, and level of education), current work characteristics (hospital department, weekly hours worked, frequency of floating departments, and years of experience at current hospital), cumulative work experience (years of experience as a nurse and years of experience using EHRs), and hospital characteristics (magnet status, type of EHR used, and if location is a teaching hospital). The first few questions in the demographic questionnaire also verified participant inclusion criteria. Refer to Appendix D for more information about instruments and measures.

Usability

Usability can be defined as how well a system achieves specific goals with efficiency (level of resources needed to perform a task), effectiveness (the ability of the user to complete a task and the quality of the task's output), and satisfaction in the context of a user's needs (International Organization for Standardization, 2018). The usability of the EHR was measured using the System Usability Scale (SUS; Brooke, 1996). SUS has shown high reliability (internal consistency reported with Cronbach's alpha = 0.91) and accurately reflects the overall usability of a technological product regardless of the type of interface (Bangor et al., 2008). The SUS is a 10-item questionnaire with 5 response options, ranging from 1 for "Strongly disagree" to 5 for "Strongly Agree". To calculate the overall SUS score, the sum of each item is calculated. For odd-numbered items (1, 3, 5, 7, and 9), the score is the scale position minus 1. For even-numbered items (2, 4, 6, 8, and 10), the score is the scale position minus 5. The sum of all scores is then multiplied by 2.5 to obtain the overall value. A higher summary score indicates a higher, or more favorable, usability. SUS composite scores range from 0 to 100, with 68 indicating average usability and 80 and above indicating above average usability; there is also an alternative

curved grading scale in which a SUS score of 68 is at the center of the range for a "C" grade, and scores ranging 84.1 - 100 merit an A+ usability grade (Lewis & Sauro, 2018).

Cognitive Workload

Nursing workload can be impacted by various healthcare technologies, either positively or negatively (Mohammadnejad et al., 2023). Perceived workload was examined using the concept of *cognitive workload*. EHRs have presented unique cognitive challenges for nurses, necessitating research for evidence-based design interventions (Wisner et al., 2019). One established method to measure these challenges is known as cognitive, or mental, workload. Cognitive workload (CW) became an established concept in ergonomics research in the 1980s and remains popular today, particularly in researching safety-critical systems (Young et al., 2015). CW is defined as the user's perceived capacity required to perform a task, including mental demand, physical demand, temporal demand, performance, effort, and frustration level (Hart & Staveland, 1988). CW is also known as mental workload, or the mental capacity required to perform a task (Boy, 2011). CW is a multidimensional construct that defines a task about its operator's performance, involving task characteristics, the operator, and the environment (Young et al., 2015). Healthcare research has linked increased CW to a greater occurrence of medical errors, patient falls, incomplete tasks, and patient mortality (Wilbanks & McMullan, 2018).

Cognitive workload was measured using the National Aeronautics and Space Administration Task Load Index (NASA-TLX; Hart & Staveland, 1988). The NASA-TLX is one of the most widely used subjective measures of workload across several industries, including nurses working in emergency departments, intensive care units, operating rooms, and other

departments (Yuan et al., 2023). NASA-TLX has also been used to measure the cognitive workload of EHRs in several studies (Wilbanks & McMullan, 2018). NASA-TLX has shown high reliability (acceptable internal consistency reported with Cronbach's alpha = 0.72) in measuring workload among 757 ICU nurses working in multiple settings (Hoonakker et al., 2011). Authors also reported NASA-TLX demonstrated convergent validity, correlating high with similar measures (Perceived Workload Scale and Rating Scale Mental Effort, r = 0.81 and r = 0.77 respectively).

The NASA-TLX has 6 items. Each item uses a 20-point visual scale to assess task load, ranging from 0 (very low) to 20 (very high). Overall cognitive workload (raw TLX) was calculated as the mean of the six subscale item ratings (Mental Demand, Temporal Demand, Physical Demand, Performance, Effort, and Frustration). Raw TLX has proven more accurate than weighted TLX scoring (Hertzum, 2021).

Technostress

Technostress can be defined as stress experienced by end users in organizations due to the use of information and communication technology and is further described by technostress creators (or technostressors) and technostress inhibitors (organizational factors that reduce technology-related stress; Ragu-Nathan et al., 2008). The 47-item Technostress Questionnaire (Ragu-Nathan et al., 2008) was used to measure technostress in this study (authors reported acceptable to good reliability, with internal consistency Cronbach's alpha values ranging from 0.71 to 0.91 for all items). The Technostress Questionnaire and its related inventories were used in various healthcare studies on technostress (Attipoe et al., 2023; Bail et al., 2023; Bernburg et al., 2024; Kaltenegger et al., 2023; Stadin et al., 2020; Su & Chao, 2022; Tell et al., 2023).

Technostress questionnaire items are ranked on a 5-point Likert scale, with 1 for "Strongly disagree", 2 for "Disagree", 3 for "Neutral", 4 for "Agree", and 5 for "Strongly Agree". Mean values will be calculated for five technostress creators (techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty), three technostress inhibitors (literacy facilitation, technical support provision, and involvement facilitation), and outcome variables related to technostress (job satisfaction, organizational commitment, and continuance commitment). According to Ragu-Nathan et al. (2008), *job satisfaction* is defined by the positive emotional state resulting from one's job experiences, *organizational commitment* refers to the employee's belief in and acceptance of the organization's goals and values, and *continuance commitment* refers to the level of need an employee feels to stay in the organization. An overall technostress composite score was calculated by averaging the scores of each of the five technostress creator dimensions. Scores range from 1 to 5 according to the 5-point Likert scale questions. A higher composite score indicates higher technostress overall.

EHR Unintended Consequences

EHR unintended consequences (EHR-UC) can be defined as unexpected effects of EHR adoption, including six dimensions: workload issues, patient safety, sociotechnical impact, workarounds, system design, and technological barriers (Gephart et al., 2016). EHR-UC was measured using the Carrington-Gephart Unintended Consequences of EHR Questionnaire (CG-UCE-Q; Carrington et al., 2015; Gephart et al., 2016). The CG-UCE-Q instrument demonstrated high overall reliability (reported as internal consistency Cronbach's alpha = 0.94), with individual subscales demonstrating borderline adequate to high internal consistency (Cronbach's alpha = 0.67 to 0.96). Exploratory factor analysis was also performed to determine construct

validity, where items and six subscales explained approximately 63% of the variance. The CG-UCE-Q was used to study EHR-UC among neonatal nurses (Dudding et al., 2018), emergency department nurses (Harmon et al., 2023), and nurses from a variety of hospital departments (Tolentino et al., 2021).

CG-UCE-Q survey scale items are ranked on a 0 to 6 scale: 0 is “Never”, 1 is “Once a year”, 2 is “Once every couple of months”, 3 is “Once a month”, 4 is “Once a week”, 5 is “Once a shift”, and 6 is “Multiple times a shift”. A mean score was calculated from all 36 questions to calculate an overall score of the frequency of EHR-related unintended consequences (EHR-UC). The higher the score, the higher the frequency of EHR-UC. The frequency of EHR-UC was also reported per subscale: workload issues (WI), patient safety (PS), sociotechnical impact (SI), workarounds (WA), system design (SD), and technological barriers (TB).

Procedures

Participants were directed to the study site via a link to the Qualtrics survey, located on the study’s poster for social media participants, or via the Prolific site for crowdsourced participants. The site included an introduction to the study, followed by the consent form and survey. Each survey submission was assigned a unique code number for identification and data management purposes. At the end of the data collection period, online surveys were closed, survey results were exported into Microsoft Excel for initial analysis, and data was saved to the PhD candidate’s University of Arizona Box account (https://arizona.account.box.com/) and Google Drive for backup. Access to both drives required the PhD candidate’s unique NetID and password, including dual-factor authentication using Duo Security (https://duo.com/).

Results were analyzed to assess for missing or invalid data. Specific methods of handling missing data will be reported in the next chapter, based on the type, amount, and pattern of missing data (Mirzaei et al., 2022). Graphics, such as scatter plots, may be used to help determine data distribution, along with specific tests. Once data was initially analyzed and cleaned, it was loaded into Stata 16.1 (https://www.stata.com/) for statistical analyses. At all times, study data will be password-protected via Qualtrics, Stata, and the PhD Candidate's encrypted laptop.

Data Analysis Strategy

Survey results were exported from Qualtrics and loaded into Stata statistical software to analyze data. Descriptive statistics, correlations, and regressions were calculated to address specific aims and research questions. For Aim 1, participant demographics and technostress characteristics (overall technostress composite score, technostress creators, technostress inhibitors, and technostress outcomes) will be described using standard descriptive statistics. Continuous variables will be reported as mean, standard deviation, and ordinal and categorical variables will be displayed as count and percentage where appropriate.

For Aims 2 and 3, correlation analysis was performed to examine relationships between technostress and other variables of interest. Distribution of continuous data and skewness were determined by visual inspection of data and appropriate testing, such as the Shapiro-Wilk test of normality. Spearman's correlations were performed to examine relationships between variables. Differences in mean outcome variables between groups were measured using analysis of variance (ANOVA). Single and multiple linear analysis was used to identify variables that predict technostress. Multiple regression evaluates the effect of each independent variable on the

outcome, while adjusting for the effects of other variables included in the model (Castro & Ferreira, 2023). Variables not significantly associated with technostress were not included in the model. A cut-off value of .05 was used for all statistical tests.

End of Chapter Summary

This chapter discussed this dissertation's study design, methods, and strategies to support rigorous research and the protection of human subjects. This dissertation used a descriptive correlational study design to collect cross-sectional data from online self-report questionnaires about technostress and other variables of interest among nurses working in hospital settings across the United States. The next chapter will discuss the study results in detail.

CHAPTER 4: RESULTS

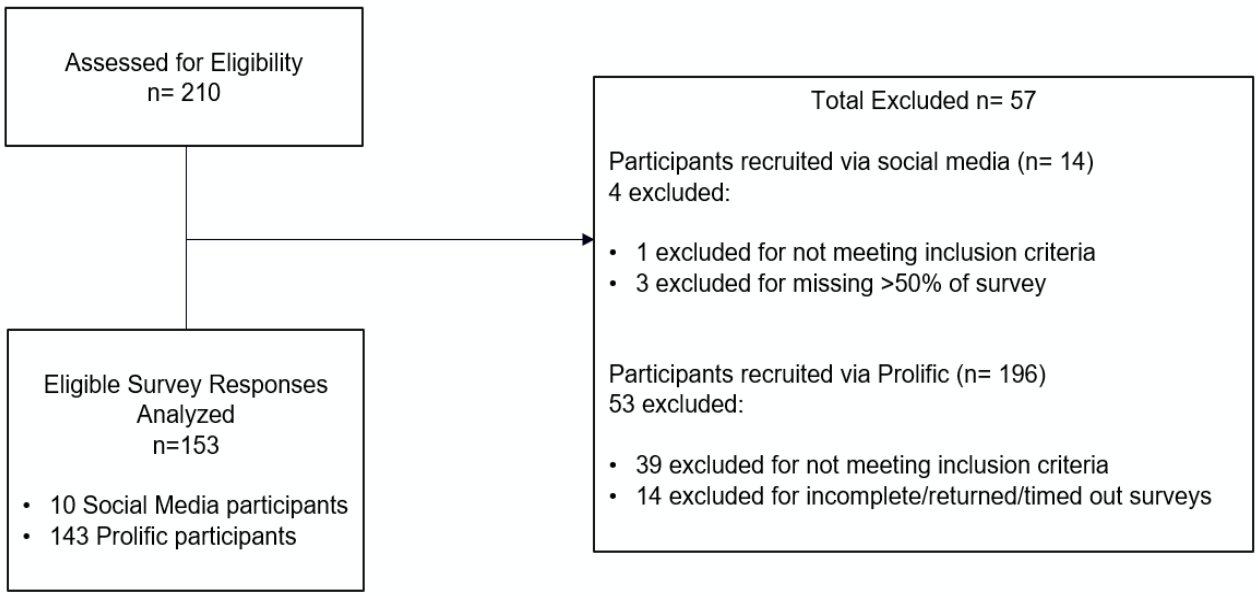
The purpose of this dissertation was to examine the unintended consequences of EHR use among nurses working in hospital environments, with particular attention to technology-related stress and ongoing EHR usability concerns. This chapter will present the results of this study, including descriptions of the sample and results by aim.

Survey Screening

During the data collection period, 210 surveys were completed in Qualtrics. After assessing for inclusion/exclusion criteria and missing data, a total of 153 surveys were analyzed, exceeding the sample size goal of 150 participants. From the final 153 surveys analyzed, 10 participants were recruited from social media sites (Facebook, Reddit, LinkedIn), and 143 were recruited from Prolific. Figure 4 provides additional participant flow details.

Figure 4

Participant Flow Chart (n=153)



Potential Fraud Detection

A multi-layered approach is the best strategy for fraud detection in Qualtrics survey research (Bonett et al., 2024). Survey data was analyzed for potential fraudulent or bot responses, such as extremely short survey completion times (under 5 minutes), incorrect answers to embedded attention check questions, and inconsistencies in answers between survey questions (Wang et al., 2023). For participants recruited from Prolific, their prescreening data was compared to demographic survey answers to check for consistency. Additionally, four attention check questions were included throughout the survey to minimize fraudulent responses. Three attention check questions prompted participants to select a specific answer from a multiple-choice question, such as: "Please select 'Strongly Disagree' to show you are paying attention to this question." One additional attention check question was worded differently, allowing respondents to answer "Yes" or "No" to "I have never used a computer." Only 10 participants answered some participant check questions incorrectly. Nine participants missed one of the four attention check questions, and one participant missed two of the four questions. All participants answered at least two of four attention check questions correctly, and none were excluded for this reason.

Qualtrics fraud detection, RelevantID, was also enabled for the survey. Survey data exported from Qualtrics included scores for potential fraudulent interference, such as bot detection (Q_RecaptchaScore), duplications (Q_RelevantIDDuplicate and Q_RelevantIDDuplicateScore), and fraudulent bot activity (Q_RelevantIDFraudScore; Qualtrics, 2024). Overall, Qualtrics' response quality ratings were very high for the final 153 survey participants. Only 14 (9%) participants had potential fraudulent RelevantID scores. Three

participants were flagged with a Q_RecaptchaScore of less than 0.5, indicating the respondent may be a bot (Qualtrics, 2024). Eleven participants had a Q_RelevantIDFraudScore greater than or equal to 30, indicating the respondent may be a bot (Qualtrics, 2024). No participants had more than one positive RelevantID score, so no participants were excluded for this reason.

Missing Data

Most survey measures had no missing data (Nursing Demographic Questionnaire, Technostress Questionnaire, and National Aeronautics and Space Administration Task Load Index [NASA TLX]). Two measures appearing towards the end of the survey had a small amount of missing data (System Usability Scale [SUS] and Unintended Consequences of Electronic Health Record Questionnaire [CG-UCE-Q]). Table 1 describes the missing data in more detail. There were no other identified patterns of missingness, and data was considered missing completely at random (MCAR). Listwise deletion was used when performing regression analyses to address the missingness of survey data, and missing data was left as missing in the dataset.

Table 1

Summary of Missing Data

Survey Measure	# of Items	# of Participants with Missing Data	Number of Participants included in the final analysis
Nursing Demographics	13	0	153
Technostress	47	0	153
Cognitive Workload (NASA TLX)	6	0	153
EHR Usability (SUS)	10	4	149
Unintended Consequences of EHRs (CG-UCE-Q)	36	17	136

Description of Sample

Descriptive and analytical analyses were conducted using Stata 16.1 statistical software for the 153 participants. Participants were first surveyed using some basic demographic information. Most nurse participants were female (80%), with a bachelor's degree (BSN) as their highest level of education (58%). The average participant's age was 39 ranging from 23 to 77 years of age. The average number of years employed as a nurse, overall, was 12 years. Overall, the average number of years employed as a nurse was 12 years. See Tables 2 and 3 for more demographic details.

Table 2

Participant Demographics (Gender, Highest Level of Education)

Variable	% (N)
Gender	
Female	80 (123)
Male	19 (29)
Nonbinary	0
Other/Prefer Not to Respond	1 (1)
Highest Level of Education	
Diploma or certificate in nursing	7 (10)
Associate's (ADN)	14 (21)
Bachelor's (BSN)	58 (89)
Master's (MSN)	20 (31)
Doctoral (DNP or PhD)	1 (2)

Note. *n* =153

Table 3

Participant Demographics (Age, Years Employed as a Nurse, Years Using EHRs)

Variable	Mean	SD	Range	Median
Age	39.04	11.12	23-77	36
Years Employed as a Nurse	12.39	9.45	1-41	10
Years Using EHRs	9.22	6.69	1-28	8

Note. *n* =153*;* EHR= electronic health record; SD = standard deviation

Next, participants were surveyed about current work characteristics. Participants worked in their organizations for 7-12 months to over 5 years, with the largest group having worked there for 2-5 years (37%). Most participants (58%) reported they currently worked at a Magnet-designated hospital. Most participants also reported they currently worked at a teaching hospital (56%). Only four (3%) of the 153 participants reported they were travel nurses for their current job position. Participants were asked to identify the hospital department where they performed most of their work. Most participants reported the medical/surgical department (37%), followed by surgery (13%), intensive care unit (12%), the emergency department (9%), behavioral health (7%), pediatrics (7%), and labor and delivery/obstetrics and gynecology (6%). Five participants (3%) reported other hospital services departments, such as radiology, inpatient rehab, and inpatient dialysis. Eight participants (5%) reported they worked in administrative roles such as IT, documentation, infectious disease, quality, case management, risk, and the rapid response team. Participants were also asked how often they "float" between departments (perform work at different departments throughout the hospital). Most participants stated they never had to float departments (48%); 45% reported they float departments once or more weekly, and 7% stated they float almost every day or multiple times a shift.

Participants were asked about the types of EHRs they use for their daily hospital work. Most participants (81%) reported using only one EHR for their daily work. The most commonly reported EHR used was Epic (46%), followed by Cerner-Oracle (18%) and MEDITECH (16%). Most participants reported working 21-40 hours per week (65%), followed by 41 hours or greater per week (28%), then 20 hours or less per week (7%). See Table 4 for more details on participant work information.

Table 4

Participant Current Work Demographics

Variable	% (N)
How long have you worked for your current organization?	
7-12 months	6 (9)
1-2 years	10 (15)
2-5 years	36 (56)
More than 5 years	48 (73)
Is the hospital you work at a Magnet-designated hospital?	
Yes	58 (89)
No	33 (50)
Unsure	9 (14)
Is the hospital you work at a teaching hospital?	
Yes	56 (85)
No	41 (63)
Unsure	3 (5)
For your current job position, are you a travel nurse?	
Yes	3 (4)
No	97 (149)
Select the hospital department where you perform most of your work:	
Medical/Surgical/Stepdown	37 (57)
Surgery	13 (20)
Intensive Care Unit	12 (19)
Emergency Department	9 (13)
Behavioral Health / Psychiatry	7 (11)
Pediatrics	7 (11)
Labor and Delivery or Obstetrics and Gynecology	6 (9)
Other Hospital Services (including radiology, inpatient rehab, and inpatient dialysis)	3 (5)
Other – Administrative and Support (including case management, IT, infectious disease, quality, risk, and rapid response team.)	5 (8)
How often do you “float”, or perform work at different departments?	
Never	48 (73)
Weekly (once a week or more)	45 (69)
Almost every day/ Multiple times a shift	7 (11)
What type(s) of electronic health record (EHR) do you use for your daily work? (Select all that apply to your current work only.)	
Cerner (Oracle)	18 (29)

Table 4 – Continued

Variable	% (N)
Epic	46 (72)
MEDITECH	16 (26)
Allscripts	7 (11)
AthenaHealth	8 (12)
Other (including CPRS/VistA, Avatar, HCS, HST, Matrix, Trubridge/CPSI)	5 (8)
Number of EHRs used	
One	81 (124)
Two	13 (20)
Three	6 (9)
How many hours do you work per week?	
20 hours or less per week	7 (10)
21-40 hours per week	65 (100)
41 hours or greater per week	28 (43)

Note. *n* =153

Test of Data Normality

Numeric variables were evaluated for normal distribution in Stata using histograms and the Shapiro-Wilk test of normality. Several variables had a Shapiro-Wilk probability of >.05, indicating normal distribution, including overall technostress (p=.86), one techno-inhibitor scores (involvement facilitation[p=.97]), two outcomes related to technostress (organizational commitment [p=.70] and continuance commitment [p=.85]), and EHR usability (p=.11). All other variables had probability of <.05, indicating these data were not normally distributed. Where applicable, non-parametric statistics were chosen for ordinal or skewed continuous independent variables, including Spearman's Rho for correlation analysis.

Results by Aim

The specific aims of this dissertation are reviewed below, along with their related research questions and results.

Research Aim 1: Describe Technostress Among Hospital Nurses

The first aim of this dissertation was to describe technostress among nurses working in hospital environments across the United States. Among the sample of hospital nurses, the average level of overall technostress was M = 2.54 (*SD* = 0.61), on a scale of 1 to 5. Average levels of each technostress creator were also analyzed, including techno-overload (M = 3.06, *SD* = 0.88), techno-invasion (M = 2.19, *SD* = 0.88), techno-complexity (M = 2.10, *SD* = 0.75), techno-insecurity (M= 2.04, *SD* = 0.79), and techno-uncertainty (M = 3.42, *SD* = 0.92). Average levels of technostress inhibitors included literacy facilitation (M = 3.90, *SD* = 0.68), technical support provision (M = 3.80, *SD* = 0.79), and involvement facilitation (M = 3.24, *SD* = 0.90). Average organizational outcomes related to technostress included job satisfaction (M= 4.11, *SD* = 0.64), organizational commitment (M = 3.33, *SD* = 0.91), and continuance commitment (M = 3.23, *SD* = 0.85). See Table 5 for more details on technostress results.

Table 5

Participants' Mean Technostress Creators and Inhibitors

Scale	M	SD	Min	Max
Technostress Creators	2.54	0.61	1	4.04
Techno-overload	3.06	0.88	1	4.8
Techno-invasion	2.19	0.88	1	5
Techno-complexity	2.10	0.75	1	4
Techno-insecurity	2.04	0.79	1	4.2
Techno-uncertainty	3.42	0.92	1	5
Technostress Inhibitors	3.67	0.66	1.85	5
Literacy facilitation	3.90	0.68	2	5
Technical support provision	3.80	0.79	1	5
Involvement facilitation	3.24	0.90	1	5
Outcomes related to technostress				
Job Satisfaction	4.11	0.64	2	5
Organizational Commitment	3.33	0.91	1	5
Continuance Commitment	3.23	0.85	1.25	5

Note. *n*=153*;* M = mean; SD = standard deviation; Min= minimum value; Max=maximum value

Relationships Between Technostress and Technostress Inhibitors

We hypothesized that the average overall technostress score differs according to levels of technostress inhibitors: literacy facilitation, technical support provision, and involvement facilitation. Spearman's rho correlations were used to assess the strength of relationship between overall technostress and technostress inhibitors. Negative correlations were hypothesized, since technostress inhibitors represent organizational activities that decrease technostress (Ragu-Nathan et al., 2008). Results of the Spearman correlation showed a significant, small negative association between technostress and technical support provision, r (153) = -.21, p = .01 (Cohen, 1988). Relationships between other variables were not significant, including the relationship between technostress and literacy facilitation (p = .05) and the relationship between technostress and involvement facilitation (p = .84). See Table 6 for more information.

Table 6

Relationships Between Technostress and Techno-Inhibitors (Correlation)

	Technostress, overall	**Literacy facilitation**	**Technical support provision**	**Involvement facilitation**
Technostress, overall	1			
Literacy facilitation	-0.16 (p=.05)	1		
Technical support provision	-0.21 (p=.01)	0.68 (p<.001)	1	
Involvement facilitation	0.02 (p=0.84)	0.58 (p<.001)	0.51 (p<.001)	1

Note. n =153, p = p-value for Spearman's correlation

Multiple linear regression was conducted to examine the relationship between technostress and three potential predictors (literacy facilitation, technical support provision, and involvement facilitation). The model showed statistical significance overall (F (3, 149) = 2.80, p

= .04). However, the model explained only a small proportion of the variance in technostress (adjusted $R^2 = 0.03$), indicating that these factors account for approximately 3% of the variability in technostress levels. Literacy facilitation showed a negative relationship with technostress (β = -.138, $p = 0.16$, 95% CI [-.33, .06]). While not statistically significant ($p < .05$ level) there's a trend suggesting that increased literacy facilitation might be associated with decreased technostress. Technical support provision also demonstrated a negative relationship with technostress (β = -.128, $p = 0.14$, 95% CI [-.30, .04]). Again, while not statistically significant, there's a trend indicating that better technical support might be linked to lower technostress levels. However, involvement facilitation shows a positive relationship with technostress (β = .100, $p = 0.15$, 95% CI [-.04, .24]). This suggests that increased involvement facilitation might be associated with higher technostress, though this relationship is not statistically significant. While none of the individual predictors reached statistical significance ($p < .05$), the overall model was significant. This suggests that these factors, taken together, have some predictive power for technostress levels, even if their individual effects are not clearly distinguishable from random variation in this sample. The low R^2 value (adjusted $R^2 = 0.03$) indicates that other factors not included in this model likely play a more substantial role in explaining variations in technostress. While these results may provide some insight into potential factors affecting technostress, they should be interpreted cautiously due to the low explained variance and lack of statistical significance for individual predictors. See Table 7 for more information.

Table 7

Linear Regression Predicting Technostress by Techno-Inhibitors

Technostress	Coef. β	SE	*t*	*p*	[95% CI]	
Intercept	3.24	.29	11.11	<.001	2.67	3.82
Literacy facilitation	-.138	.099	-1.40	0.16	-.33	.06
Technical Support Provision	-.128	.086	-1.49	0.14	-.30	.04
Involvement Facilitation	.100	.069	1.45	0.15	-.04	.24
Results of model: F (3, 149) = 2.80 p= .04, Adjusted R^2 = 0.03						

Note. CI = confidence interval; SE = standard error

Research Aim 2: Explore Relationships Between Technostress and Work Experience

The second aim of this dissertation was to explore relationships between nurses' overall technostress and hospital characteristics (magnet status, type of EHR used, and if the location is a teaching hospital), current work characteristics (hospital department, weekly hours worked, frequency of floating departments, and years of experience at current hospital), and cumulative work experience (years of experience as a nurse and years of experience using EHRs).

Relationships Between Technostress and Hospital Characteristics

A one-way ANOVA was used to evaluate the relationships between hospital characteristics (magnet status, type of EHR used, and if the location is a teaching hospital) and the dependent variable of technostress. Results showed no statistically significant differences in mean technostress by magnet status (F= 0.06, p = .94), teaching hospital (F= 0.09, p = .91), or type of EHR (F= 1.27, p =.27). See Table 8 for more details.

Table 8

One-Way Analysis of Variance Between Technostress and Hospital Characteristics

Hospital Characteristics	% (N)	Mean	SD	F	p-value
Magnet status					
Yes	58 (89)	2.55	.627		
No	33 (50)	2.54	.588		
Unsure	9 (14)	2.48	.636		
Total	100 (153)	2.54	.611	0.06	*p*=.94
Teaching hospital					
Yes	56 (85)	2.53	.643		
No	41 (63)	2.56	.587		
Unsure	3 (5)	2.47	.386		
Total	100 (153)	2.54	.611	0.09	*p*=.91
Type of EHR					
Allscripts	4 (6)	2.33	.812		
AthenaHealth	4 (6)	2.65	.518		
Cerner (Oracle)	14 (22)	2.59	.561		
Epic	43 (65)	2.57	.604		
MEDITECH	11 (17)	2.37	.511		
Other	5 (8)	2.13	.711		
2 of these EHRs	13 (20)	2.57	.707		
3 of these EHRs	6 (9)	2.87	.460		
Total	100 (153)	2.54	.611	1.27	*p*=.27

Note. n=153; EHR = electronic health record; SD = standard deviation; *p*= *p*-value for ANOVA.

Relationships Between Technostress and Current Work Characteristics

A one-way ANOVA was used to examine relationships between technostress and current work characteristics (hospital department, weekly hours worked, frequency of floating departments, and years of experience at the current hospital). There was a statistically significant difference in technostress between at least two groups for frequency of floating departments (F= 3.41, p=.04). Results revealed no statistically significant differences in technostress between at least two groups for hospital department (F= 0.81, p = .59), weekly hours worked (F= 0.25, p = .78) or years of experience at current hospital (F= 0.08, p = .97). See Table 9 for more details.

Table 9

One-Way Analysis of Variance Between Technostress and Current Work Characteristics

Current Work Characteristics	% (N)	Mean	SD	F	p-value
Hospital department					
Behavioral Health / Psychiatry	7 (11)	2.38	.710		
Emergency Department	9 (13)	2.46	.663		
Intensive Care Unit	13 (19)	2.69	.703		
Labor and Delivery or OB-GYN	6 (9)	2.41	.504		
Medical/Surgical	37 (57)	2.65	.574		
Pediatrics	7 (11)	2.37	.709		
Surgery	13 (20)	2.42	.619		
Other - Administrative	5 (8)	2.58	.468		
Other - Hospital Services	3 (5)	2.35	.442		
Total	100 (153)	2.54	.611	0.81	*p*=.59
Weekly hours worked					
20 hours or less per week	(10)	2.59	.496		
21-40 hours per week	(100)	2.56	.633		
41 hours or greater per week	(43)	2.49	.593		
Total	100 (153)	2.54	.611	0.25	*p*=.78
Frequency of floating departments					
Never	(73)	2.42	.635		
Weekly	(69)	2.63	.574		
Almost every day/ Multiple times a shift	(11)	2.81	.532		
Total	100 (153)	2.54	.611	3.41	*p*=.04
Years of experience at current hospital					
7-12 months	(9)	2.48	.819		
1-2 years	(15)	2.6	.440		
2-5 years	(56)	2.54	.672		
More than 5 years	(73)	2.53	.575		
Total	100 (153)	2.54	.611	0.08	*p*=.97

Note. *n*=153*;* SD = standard deviation

Spearman's rho correlations were used to examine relationships between technostress and some current work characteristics. No significant relationships were found between technostress and weekly hours worked (*p*=.66), frequency of floating departments (*p*=.39), or years of experience at hospital (*p*=.93). See Table 10 for more details.

Table 10

Relationships Between Technostress and Current Work Characteristics (Correlation)

	Technostress, overall	Weekly hours worked	Frequency of floating departments	Years of experience at hospital
Technostress, overall	1			
Weekly hours worked	-0.04 (*p*=.66)	1		
Frequency of floating departments	0.07 (*p*=.39)	0.04 (*p*=.59)	1	
Years of experience at hospital	-0.01 (*p*=.93)	0.00 (*p*=.97)	0.04 (*p*=.64)	1

Note. *n*=153; p = *p*-value for Spearman's correlation.

Relationships Between Technostress and Cumulative Work Experience

Spearman's rho correlations were used to examine relationships between technostress and cumulative work experience (years of experience as a nurse and years of experience using EHRs). No significant relationships were found between technostress and years of experience as a nurse (*p*=.51) or years of experience using EHRs (*p*=.62). See Table 11 for more details.

Table 11

Relationships Between Technostress and Cumulative Work Experience (Correlation)

	Technostress, overall	Years of experience as a nurse	Years of experience using EHRs
Technostress, overall	1		
Years of experience as a nurse	0.05 (*p*=.51)	1	
Years of experience using EHRs	0.04 (*p*=.62)	0.83 (***p*=<.001**)	1

Note. *n*=153, *p* = *p*-value for Spearman's correlation.

Research Aim 3: Explore Relationships Between Technostress, EHR factors, and Workload

The third aim of this dissertation was to explore relationships between overall technostress, EHR usability, cognitive workload, and EHR unintended consequences (workload issues, patient safety, sociotechnical impact, workarounds, system design, and technological barriers).

Relationships Between Technostress and EHR Usability

Among the sample of hospital nurses reporting usability (*n*=149), the average EHR usability reported was M= 62.03 (*SD* 16.97, ranging from 15 to 100), indicating below-average usability (Lewis & Sauro, 2018). A simple linear regression was used to investigate the relationship between EHR usability and the outcome of technostress. Results of the model were significant, F (1, 147) = 51.62, p <.001, and explained approximately 30% of the variance (R^2 = 0.30), indicating that approximately 30% of the variance in technostress is explainable by EHR usability. EHR usability significantly predicted technostress (*B*= -0.02, 95% CI [-.25, -,01], p<.001). See Table 12 for more details.

Table 12

Linear Regression Predicting Technostress by EHR Usability

Technostress	Coef. β	SE	*t*	*p*	[95% CI]	
Intercept	3.74	.179	20.86	<.001	3.38	4.09
EHR Usability	-.019	.002	-7.18	<.001	-.0247	-.0140
Results of model: F (1, 147) = 51.62 , Adjusted R^2 = 0.30						

Note. *n*= 149; CI = confidence interval; SE = standard error

Relationships Between Technostress and Cognitive Workload

Among the sample of hospital nurses reporting cognitive workload (*n*=153), the average overall cognitive workload was M= 14.62 (*SD* 2.43, ranging from 5.3 to 19.7). See Table 13 for a breakdown of cognitive workload results, along with averages for subscales.

Table 13

Summary Statistics for Cognitive Workload

Scale	M	SD	Min	Max
Overall Cognitive Workload	14.62	2.43	5.3	19.7
Mental Demand	17	3.03	4	20
Physical Demand	13.5	5.36	0	20
Temporal Demand	15.05	4.18	0	20
Performance	15.99	3.09	7	20
Effort	16	3.50	3	20
Frustration	10.14	5.35	0	20

Note. *n*=153*;* M = mean; SD = standard deviation; Min= minimum value; Max=maximum value

Spearman's rho correlation was used to assess the strength of the relationship between overall technostress and cognitive workload, with correlations for each subscale. Cohen's (1988) guidelines for interpreting the magnitude of a correlation were used, which recommended r = 0.10, r = 0.30, and r = 0.50 to be considered small, medium, and large in magnitude, respectively. Results indicated a small, positive correlation between technostress and the overall cognitive workload score, which was statistically significant (r (153) = 0.27, p<.001). Results showed a medium statistically significant positive correlation between technostress and the cognitive workload subscore for frustration (r (153) = 0.36, p<.001) and a small, statistically significant positive correlation between technostress and the cognitive workload subscore for temporal demand (r (153) = 0.26, p=.001). See Table 14 for more details.

Table 14

Relationships Between Technostress and Cognitive Workload

	TS	CW	MD	PD	TD	P	E	F
Technostress, overall (TS)	1							
Cognitive Workload (CW)	0.27**	1						
Mental Demand (MD)	0.12	0.61**	1					
Physical Demand (PD)	0.08	0.75**	0.41**	1				
Temporal Demand (TD)	0.26*	0.73**	0.42**	0.45**	1			
Performance (P)	-0.14	0.05	0.08	0.03	-0.12	1		
Effort (E)	0.19	0.69**	0.63**	0.48**	0.50**	0.09	1	
Frustration (F)	0.36**	0.53**	0.09	0.20*	0.35**	-0.37**	0.09	1

Note. *n*=153; **p*-value less than .05; ** *p*-value less than .001
Abbreviation: Technostress (TS); Cognitive Workload, overall (CW); Mental Demand (MD); Physical Demand (PD); Temporal Demand (TD); Performance (P); Effort (E); Frustration (F)

Relationships Between Technostress and EHR Unintended Consequences (EHR-UC)

Among the sample of hospital nurses reporting EHR unintended consequences (*n*=136), the average was M= 2.29 (*SD* 1.16, ranging from 0.19 to 4.89), indicating that UC-EHR incidents occurred, on average, once every couple of months. For subscale scores, the highest rated average was sociotechnical impact (M= 3.19, *SD* 1.45), followed by workload issues (M= 2.73, *SD* 1.29), system design (M= 2.64, *SD* 1.40), technological barriers (M= 2.42, *SD* 1.32), patient safety (M= 1.82, *SD* 1.63), and workarounds (M= 1.65, *SD* 1.33). See Table 15 for a breakdown of EHR-UC results.

Table 15

Summary Statistics for Unintended Consequences of Electronic Health Records

Scale	Observation (n)	M	SD	Min	Max
EHR-UC, overall	136	2.29	1.16	0.19	4.89
Workload Issues (WI)	151	2.73	1.29	0	5.5
Patient Safety (PS)	144	1.82	1.63	0	5.86
Sociotechnical Impact (SI)	151	3.19	1.45	0	6
Workarounds (WA)	147	1.65	1.33	0	5
System Design (SD)	149	2.64	1.40	0.14	6
Technological Barriers (TB)	151	2.42	1.32	0	5.75

Note. M = mean; SD = standard deviation; Min= minimum value; Max=maximum value

Spearman's rho correlation was used to assess the strength of the relationship between overall technostress and EHR-UC, with correlations for each subscale. Results showed a medium, statistically significant positive correlation between technostress and the EHR-UC overall score (r (136) = 0.46, p<.001). Most EHR-UC subscores also resulted in medium, statistically significant positive correlations with technostress, including workload issues (r (151) = 0.49, p<.001), patient safety(r (144) = 0.37, p<.001), workarounds (r (147) = 0.31, p<.001), system design (r (149) = 0.42, p<.001), and technological barriers (r (151) = 0.32, p<.001). Results showed a small to medium statistically significant positive correlation between technostress and the EHR-UC subscore for sociotechnical impact (r (151) = 0.29, p<.001). See Table 16 for more details.

Table 16

Relationships Between Technostress and EHR Unintended Consequences (Correlation)

	TS	EHR-UC	WI	PS	SI	WA	SD	TB
Technostress, overall (TS)	1							
EHR-UC, overall	0.46*	1						
Workload Issues (WI)	0.49*	0.77*	1					
Patient Safety (PS)	0.37*	0.90*	0.55*	1				
Sociotechnical Impact (SI)	0.29*	0.63*	0.62*	0.34*	1			
Workarounds (WA)	0.31*	0.71*	0.56*	0.59*	0.32*	1		
System Design (SD)	0.42*	0.72*	0.61*	0.46*	0.73*	0.41*	1	
Technological Barriers (TB)	0.32*	0.86*	0.61*	0.83*	0.41*	0.66*	0.46*	1

Note. * *p*-value less than .001
Abbreviation: Technostress, overall (TS); Electronic Health Record Unintended Consequences, overall (EHR-UC); Workload Issues (WI); Patient Safety (PS); Sociotechnical Impact (SI); Workarounds (WA); System Design (SD); Technological Barriers (TB)

Multiple linear regression was conducted to predict technostress by each EHR-UC subscale (workload issues, patient safety, sociotechnical impact, workarounds, system design, and technological barriers). The overall linear regression model was significant, F (6, 129) = 9.46, p <.001, Adjusted R^2 = 0.27, indicating that approximately 27% of the variance in technostress is explainable by the six subscale elements of EHR-UC. Results showed that workload issues significantly predicted technostress (B= .205, 95% CI [.098, .314], p<.001), as did system design (B= .104, 95% CI [.005, .203], p=.04). See Table 17 for more details.

Table 17

Multiple Regression Predicting Technostress by EHR Unintended Consequences

Technostress	Coef. β	SE	*t*	*p*	[95% CI]	
Intercept	1.92	.124	15.53	*p*<.001	1.67	2.16
Workload Issues	.205	.054	3.77	***p*<.001**	.097	.313
Patient Safety	.092	.048	1.90	*p*=.06	-.003	.188
Sociotechnical Impact	-.059	.051	-1.15	*p*=.25	-.161	.042
Workarounds	-.004	.047	-0.09	*p*=.93	-.097	.088
System Design	.104	.050	2.08	***p*=.04**	.004	.203
Technological Barriers	-.080	.069	-1.17	*p*=.25	-.217	.055
Results of model: $F(6, 129) = 9.46$ $p<.001$, Adjusted $R^2 = 0.27$						

Note: CI = confidence interval; SE = standard error

Overall Model of Factors Associated with Technostress

A stepwise multiple linear regression was used to identify possible predictors of technostress including the following variables: frequency of floating departments, EHR usability, cognitive workload, EHR unintended consequences (EHR-UC; the overall score), and technical support provision. A backward selection strategy was used to identify the best subset of predictors. Analysis began with all candidate variables included in the model. At each step, variables were removed based on individual *p*-values (greater than or equal to .05). Analysis stopped once the model contained only variables with $p < .05$. Table 18 shows the full model. Table 19 shows the final model.

Table 18

Full Model: Stepwise Linear Regression Predicting Technostress by Candidate Variables

Technostress	Coef. β	SE	*t*	*p*	[95% CI]	
Intercept	2.35	.440	5.35	<.001	1.48	3.22
Floating - Never	-.068	.172	-0.40	0.69	-.409	.272
Floating - Weekly	.072	.168	0.43	0.66	-.260	.404
EHR usability	-.018	.002	-6.27	**<.001**	-.024	-.012
Cognitive workload	.047	.018	2.63	**0.01**	.011	.084
EHR-UC	.098	.047	2.08	**0.04**	.004	.192
Technical support provision	.105	.056	1.88	**0.06**	-.005	.217
Results of model: $F(6, 125) = 17.55$ $p<.001$, Adjusted $R^2 = 0.43$						

Note. $n = 132$

Abbreviation: CI = confidence interval; SE = standard error; EHR-UC = Electronic Health Record Unintended Consequences, overall

Table 19

Final Model: Stepwise Linear Regression Predicting Technostress by Candidate Variables

Technostress	Coef. β	SE	*t*	*p*	[95% CI]	
Intercept	2.56	.347	7.39	<.001	1.87	3.25
EHR usability	-.016	.002	-5.72	<.001	-.021	-.010
Cognitive workload	.050	.018	2.71	<.001	.013	.086
EHR-UC	.103	.045	2.30	0.02	.014	.192
Results of model: F (3, 128) = 31.84 $p<.001$, Adjusted $R^2 = 0.41$						

Note. $n = 132$

Abbreviation: CI = confidence interval; SE = standard error; EHR-UC = Electronic Health Record Unintended Consequences, overall

Results of the final model were significant F (3, 128) = 31.84, p <.001, Adjusted R^2 = 0.41, and explained approximately 41% of the variance ($R^2 = 0.41$), indicating that approximately 41% of the variance in technostress is explainable by EHR usability (*B*= -.016, 95% CI [-.021, -.010], p <.001), cognitive workload (*B*= .05, 95% CI [.013, .086], p <.001), and EHR-UC (*B*= .103, 95% CI [.014, .192], p = .02). The final model did not include frequency of floating departments or technical support provision.

Summary of Results

The first aim of this dissertation was to describe technostress among nurses working in hospital environments across the United States. Our first aim was to describe technostress among nurses working in hospital environments across the United States. The first research question for Aim 1 asked: Among the sample of hospital nurses, what is the average level of overall technostress? Among the sample of hospital nurses, the average level of overall technostress was 2.54. The second research question for Aim 1 was: Among the sample of hospital nurses, what are the average levels of technostress creators (techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty)? Average levels of each technostress creator were: techno-overload (3.06), techno-invasion (2.19), techno-complexity (2.10), techno-insecurity (2.04), and techno-uncertainty (3.42). The third research question for Aim 1 was: Among the sample of hospital nurses, what are the average levels of technostress inhibitors (literacy facilitation, technical support provision, and involvement facilitation)? Average levels of technostress inhibitors were: literacy facilitation (3.90), technical support provision (3.80), and involvement facilitation (3.24). The fourth research question for Aim 1 was: Among the sample of hospital nurses, what are the average levels of organizational outcomes related to technostress, including job satisfaction, organizational commitment, and continuance commitment? Average organizational outcomes related to technostress were: job satisfaction (4.11), organizational commitment (3.33), and continuance commitment (3.23). For Aim 1, we hypothesized that the average overall technostress score differs according to levels of technostress inhibitors: literacy facilitation, technical support provision, and involvement facilitation. However, only one technostress inhibitor (technical support provision) showed

a significant correlation with technostress. Results of the Spearman correlation showed a significant, small negative association between technostress and technical support provision.

The second aim of this dissertation was to explore relationships between nurses' overall technostress and hospital characteristics (magnet status, type of EHR used, and if the location is a teaching hospital), current work characteristics (hospital department, weekly hours worked, frequency of floating departments, and years of experience at current hospital), and cumulative work experience (years of experience as a nurse and years of experience using EHRs). The first research question for Aim 2 asked: Are there significant relationships between nurses' technostress and hospital characteristics (magnet status, type of EHR used, and if the location is a teaching hospital)? We found no statistically significant differences in mean technostress by these factors. The second research question for Aim 2 was: Are there significant relationships between nurses' technostress and current work characteristics (hospital department, weekly hours worked, frequency of floating departments, and years of experience at the current hospital)? There was a statistically significant difference in technostress between at least two groups for the frequency of floating departments. We found no statistically significant differences in mean technostress by other factors. The third research question for Aim 2 was: Are there significant relationships between nurses' technostress and cumulative work experience (years of experience as a nurse and years of experience using EHRs)? No significant relationships were found between technostress and years of experience as a nurse or years of experience using EHRs. For Aim 2, we hypothesized that hospital characteristics, current work characteristics, and cumulative work experience predict technostress. However, only one factor for current work characteristics showed a significant correlation. There was a statistically

significant difference in technostress between at least two groups for the frequency of floating departments.

The third aim of this dissertation was to explore relationships between overall technostress, EHR usability, cognitive workload, and EHR unintended consequences (workload issues, patient safety, sociotechnical impact, workarounds, system design, and technological barriers). The first research question for Aim 3 asked: Are there significant relationships between nurses' technostress and EHR usability? Linear regression was used to investigate the relationship between EHR usability and the outcome of technostress. Results of the model were significant, indicating that approximately 30% of the variance in technostress is explainable by EHR usability. The second research question for Aim 3 asked: Are there significant relationships between nurses' technostress and cognitive workload? Spearman's rho correlation was used to assess the strength of the relationship between overall technostress and cognitive workload and its subscales. Results indicated a small, positive correlation between technostress and the overall cognitive workload score, which was statistically significant. Results showed a medium statistically significant positive correlation between technostress and the cognitive workload subscore for frustration and a small, statistically significant positive correlation between technostress and the cognitive workload subscore for temporal demand. The third research question for Aim 3 asked: Are there significant relationships between nurses' technostress and unintended EHR consequences (workload issues, patient safety, sociotechnical impact, workarounds, system design, technological barriers)? Spearman's rho correlation was used to assess the strength of the relationship between overall technostress and EHR-UC, with correlations for each subscale. Results showed a medium, statistically significant positive

correlation between technostress and the EHR-UC overall score. Most EHR-UC subscores also resulted in medium, statistically significant positive correlations with technostress, including workload issues, patient safety, workarounds, system design, and technological barriers. Results showed a small to medium statistically significant positive correlation between technostress and the EHR-UC subscore for sociotechnical impact. For Aim 3, we hypothesized that EHR usability, cognitive workload, and unintended consequences of EHRs predict technostress. Results of the final multiple regression model were significant and indicated that approximately 41% of the variance in technostress is explainable by EHR usability, cognitive workload, and EHR-UC.

End of Chapter Summary

This chapter presented the results of all data analyses for each aim of this dissertation. Descriptive statistics were used to describe this study's participants, including average levels of individual factors such as technostress, technostress inhibitors, hospital characteristics, current work characteristics, cumulative work experience, cognitive workload, and EHR factors (usability and unintended consequences). Relationships between technostress and individual factors were examined using Spearman's rho correlations, ANOVA, and regression analysis when applicable. The next chapter will review and interpret this study's main findings, as well as its strengths, limitations, and implications for future practice and research.

CHAPTER 5: DISCUSSION

The previous chapters have explored the multifaceted phenomenon of technostress, including its potential impact on healthcare workers, the measurement of this phenomenon, and possible approaches to alleviate technology-induced stress. This dissertation sought to describe this phenomenon further among nurses working in hospitals across the United States. The results of this study shed light on some underlying factors associated with technostress in nursing, providing valuable insights into this issue. This chapter will review this study's main findings, as well as its strengths, limitations, and implications for future practice and research.

Restating Study Main Findings

Aim 1: Technostress and Inhibitors

Firstly, technostress among the hospital nurses was examined. Among our sample of 153 hospital nurses, the average level of overall technostress was 2.54 (on a scale of 1 to 5). The classic literature on technostress (Ragu-Nathan et al., 2008; Tarafdar et al., 2007) does not establish specific benchmarks for high or low levels, but we define the average score of 2.54 as moderate, as it exists near the middle of the 1 to 5 scale. Due to the lack of studies involving nurses and technostress in the United States, we are unable to make close comparisons. However, these results are consistent with other studies that found moderate technostress among healthcare professionals in other countries (Bail et al., 2023; Bernburg et al., 2024; Golz et al., 2021a; Golz et al., 2021b; Tell et al., 2023). Average levels of each technostress subscore were also analyzed, including techno-overload (3.06), techno-invasion (2.19), techno-complexity (2.10), techno-insecurity (2.04), and techno-uncertainty (3.42). Techno-uncertainty scored the highest of all technostress constructs and refers to a state of ambiguity experienced due to the

rapid pace of technological change (Ragu-Nathan et al., 2008). These results are consistent with similar studies with physicians, where techno-overload was reported as the highest category of technostress, followed by techno-uncertainty (Bail et al., 2023; Tell et al., 2023).

Technostress inhibitors refer to organizational strategies that can reduce technostress (Ragu-Nathan et al., 2008). Our sample of 153 hospital nurses reported moderate to high levels of technostress inhibitors, including literacy facilitation (3.90), technical support provision (3.80), and involvement facilitation (3.24). These levels are notably higher than similar studies of German physicians (Bail et al., 2023; Bernburg et al., 2024; Tell et al., 2023). However, EHR adoption and support is markedly different in United States hospitals than clinics and emergency departments in Germany. For example, Bail et al. (2023) did not measure technical support provision in their participants, since end-user helpdesks were not available in their inpatient clinics. We hypothesized that the average technostress score would vary significantly depending on the levels of technostress inhibitors, with higher levels of inhibitors expected to correlate with lower levels of overall technostress. We found a small, negative correlation between technostress and technical support provision, partially supporting our hypothesis. This indicates that better technical support is more likely to be associated with lower levels of technostress. While other results were not statistically significant ($p < .05$), involvement facilitation exhibited a positive correlation with technostress, suggesting that increased involvement might increase technostress. Involvement facilitation involves organizational actions that foster user engagement in technological change, including encouraging, rewarding, and consulting employees about new technology updates (Ragu-Nathan et al., 2008). While these activities are meant to decrease technostress, hospital nurses may feel they detract from their time dedicated to patient care.

There are several factors that may limit the generalizability of findings. Most nurses (89 of 153) reported working at a magnet-designated hospital. According to the American Nurses Credentialing Center (2024), only 9.8% of United States hospitals are designated with magnet status. Additionally, our sample reported an exceptionally high average job satisfaction score of 4.11 and moderate to high levels of organizational outcomes related to technostress, including organizational commitment (3.33), and continuance commitment (3.23). While we did not find significant correlations between technostress and literacy facilitation or involvement facilitation, it's noteworthy that the average scores for technostress inhibitors were higher than those for technostress creators. These factors suggest that many participants were satisfied with their workplace and the technological support and services offered to mitigate technostress. These findings suggest that further research is needed to confirm and generalize these results, as they may not be representative of all populations.

Aim 2: Technostress and Work Factors

Secondly, we examined relationships between nurses' technostress, hospital characteristics (magnet status, type of EHR used, and if the location is a teaching hospital), current work characteristics (hospital department, weekly hours worked, frequency of floating departments, and years of experience at current hospital), and cumulative work experience (years of experience as a nurse and years of experience using EHRs). We hypothesized that hospital characteristics, current work characteristics, and cumulative work experience predict technostress. However, our analysis revealed that only the frequency of floating departments was significantly associated with technostress. Despite this initial association, frequency of floating departments was not found significant in our final linear regression model. Thus, we rejected our

second hypothesis. This is the first known study to explore technostress and work factors among working hospital nurses in the United States. One major assumption of this study was that increased experience with EHRs would significantly impact technostress. Surprisingly, no significant relationships were found between technostress and cumulative work experience (years of experience as a nurse or years of experience using EHRs). We also found no significant associations between the hospital department and technostress. Golz et al. (2021b) found technostress differed between settings for Swiss health professionals, but this compared acute care hospitals with psychiatric hospitals, nursing homes, and home care organizations. No known studies have compared technostress and hospital setting, but organizational elements of the professional practice environment and unintended consequences of EHRs (EHR-UC) were examined, showing less frequent EHR-UCs in environments with better leadership and autonomy (Gephart et al., 2016). When combined with our findings for Aim 3, these results indicate that technostress is more likely influenced by the complex interplay of social, technological, and organizational factors rather than individual nurse characteristics.

Aim 3: Technostress and Technology Factors

Thirdly, we explored the relationships between technostress, EHR usability, cognitive workload, and EHR unintended consequences (workload issues, patient safety, sociotechnical impact, workarounds, system design, and technological barriers). We hypothesized that EHR usability, cognitive workload, and unintended consequences of EHRs predict technostress. Our final regression model revealed that EHR usability, cognitive workload, and EHR-UC significantly predicted technostress and approximately 41% of the variance in technostress is explained by these three factors. Thus, we accepted our third hypothesis.

Relationships between technostress and technological factors were also explored separately. We found a significant negative relationship between EHR usability and technostress among the sample of hospital nurses, with EHR usability explaining approximately 30% of the variance in technostress. The findings suggest that improving EHR usability could contribute to a reduction in technostress among hospital nurses. We also found a small but significant positive correlation between overall technostress and cognitive workload. For cognitive workload subscores, a medium positive correlation was found between technostress and frustration and a small positive correlation between technostress and temporal demand. While this was the first known study to explore technostress and cognitive load among nurses, researchers have found significant correlations between cognitive workload and UC-EHR in ED nurses (Harmon et al., 2023). These findings suggest that strategies aimed at reducing cognitive workload may also be effective in mitigating technostress among hospital nurses, particularly with efforts to decrease the frustration and temporal demand aspects of cognitive workload. We found a significant positive moderate correlation between technostress and EHR-UC, with small to medium correlations for all subscales. These findings suggest that addressing unintended EHR consequences (such as workload issues, patient safety concerns, technological barriers, and system design issues) could effectively mitigate technostress among hospital nurses. Based on these findings, it appears that strategies aimed at enhancing EHR usability, mitigating cognitive workload, and addressing unintended EHR consequences could be beneficial in addressing technostress among hospital nurses.

Overall Interpretation of Results

This study was among the first to explore technostress among hospital nurses in the United States. Our findings indicate that hospital nurses experience moderate levels of technostress, with techno-uncertainty and techno-overload as the highest concerns. The primary factors influencing technostress in this study were EHR usability, cognitive workload, and unintended EHR consequences. Other factors (hospital characteristics, current work characteristics, and cumulative work experience) did not appear to be closely related to technostress in our sample. While technical support provision emerged as a significant inhibitor of technostress in our sample, efforts to improve EHR usability, cognitive workload, and unintended EHR consequences could also be considered potential technostress inhibitors for hospital nurses. Our findings suggest that technostress is primarily shaped by the intricate relationship between social, technological, and organizational elements, rather than individual nurse traits. Thus, technology optimization efforts by nurse informaticists and leadership could prove the most effective at combating technostress. These findings align with the overall effort to improve EHR usability to improve health outcomes for clinicians and patients (National Academies of Science, Engineering, and Medicine, 2019; Office of the Surgeon General, 2022).

Technostress is a systemic issue that extends beyond the limitations of EHRs. It is influenced by the cumulative impact of all the technological tools and systems that nurses are required to use in their work, creating a complex and often overwhelming technological landscape. Nurses in this study reported the highest levels of technostress specifically related to uncertainty about technology. Hospital nurses can experience techno-uncertainty as frequent technological changes in their organizational environment, such as updates to computer software,

hardware, and networks, necessitating constant learning and adaptation. Rapid technological changes cause distress for frontline nurse leaders, who may already feel overwhelmed by insufficient training and loss of break time (Laukka et al., 2023). While frequent changes can be stressful, techno-uncertainty also highlights the confusion that can arise in a constantly evolving sociotechnical environment, particularly regarding employee expectations and outcomes (Ragu-Nathan et al., 2008).

High scores for techno-uncertainty could also be explained by the recent rise in artificial intelligence (AI) in healthcare. Potential unintended consequences of AI in the nursing profession is a serious consideration (Pailaha, 2023). Many nurses have reported ethical and privacy concerns with AI (Rony et al., 2024) and limited knowledge of its use in practice (Alruwaili et al., 2024; Sommer et al., 2024). A recent scoping review of AI applications in healthcare revealed that 36.6% of studies lacked discussion of ethical considerations and 33.3% of studies did not report involvement of nurses in their AI technology development, implementation, or operational phases (von Gerich et al., 2022). Some nurses feel they have a duty to protect their patients from potential harms AI may bring (Rony et al., 2024; Sockolow et al., 2024). A survey of over 2,300 registered nurses and members of National Nurses United (2024) reported that 60% of nurses disagreed with the statement: “I trust my employer will implement A.I. with patient safety as the first priority.” Nurses have recently protested their concerns surrounding the rushed implementation of AI technology at California hospitals, citing patient safety concerns (Fox, 2024; Walker, 2024). Given their past experiences with EHR adoptions, many nurses may approach the introduction of AI with caution, fearing that it could lead to negative unintended consequences and increase their technostress and uncertainty about

their job duties and requirements. Although this study also investigated UC-EHR, AI is not included in that measure. There is an opportunity for future research to revise this measure to explore unintended consequences of AI use in hospitals.

Nurses in this study reported the second highest level of technostress specifically related to techno-overload, where they feel technology forces them to work longer and faster. This could be related to both increased cognitive workload and the phenomenon of documentation burden, described as an increased effort and time spent documenting in the EHR (Moy et al., 2021a). For example, clinicians often face the burden of double documentation, where they must input the same information in multiple locations, leading to frustration (Bernburg et al., 2024). Efforts by nurse informaticists and leadership to decrease documentation burden and increase transparency and education surrounding AI could help alleviate technostress for frontline hospital nurses.

Study Strengths

This study represents one of the first investigations of technostress among hospital nurses in the United States, providing a valuable foundation for future research. We successfully identified key factors influencing technostress and offered suggestions for future research directions. The nationwide recruitment of participants, rather than relying on a local convenience sample, may enhance the generalizability of our findings. Additionally, our study achieved a sample size of 153, exceeding the estimated requirement of 123. We also employed validated instruments to measure technostress, usability, cognitive workload, and EHR-UC, which allows for future comparisons. This study was grounded in theoretical models of technostress and nurse science. This was a strength because it provided a robust theoretical framework for understanding and analyzing the complex relationship between technology and nursing practice.

The theoretical models offered a solid foundation for developing research questions, interpreting findings, and drawing meaningful conclusions. These strengths position this study as a solid foundation for future research.

Study Limitations

External validity refers to how well results can be generalized beyond the study itself (Trochim, 2022). Most limitations of this study are common to cross-sectional, online research. One limitation of this study design is that it uses subjective self-report questionnaires to measure variables of interest. Self-report data is vulnerable to an external validity threat, reactivity, where participants' awareness of the measure could influence their performance (Kazdin, 2022). However, this research aimed to investigate technostress and other variables of interest that are subjective in nature. Some strategies were used to minimize the influence of subject awareness, including using an electronic survey process, encouraging honest responses, and making it clear to participants that all survey data will remain anonymous (Kazdin, 2022). In addition, using a convenience sample and cross-sectional data collection may have limited the generalizability of results. Cross-sectional data collection provided a snapshot of technostress and its correlates at a single point in time, limiting our ability to draw conclusions about causality or changes over time. Future research could address these limitations by using longitudinal data collection to examine the temporal dynamics of technostress. Additionally, online recruitment of nurses may have contributed to a sampling bias by attracting a sample of nurses more likely to participate in online surveys or studies, potentially leading to a biased sample that does not accurately represent the broader population of nurses. Another limitation may be the potential for false positives, where fraudulent or bot responses were mistakenly identified as legitimate and

included in the analysis. However, our survey used a multi-layered approach to mitigate fraudulent and bot responses. Only 14 participants had one potential fraudulent RelevantID score, representing 9% of the study population. Since these 14 participants had no other potentially fraudulent scores, they were not removed from analysis.

Some aspects of our sample may have limited the representativeness and, thus, the generalizability of our study results. Nurses reported a high average value for job satisfaction (4.11), which could indicate that the sample may not be representative of nurses experiencing higher levels of work stress and dissatisfaction. Additionally, this study did not include nurses working in non-hospital locations, such as clinics. To gain a comprehensive understanding of technostress, future research should focus on defining and examining this phenomenon among nurses outside of hospital settings.

Implications for Practice

Technostress provides a framework for nurses to articulate their stress related to workplace technology. While much attention has been given to EHRs, hospital nurses utilize a wide range of technological tools, including email, patient monitoring systems, medication administration systems, communication devices, and various software applications. These tools, while essential for modern healthcare delivery, can contribute to technostress if not used effectively or in conjunction with appropriate support and training. Nurses may also experience technostress due to factors such as:

- Techno-overload: The constant influx of information and alerts from multiple technological sources can lead to feelings of being overwhelmed.

- Techno-invasion: Nurses may feel constantly connected to the technology, disrupting boundaries between work and personal life.
- Techno-complexity: The increasing complexity of workplace technology can demand more time and effort to learn and use effectively.
- Techno-insecurity: Nurses may fear job loss due to automation or colleagues with greater technological expertise.
- Techno-uncertainty: The rapid pace of technological change can require frequent learning and adaptation, leading to feelings of uncertainty and insecurity.

Nurse informaticists are well-suited to address technostress among nurses working in technologically complex hospital environments. The findings of this study indicate that enhancing EHR usability and decreasing cognitive workload could potentially alleviate technostress among hospital nurses, with some specific factors to consider. Among technostressors, techno-uncertainty was reported to have the highest average level by our study participants, followed by techno-overload. There is an overwhelming need to decrease the cognitive demand of EHRs which contributes to burnout among clinicians (Alexander & Staggers, 2009; Dyrbye et al., 2020). Nurses may be overwhelmed by the constant communication regarding technological changes at their organization, or they may feel that the time spent learning these changes detracts from their patient care responsibilities, leading to feelings of techno-overload. New technological implementation efforts, such as AI, may be contributing to nurses' techno-uncertainty due to ambiguous benefits, limited training, and unclear responsibilities. Nurse informaticists can consider these points when designing and supporting both new and existing technologies. Addressing technostress requires a multifaceted

approach that involves optimizing technology design, providing adequate training and support, promoting work-life balance, and fostering a supportive work environment. By implementing these strategies, healthcare organizations can help nurses manage the challenges of technology-driven work and improve overall job satisfaction and patient care.

Implications for Research

Little is still known about the overall state of technology-related stress among healthcare workers, which is often measured as technostress in other fields. Technostress is an understudied yet significant concern for healthcare professionals, with potential negative consequences such as mental distress, decreased work engagement, and burnout. Most technostress studies among healthcare professionals have been conducted in Europe, primarily focusing on physicians using a variety of measurements. The findings of this study can serve as a catalyst for future research on technostress among nurses working in the United States. To obtain a broader perspective on technostress among United States nurses, additional studies are needed. Future studies are needed to further define technostress among both hospital and non-hospital nurses, explore factors contributing to technostress, and evaluate interventions to reduce technostress. Researchers should investigate the potential role of involvement facilitation as a techno-inhibitor among nurses, as it may inadvertently contribute to technostress rather than alleviating it.

While this study included a diverse sample of nurses from various specialties and departments, limitations may have prevented us from identifying significant work factors related to technostress. Future research might benefit from examining more homogeneous groups of nurses, such as nurses from one large hospital organization. This would allow for a more in-depth examination of how specific factors, such as organizational culture, work environment,

and individual characteristics, might influence technostress levels among nurses. Our conclusions align with previous research emphasizing the need for further efforts to improve EHR usability, cognitive workload, and unintended EHR consequences, as these factors were found to be related to technostress.

Conclusion

This study was among the first to explore technostress among hospital nurses in the United States. Technostress poses a significant challenge to the nursing profession, with far-reaching implications for nurses' health, well-being, and patient care. By understanding the factors contributing to technostress and implementing strategies to mitigate its effects, nursing organizations and individuals can create healthier and more supportive work environments for nurses. Future research is needed to further explore this important issue and develop effective interventions to address technostress.

APPENDIX A

THE UNIVERSITY OF ARIZONA INSTITUTIONAL REVIEW BOARD APPROVAL LETTER

THE UNIVERSITY OF ARIZONA
Research
Innovation & Impact

University of Arizona IRB
845 N Park Ave., Suite 537A
Tucson, AZ 85719
Fax: 520-621-9810
VPR-IRB@arizona.edu

MINIMAL RISK APPROVAL

July 2, 2024

Dear Krista Brandon:

On 7/2/2024, the IRB reviewed the following submission:

Type of Review:	Initial Study
Title:	Technostress and Contributing Factors Among Hospital Nurses
Investigator:	Krista Brandon
IRB Submission ID:	STUDY00004668
Sponsor:	None
Prime Sponsor:	None
Documents Reviewed:	• IRB Protocol for Human Subjects Research KnB, Category: IRB Protocol; • 3 Recruitment Post on Social Media.docx, Category: Recruitment Materials; • 3 Recruitment_flyer.docx, Category: Recruitment Materials; • Advisor Attestation, Category: Institutional Approval; • Appendix for Waiver or Alteration of Consent or PHI, Category: Other; • Attestation for Scientific Review and Department Review, Category: Institutional Approval; • Consent-Disclosure Form, Category: Consent Form; • PI CV, Category: CV; • Study Questionnaire, Category: Data Collection Tool;

The IRB approved the protocol from 7/2/2024 .

The consent form(s) were approved with this submission. Please ensure to download the stamped consent forms located on the main study workspace in the "Final" column of the Study Documents tab.

THE UNIVERSITY OF ARIZONA
Research
Innovation & Impact

University of Arizona IRB
845 N Park Ave., Suite 537A
Tucson, AZ 85719
Fax: 520-621-9810
VPR-IRB@arizona.edu

Regulatory determinations:

- **Risk Level:** No greater than minimal risk
- **Pediatric Risk Level:** None
- **Review Level:** Exempt; Minimal Risk 2018: The project is not federally funded or supported and has been deemed to be no more than minimal risk.
- **Special Determinations:** None

This project has been reviewed and approved by the IRB or designee. All documents referenced in this submission have been reviewed and approved. The University of Arizona maintains a Federalwide Assurance (FWA) with the Office for Human Research Protections (OHRP) (FWA #00004218). This Institution assures that all of its activities related to human subjects research, regardless of the source of support, will be guided by the Belmont Report and applicable regulations according to 45 CFR 46.111 and/or 21 CFR Part 50. Modifications may be needed for Minimal Risk research. Please refer to the Guidance *Exempt/Minimal Risk Research* for a list of changes that would require a Modification submission. All research procedures should be conducted according to the approved protocol and the policies and guidance of the IRB. The Principal Investigator should notify the IRB immediately of any proposed changes that affect the protocol and report any unanticipated problems involving risks to participants or others. Please refer to Guidance *Investigators Responsibility after IRB Approval*, *Reporting New Information*, and *Exempt/Minimal Risk Research*.

We value your feedback and would appreciate you taking the time to complete our survey about your experience with the IRB staff:
https://uarizona.co1.qualtrics.com/jfe/form/SV_ehQ04WxNA06b42i.

If questions arise at any time during your study, please email the general IRB inbox at VPR-IRB@arizona.edu.

APPENDIX B

RESEARCH DISCLOSURE FORM

- **Social Media Participants: Consent Form**

- **University of Arizona**
- **Consent to Participate in Research**
-

Study Title: Technostress and Contributing Factors Among Hospital Nurses
Principal Investigator: Krista Brandon MSN, RN (PhD Candidate)
Consent Version: 05/20/2024

You are being asked to participate in a research study. Your participation in this research study is voluntary and you do not have to participate. This document contains important information about this study and what to expect if you decide to participate. Please consider the information carefully. Feel free to ask questions before making your decision whether to participate.

The purpose of this study is to examine the unintended consequences of technology use among nurses working in hospitals, with particular attention to technology-related stress (technostress). We aim to describe technostress among hospital nurses and identify factors that are significantly related to technostress among nurses. Your participation will contribute to academic knowledge regarding this understudied topic in the nursing profession.

To participate in this study, you must be a nurse (LPN or RN) working in a hospital setting in the United States. Work settings such as outpatient clinics and skilled nursing facilities are excluded from this study. To participate in this study, you must also be 18 years of age or older, live and work in the United States, be fluent in the English language, and have at least 6 months of experience using an electronic health record (EHR) as part of your current hospital work.

You will be asked to complete a demographic questionnaire and answer surveys pertaining to this research focus. The total estimated time it takes to complete all questionnaires is 30 minutes. There are no direct benefits to participating in this study. The only cost to you is your time. There are no known immediate physical, social, legal, or economic risks associated with participation in this research.

The information that you give in the study will be anonymous. Your name will not be collected or linked to your answers. Because of the nature of the data, it may be possible to deduce your identity; however, there will be no attempt to do so, and your data will be reported in a way that will not identify you. Once your questionnaire data has been collected for this study, your information cannot be withdrawn, as there are no subject identifiers (such as name and address) attached to any of the surveys. This is for your protection, as only group data will be analyzed. Individuals in this study will not be identified. Your information may be used for future research or shared with another researcher for future research studies without additional consent.

The information that you provide in the study will be handled confidentially. However, there may be circumstances where this information must be released or shared as required by law. The University of Arizona Institutional Review Board; other federal, state, or international regulatory

agencies, may review the research records for monitoring purposes. The University of Arizona Institutional Review Board (IRB) has approved this research study.

For questions, concerns, or complaints about the study you may contact**:** Krista Brandon (Primary Investigator), PhD candidate, MSN, RN at kristabrandon@arizona.edu.

For questions about your rights as a participant in this study, or to discuss other study-related concerns or complaints with someone who is not part of the research team, you may contact the Human Subjects Protection Program Director at 520-626-8630 or online at https://research.arizona.edu/compliance/human-subjects-protection-program.

Completing the online questionnaire implies that you have read the information in this letter and consent to participate in this research.

Thank you for your time and participation!

APPENDIX C

RECRUITMENT MATERIALS

Social Media Recruitment Post

My name is Krista Brandon. I am a PhD Candidate at the University of Arizona, and I invite you to participate in a study I am conducting for my dissertation.

I am interested in how electronic health records and other workplace technologies contribute to technostress among hospital nurses. There is little research related to technostress among nurses, and your participation would greatly contribute to describing this phenomenon among hospital nurses in the United States. If you are interested, please see additional details in the attached flyer.

Thank you for your support!

NOTE: An Institutional Review Board responsible for human subjects research at The University of Arizona reviewed this research project and found it to be acceptable, according to applicable state and federal regulations and University policies designed to protect the rights and welfare of participants in research.

Social Media Recruitment Flyer

NURSE PARTICIPANTS NEEDED FOR TECHNOSTRESS RESEARCH STUDY

Are you a nurse working in a hospital setting in the United States? Do you use an electronic health record (EHR) to document patient care? If so, please consider participating.

What is the study about?

We want to better understand how electronic health records and other workplace technologies contribute to stress among hospital nurses.

Who can participate?

- Registered nurses (RNs) or licensed practical nurses (LPNs) that work in hospitals in the United States
- 18 years of age or older
- Can read and write in English
- Greater than 6 months of experience using the electronic health record (EHR) as part of your current hospital work

What does the study involve?

You will be asked to complete a series of online questionnaires. The estimated time to complete all questionnaires is 30 minutes or less. All survey results are anonymous and confidential. Click the link at the bottom of this form to access the study information and questionnaires.

INTERESTED? Please join now:

https://uarizona.co1.qualtrics.com/jfe/form/SV_3Q5YG5STxjPWr0W

An Institutional Review Board responsible for human subjects research at The University of Arizona reviewed this research project and found it to be acceptable, according to applicable state and federal regulations and University policies designed to protect the rights and welfare of participants in research.

Crowdsource Recruitment Material:
Study Information included in Amazon MTurk and/or Prolific

Title of Study: Technostress Among Hospital Nurses

Description/Instructions:

The purpose of this study is to examine the unintended consequences of technology use among nurses working in hospitals, with particular attention to technology-related stress (technostress). We aim to describe technostress among hospital nurses and identify factors that are significantly related to technostress among nurses. Your participation will contribute to academic knowledge regarding this understudied topic in the nursing profession.

To participate in this study, you must be a nurse (LPN or RN) working in a hospital setting in the United States. Work settings such as outpatient clinics and skilled nursing facilities are excluded from this study. To participate in this study, you must also be 18 years of age or older, live and work in the United States, be fluent in the English language, and have at least 6 months of experience using an electronic health record (EHR) as part of your current hospital work. If you are not currently located in the United States and/or are under the age of 18, please do not complete this survey.

If you are NOT a nurse working in a hospital in the United States, please do not complete this survey. If you are not currently located in the United States and/or are under the age of 18, please do not complete this survey.

You will be asked to complete a demographic questionnaire and answer surveys pertaining to this research focus. The estimated time it takes to complete all questionnaires is 15 minutes.

NOTE: An Institutional Review Board responsible for human subjects research at The University of Arizona reviewed this research project and found it to be acceptable, according to applicable state and federal regulations and University policies designed to protect the rights and welfare of participants in research.

APPENDIX D

INSTRUMENTS AND MEASURES

Nursing Demographic Questionnaire

The following section will ask questions about your current work:

1. NDQ01
   How long have you worked for your current organization?
   - Less than 2 months
   - 2-4 months
   - 5-6 months
   - 7-12 months
   - 1-2 years
   - 2-5 years
   - More than 5 years
   - Other (e.g. I work for more than one organization)
   - Don't know
   - Not applicable / rather not say

2. NDQ02
   Please try to estimate: How many hours do you work per week?
   - 1-10 hours per week
   - 11-20 hours per week
   - 21-30 hours per week
   - 31-40 hours per week
   - 41-50 hours per week
   - 51-60 hours per week
   - More than 60 hours per week
   - None

3. NDQ03: For your current job position, are you a travel nurse? (Yes/No)

4. NDQ04
   Is the hospital you work at a Magnet-designated* hospital? (Yes/No/Unsure)
   (*Magnet hospitals are certified by the American Nurses' Credentialing Center (ANCC) as institutions where nurses are empowered to not only take the lead on patient care but to be the drivers of institutional health care change and innovation.)

5. NDQ05
   Is the hospital you work at a teaching hospital? (Yes/No/Unsure)

6. NDQ06
   Select the hospital department where you perform most of your work:
   - Behavioral Health / Psychiatry
   - Inpatient department - Intensive Care Unit
   - Inpatient department - Medical/Surgical

- Inpatient department - Labor and Delivery or Obstetrics and Gynecology
- Inpatient department - Pediatrics
- Inpatient department – Stepdown or Telemetry
- Outpatient department - Emergency Department
- Outpatient department - Radiology
- Outpatient department - Surgery
- Other/Not Listed (freetext)

7. NDQ07
   How often do you "float", or perform work at different departments in the hospital?
   - Never
   - At least once a week
   - More than once a week
   - Almost every day
   - Multiple times a shift

8. NDQ08
   What type of electronic health record (EHR) do you use for your daily work?

   - Cerner (Oracle)
   - Epic
   - MEDITECH
   - Allscripts
   - AthenaHealth
   - Other/Not Listed (freetext)

The following section will ask questions about your overall work experience and other details:

9. NDQ09
   Please enter your age (in years): (numerical)

10. NDQ10
    Please select your gender:
    - Female
    - Male
    - Nonbinary
    - Other
    - Prefer Not to Respond

11. NDQ11
    Please select your highest level of education in nursing:
    - Diploma or certificate in nursing
    - Associate's (ADN)

- Bachelor's (BSN)
- Master's (MSN)
- Doctoral (DNP or PhD)

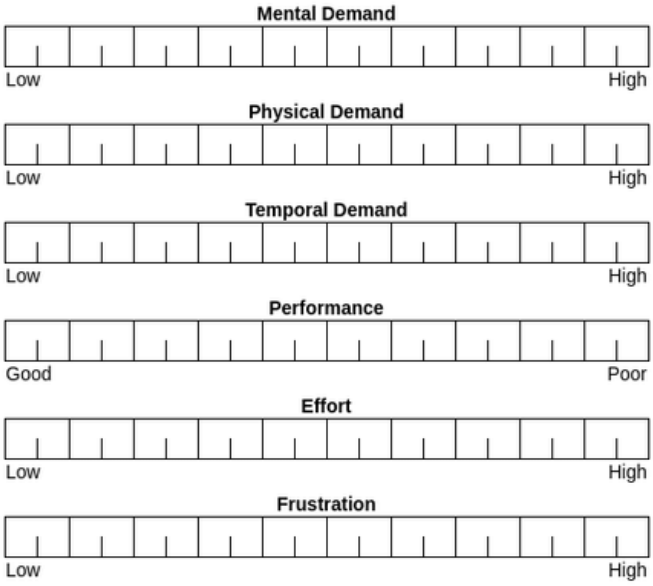
12. NDQ12
    Please enter your **total** number of years employed as a nurse, overall:
    (numerical)

13. NDQ13
    Please enter your **total** number of years using electronic health records (EHRs) as a nurse:
    (numerical)

National Aeronautics and Space Administration Task Load Index (NASA TLX; adapted from Hart & Staveland, 1988)

Directions: Please reflect on a day you performed work at the hospital during the last 1 - 2 weeks that is representative of a typical workday. Then, click on each scale at the point that best indicated your efforts documenting in the electronic health record (EHR).

1. Mental Demand: How mentally demanding was the task?
2. Physical Demand: How physically demanding was the task?
3. Temporal Demand: How hurried or rushed was the pace of the task?
4. Performance: How successful were you in accomplishing what you were asked to do?
5. Effort: How hard did you have to work to accomplish your level of performance?
6. Frustration: How insecure, discouraged, irritated, stressed, and annoyed were you?



Notes on scoring this instrument:

NASA TLX survey scale items are ranked on a 0–20 scale, with 0 for “Very Low” and 20 for “Very High”. A mean score is calculated from the 6 questions to calculate an overall summary workload score. A higher summary score indicates a higher cognitive load.

System Usability Scale (SUS; adapted from Brooke, 1996)

Directions: Please reflect on a day you performed work at the hospital during the last 1 - 2 weeks that is representative of a typical workday. Then, score the following items in relation to your efforts documenting in the electronic health record (EHR).

Strongly Disagree				Strongly Agree
1	2	3	4	5

1. I think that I would like to use this system frequently.
2. I found the system unnecessarily complex.
3. I thought the system was easy to use.
4. I think that I would need the support of a technical person to be able to use this system.
5. I found the various functions in this system were well integrated.
6. I thought there was too much inconsistency in this system.
7. I would imagine that most people would learn to use this system very quickly.
8. I found the system very cumbersome to use.
9. I felt very confident using the system.
10. I needed to learn a lot of things before I could get going with this system.

Notes on scoring this instrument:

Survey scale items are ranked on a 5-point Likert scale, with 1 for “Strongly disagree” and 5 for “Strongly Agree”. To calculate the overall SUS score, the sum of each item is calculated. For items 1, 3, 5, 7, and 9, the score is the scale position minus 1. For items 2, 4, 6, 8 and 10, the score is the scale position minus 5. The sum of all scores is then multiplied by 2.5 to obtain the overall value. SUS scores have a range of 0 to 100. A higher summary score indicates a higher, or more favorable, usability.

Technostress Questionnaire (Ragu-Nathan et al., 2008)

Directions: Please score the following items in relation to your current work experience. Please note that the term this technology refers to all computer-based applications you use for your current work (in addition to the EHR), such as e-mail, medication scanners, automated medication dispensing systems, smartphones, portable monitors, smart IV pumps, smart beds, wearable technology (such as call devices), telehealth applications, point-of-care technology, and more.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5

Technostress Creators Inventory

1. TCI_TO1: I am forced by this technology to work much faster.
2. TCI_TO2: I am forced by this technology to do more work than I can handle.
3. TCI_TO3: I am forced by this technology to work with very tight time schedules.
4. TCI_TO4: I am forced to change my work habits to adapt to new technologies.
5. TCI_TO5: I have a higher workload because of increased technology complexity.
6. TCI_TI1: I spend less time with my family due to this technology.
7. TCI_TI2: I have to be in touch with my work even during my vacation due to this technology.
8. TCI_TI3: I have to sacrifice my vacation and weekend time to keep current on new technologies.
9. TCI_TI4: I feel my personal life is being invaded by this technology.
10. TCI_TC1: I do not know enough about this technology to handle my job satisfactorily.
11. TCI_TC2: I need a long time to understand and use new technologies.
12. TCI_TC3: I do not find enough time to study and upgrade my technology skills.
13. TCI_TC4: I find new recruits to this organization know more about computer technology than I do.
14. TCI_TC5: I often find it too complex for me to understand and use new technologies.
15. TCI_TIN1: I feel constant threat to my job security due to new technologies.
16. TCI_TIN2: I have to constantly update my skills to avoid being replaced.
17. TCI_TIN3: I am threatened by coworkers with newer technology skills.
18. TCI_TIN4: I do not share my knowledge with my coworkers for fear of being replaced.
19. TCI_TIN5: I feel there is less sharing of knowledge among coworkers for fear of being replaced.
20. TCI_TU1: There are always new developments in the technologies we use in our organization.
21. TCI_TU2: There are constant changes in computer software in our organization.
22. TCI_TU3: There are constant changes in computer hardware in our organization.
23. TCI_TU4: There are frequent upgrades in computer networks in our organization.

Technostress Inhibitors Scale

24. TIS_LF1: Our organization encourages knowledge sharing to help deal with new technology.
25. TIS_LF2: Our organization emphasizes teamwork in dealing with new technology-related problems.
26. TIS_LF3: Our organization provides end-user training before the introduction of new technology.
27. TIS_LF4: Our organization fosters a good relationship between IT department and end users.
28. TIS_LF5: Our organization provides clear documentation to end users on using new technologies.
29. TIS_TS1: Our end-user help desk does a good job of answering questions about technology.
30. TIS_TS2: Our end-user help desk is well staffed by knowledgeable individuals.
31. TIS_TS3: Our end-user help desk is easily accessible.
32. TIS_TS4: Our end-user help desk is responsive to end-user requests.
33. TIS_IF1: Our end users are encouraged to try out new technologies.
34. TIS_IF2: Our end users are rewarded for using new technologies.
35. TIS_IF3: Our end users are consulted before introduction of new technology.
36. TIS_IF4: Our end users are involved in technology change and/or implementation.

Outcomes Related to Technostress

37. TOC_JS1: I like doing the things I do at work.
38. TOC _JS2: I feel a sense of pride in doing my job.
39. TOC _JS3: My job is enjoyable.
40. TOC _OC1: I would be happy to spend the rest of my career in this organization.
41. TOC _OC2: I enjoy discussing my organization with people outside it.
42. TOC _OC3: I really feel as if this organization's problems are my own.
43. TOC _OC4: This organization has great deal of personal meaning for me.
44. TOC _CC1: Too much of my life would be disrupted if I decided I want to leave my organization right now.
45. TOC _CC2: Right now, staying with my organization is a matter of necessity as much as desire.
46. TOC _CC3: I believe that I have too few options to consider leaving this organization.
47. TOC _CC4: It would be very hard for me to leave my organization right now even if I wanted to.

Note: Items on the technostress creator inventory (TCI) are also reported per subscale: techno-overload (TO), Techno-invasion (TI), techno-complexity (TC), techno-insecurity (TIN), and techno-uncertainty (TU). Items from the technostress inhibitor scale (TIS) are reported per subscale: literacy facilitation (LF), technical support provision (TS), and involvement facilitation (IF). Organizational outcomes related to technostress (TOC) are reported per construct: job satisfaction (JS), organizational commitment (OC), and continuance commitment (CC). Subscale item acronyms are not shown in the actual survey questions but included here for reference.

Carrington-Gephart Unintended Consequences of Electronic Health Record Questionnaire
(CG-UCE-Q; Carrington et al., 2015; Gephart et al., 2016)

Directions: Please score the following items in relation to your efforts documenting in the electronic health record (EHR) at your organization.

Never	Once a year	Once every couple of months	Once a month	Once a week	Once a shift	Multiple times a shift
0	1	2	3	4	5	6

1. WI: How often does using the EHR increase your workload?
2. WI: When using electronic health records, how often have you experienced changes to your workflow?
3. TB: All information systems require information technology support to maintain the system. In your organization, how often is your work disrupted during hardware and software updates?
4. SI: How often have you experienced differences in communication patterns using the EHR versus other communication methods in your institution?
5. PS: How often have you seen patient safety issues (e.g., documenting or entering orders on the wrong patient) arise from using EHRs?
6. WI: How often have you experienced power shifts while using the EHR?
7. WA: How often are you unable to access patient information in the EHR because of problems with your password?
8. WA: How often in your practice do you add to your nursing note through the shift to edit for details but do not sign it each time?
9. WA: How often do you save the note without signing it because of concerns that, once signed, it becomes a permanent part of the EHR?
10. WA: How often do you deal with a computer that doesn't work by documenting on paper?
11. TB: If one computer is not working, how often do you use a different computer station?
12. PS: Please indicate how often this EHR issue creates an unsafe patient care situation: when you are reviewing orders.
13. TB: Please indicate how often this EHR issue creates an unsafe patient care situation: when you need to administer a medication urgently.
14. PS; TB: Please indicate how often this EHR issue creates an unsafe patient care situation: when your patient comes to the hospital in critical condition.
15. PS: Please indicate how often this EHR issue creates an unsafe patient care situation: when a patient is admitted to the hospital.
16. PS: Please indicate how often this EHR issue creates an unsafe patient care situation: when a patient is admitted to your setting.
17. PS: Please indicate how often this EHR issue creates an unsafe patient care situation: when a change in patient status occurs.

18. PS: Please indicate how often these EHR issues create an unsafe patient care situation: when a patient is transferred within the hospital.
19. PS: Please indicate how often these EHR issues create an unsafe patient care situation: when a patient is transferred to another hospital or care setting (e.g., long-term care) from your hospital.
20. PS: Please indicate how often these EHR issues create an unsafe patient care situation: when a patient is transferred to your hospital from another setting.
21. PS: Please indicate how often these EHR issues create an unsafe patient care situation: when a patient is discharged home.
22. PS: Please indicate how often EHR issues create an unsafe patient care situation: when you are trying to assess risk for complications (egg, related to diagnosis, comorbidities).
23. PS: Please indicate how often these EHR issues create an unsafe patient care situation: when you need to teach your patients.
24. PS: Please indicate how often these EHR issues create an unsafe patient care situation: when you need to coordinate care while your patient is on your unit.
25. PS: Please indicate how often these EHR issues create an unsafe patient care situation: when you need to coordinate care for your patient once they leave your unit.
26. SD: How often do you have trouble documenting because the system is slow?
27. WI: How often, when attempting to use the EHR, do the computers not work (e.g., because they are not turned on or they have lost power)?
28. SI: How often, when entering data into the EHR, do you have to leave your computer before finishing because you get interrupted?
29. SI: How often, when entering data into the EHR, do you have to leave your computer before finishing your task because you remembered you needed to do something and had to leave your computer?
30. SI: How often does documenting take too long so that you cannot do important parts of your other work?
31. SD: How often, when entering data, do you enter the same data repeatedly in different places?
32. SD: How often in your practice, as a result of needing to enter the same patient information in more than one place, do you make mistakes documenting in the EHR?
33. SD: How often, when retrieving data from the EHR, do you find there is no nursing note to help you understand what is going on with the patient?
34. SD: How often is it difficult to locate significant information (e.g., changes in clinical status) about your patient in the EHR?
35. SD: How often, when you need to make a decision about your patient, is there too little patient information documented for you to understand the clinical picture?
36. SD: How often, when you go back into the EHR to find information you know you entered, is it difficult to find patient information you entered?

Notes on scoring this instrument:

Survey scale items are ranked on a 0 to 6 scale: 0 is “Never”, 1 is “Once a year”, 2 is “Once every couple of months”, 3 is “Once a month”, 4 is “Once a week”, 5 is “Once a shift”, and 6 is “Multiple times a shift”. A mean score is calculated from all questions to calculate an overall score of the frequency of EHR-related unintended consequences (UC-EHR). The higher the score, the higher the frequency of UC-EHR. Frequency of UC-EHR is also reported per subscale: workload issues (WI), patient safety (PS), sociotechnical impact (SI), workarounds (WA), system design (SD), and technological barriers (TB). Subscale acronyms are not shown in the actual survey questions but included here for reference.

REFERENCES

Adams, T. L., Li, Y., & Liu, H. (2020). A replication of Beyond the Turk: Alternative platforms for crowdsourcing behavioral research – Sometimes preferable to student groups. *AIS Transactions on Replication Research*, *6*, 15. https://doi.org/10.17705/1atrr.00058

Albert, D. A., & Smilek, D. (2023). Comparing attentional disengagement between Prolific and MTurk samples. *Scientific Reports*, *13*(1), 20574. https://doi.org/10.1038/s41598-023-46048-5

Alexander, G., & Staggers, N. (2009). A systematic review of the designs of clinical technology: Findings and recommendations for future research. *ANS: Advances in Nursing Science*, *32*(3), 252–279. https://doi.org/10.1097/ANS.0b013e3181b0d737

Alghamdi, M. G. (2016). Nursing workload: A concept analysis. *Journal of Nursing Management*, *24*(4), 449–457. https://doi.org/10.1111/jonm.12354

American Nurses Credentialing Center. (ANCC). (2024, January). *Find a Magnet organization.* American Nurses Enterprise. https://www.nursingworld.org/organizational-programs/magnet/find-a-magnet-organization/

Alobayli, F., O'Connor, S., Holloway, A., & Cresswell, K. (2023). Electronic health record stress and burnout among clinicians in hospital settings: A systematic review. *Digital Health*, *9*, 20552076231220241. https://doi.org/10.1177/20552076231220241

Alruwaili, M. M., Abuadas, F. H., Alsadi, M., Alruwaili, A. N., Elsayed Ramadan, O. M., Shaban, M., Al Thobaity, A., Alkahtani, S. M., & El Arab, R. A. (2024). Exploring nurses' awareness and attitudes toward artificial intelligence: Implications for nursing practice. *Digital Health*, *10*, 20552076241271803. https://doi.org/10.1177/20552076241271803

Arnetz, B. B., & Wiholm, C. (1997). Technological stress: Psychophysiological symptoms in modern offices. *Journal of Psychosomatic Research, 43*(1), 35–42. https://doi.org/10.1016/S0022-3999(97)00083-4

Atashzadeh-Shoorideh, F., Monjazabi, F., Fathollahzadeh, E., & Parastoo, O. (2021). The obstacles to nurses being present with patients. *Nursing Open*, *8*(3), 1115–1124. https://doi.org/10.1002/nop2.723

Attipoe, S., Walker, D. M., Schweikhart, S. B., & Hefner, J. L. (2023). A qualitative study of the dark and bright sides of physicians' electronic health record work outside work hours. *Health Care Management Review*, *48*(2), 140-149. https://doi.org/10.1097/HMR.0000000000000361

Ayyagari, R., Grover, V., & Purvis, R. (2011). Technostress: Technological antecedents and implications. *MIS Quarterly*, *35*(4), 831–858. https://doi.org/10.2307/41409963

Bahr, T. J., Ginsburg, S., Wright, J. G., & Shachak, A. (2023). Technostress as source of physician burnout: An exploration of the associations between technology usage and physician burnout. *International Journal of Medical Informatics*, *177*, 105147. https://doi.org/10.1016/j.ijmedinf.2023.105147

Bail, C., Harth, V., & Mache, S. (2023). Digitalization in urology—A multimethod study of the relationships between physicians' technostress, burnout, work engagement and job satisfaction. *Healthcare (2227-9032)*, *11*(16), 2255. https://doi.org/10.3390/healthcare11162255

Bakhai, A., McCauley, L., Stones, L., Khalil, S., Mehta, J., Price, N., . . . Hughes, D. (2022). Shining a light on an additional clinical burden: Work-related digital communication survey study - COVID-19 impact on NHS staff wellbeing. *Humanities & Social Sciences Communications*, *9*(1), 414. https://doi.org/10.1057/s41599-022-01427-7

Bangor, A., Kortum, P. T., & Miller, J. T. (2008). An empirical evaluation of the system usability scale. *International Journal of Human-Computer Interaction*, *24*(6), 574–594. https://doi.org/10.1080/10447310802205776

Bates, D. W., & Singh, H. (2018). Two decades since to err is human: An assessment of progress and emerging priorities in patient safety. *Health Affairs*, *37*(11), 1736–1743. https://doi.org/10.1377/hlthaff.2018.0738

Bernburg, M., Tell, A., Groneberg, D. A., & Mache, S. (2024). Digital stressors and resources perceived by emergency physicians and associations to their digital stress perception, mental health, job satisfaction and work engagement. *BMC Emergency Medicine*, *24*(1), 31. https://doi.org/10.1186/s12873-024-00950-x

Bøgeskov, B. O., & Grimshaw-Aagaard, S. L. S. (2018). Essential task or meaningless burden? Nurses' perceptions of the value of documentation. *Nordic Journal of Nursing Research*, *39*(1), 9–19. https://doi.org/10.1177/2057158518773906

Bondanini, G., Giorgi, G., Ariza-Montes, A., Vega-Muñoz, A., & Andreucci-Annunziata, P. (2020). Technostress: Dark side of technology in the workplace: A scientometric analysis. *International Journal of Environmental Research and Public Health*, *17*(21), 8013. https://doi.org/10.3390/ijerph17218013

Bonett, S., Lin, W., Sexton Topper, P., Wolfe, J., Golinkoff, J., Deshpande, A., Villarruel, A., & Bauermeister, J. (2024). Assessing and improving data integrity in web-based surveys: Comparison of fraud detection systems in a COVID-19 study. *JMIR Formative Research*, *8*, e47091. https://doi.org/10.2196/47091

Boy, G. A. (2011). *The handbook of human-machine interaction: A human-centered design approach*. Ashgate Publishing.

Brod, C. (1984). *Technostress: The human cost of the computer revolution*. Addison-Wesley.

Brooke, J. (1996). SUS: A "quick and dirty" usability scale. In P. W. Jordan, B. Thomas, B. A. Weerdmeester, & I. L. McClelland (Eds.), *Usability evaluation in industry* (pp. 189–194). London: Taylor & Francis.

Brown, J. A., Cooper, A. L., & Albrecht, M. A. (2020). Development and content validation of the burden of documentation for nurses and midwives (BurDoNsaM) survey. *Journal of Advanced Nursing*, *76*(5), 1273–1281. https://doi.org/10.1111/jan.14320

Burke, M. S. (2009). The incidence of technological stress among baccalaureate nurse educators using technology during course preparation and delivery. *Nurse Education Today*, *29*(1), 57–64. https://doi.org/10.1016/j.nedt.2008.06.008

Butts, J. B. & Rich, K.L. (2018). *Philosophies and theories for advanced nursing practice* (3rd ed.). Jones & Bartlett Publishers.

Carper, B. (1978). Fundamental patterns of knowing in nursing. *ANS. Advances in Nursing Science*, *1*(1), 13–23. https://doi.org/10.1097/00012272-197810000-00004

Carrington, J. M., Gephart, S. M., Verran, J. A., & Finley, B. A. (2015). Development of an instrument to measure the unintended consequences of EHRs. *Western Journal of Nursing Research*, *37*(7), 842–858. https://doi.org/10.1177/0193945915576083

Castro, H. M., & Ferreira, J. C. (2023). Linear and logistic regression models: When to use and how to interpret them? *Jornal Brasileiro de Pneumologia*, *48*(6), e20220439. https://doi.org/10.36416/1806-3756/e20220439

Chandler, J., & Shapiro, D. (2016). Conducting clinical research using crowdsourced convenience samples. *Annual Review of Clinical Psychology*, *12*, 53–81. https://doi.org/10.1146/annurev-clinpsy-021815-093623

Chen, R. F., & Hsiao, J. L. (2021). Health professionals' perspectives on electronic medical record infusion and individual performance: Model development and questionnaire survey study. *JMIR Medical Informatics*, *9*(11), e32180. https://doi.org/10.2196/32180

Chinn, P. L., Kramer, M. K., & Sitzman, K. (2022). *Knowledge development in nursing: Theory and process* (11th ed.). Elsevier.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Routledge.

Colicchio, T. K., Cimino, J. J., & Del Fiol, G. (2019). Unintended consequences of nationwide electronic health record adoption: Challenges and opportunities in the post-meaningful use era. *Journal of Medical Internet Research, 21*(6), e13313. https://doi.org/10.2196/13313

Colligan, L., Potts, H. W., Finn, C. T., & Sinkin, R. A. (2015). Cognitive workload changes for nurses transitioning from a legacy system with paper documentation to a commercial electronic health record. *International Journal of Medical Informatics*, *84*(7), 469–476. https://doi.org/10.1016/j.ijmedinf.2015.03.003

Collins, S., Couture, B., Kang, M. J., Dykes, P., Schnock, K., Knaplund, C., Chang, F., & Cato, K. (2018). Quantifying and visualizing nursing flowsheet documentation burden in acute and critical care. *AMIA ... Annual Symposium proceedings. AMIA Symposium*, *2018*, 348–357.

Congdon, J. G., & Magilvy, J. K. (1995). The changing spirit of rural community nursing: Documentation burden. *Public Health Nursing (Boston, Mass.)*, *12*(1), 18–24. https://doi.org/10.1111/j.1525-1446.1995.tb00118.x

Cooper, & Zmud, R. W. (1990). Information technology implementation research: A technological diffusion approach. *Management Science, 36*(2), 123–139. https://doi.org/10.1287/mnsc.36.2.123

Cooper, A. L., Kelly, M. S., & Brown, J. A. (2023). Co-design of an intervention to reduce the burden of clinical documentation: A clinician-researcher collaboration. *Applied Nursing Research: ANR*, *73*, 151730. https://doi.org/10.1016/j.apnr.2023.151730

Cooper, C. L., Dewe, P., O'Driscoll, M. P. (2001). *Organizational stress a review and critique of theory, research, and applications*. Sage Publications.

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

De Groot, K., De Veer, A. J. E., Munster, A. M., Francke, A. L., & Paans, W. (2022). Nursing documentation and its relationship with perceived nursing workload: A mixed-methods study among community nurses. *BMC Nursing*, *21*(1), 34. https://doi.org/10.1186/s12912-022-00811-7

Deng, W., Yang, T., Deng, J., Liu, R., Sun, X., Li, G., & Wen, X. (2023). Investigating factors influencing medical practitioners' resistance to and adoption of internet hospitals in China: Mixed methods study. *Journal of Medical Internet Research*, *25*, e46621. https://doi.org/10.2196/46621

DesRoches, C., Donelan, K., Buerhaus, P., & Zhonghe, L. (2008). Registered nurses' use of electronic health records: Findings from a national survey. *Medscape Journal of Medicine*, *10*(7), 164.

Dias, R. D., Ngo-Howard, M. C., Boskovski, M. T., Zenati, M. A., & Yule, S. J. (2018). Systematic review of measurement tools to assess surgeons' intraoperative cognitive workload. *The British Journal of Surgery*, *105*(5), 491–501. https://doi.org/10.1002/bjs.10795

Douglas, B. D., Ewell, P. J., & Brauer, M. (2023). Data quality in online human-subjects research: Comparisons between MTurk, Prolific, CloudResearch, Qualtrics, and SONA *PloS ONE*, *18*(3), e0279720. https://doi.org/10.1371/journal.pone.0279720

Dudding, Gephart, S. M., & Carrington, J. M. (2018). Neonatal nurses experience unintended consequences and risks to patient safety with electronic health records. *Computers, Informatics, Nursing*, *36*(4), 167–176. https://doi.org/10.1097/CIN.0000000000000406

Dyrbye, L. N., West, C. P., Leep Hunderfund, A., Johnson, P., Cipriano, P., Peterson, C., Beatty, D., Major-Elechi, B., & Shanafelt, T. (2020). Relationship between burnout and professional behaviors and beliefs among US nurses. *Journal of Occupational and Environmental Medicine*, *62*(11), 959–964. https://doi.org/10.1097/JOM.0000000000002014

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyzes using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*, 1149-1160.

Fawcett, J. (1993). From a plethora of paradigms to parsimony in worldviews. *Nursing Science Quarterly, 6* (2), 56-58.

Fischer, T., Reuter, M., & Riedl, R. (2021). The digital stressors scale: Development and validation of a new survey instrument to measure digital stress perceptions in the workplace context. *Frontiers in Psychology*, *12*, 607598. https://doi.org/10.3389/fpsyg.2021.607598

Fischer, T., Reuter, M., & Riedl, R. (2021). The digital stressors scale: Development and validation of a new survey instrument to measure digital stress perceptions in the workplace context. *Frontiers in Psychology*, *12*, 607598. https://doi.org/10.3389/fpsyg.2021.607598

Fox, A. (2024, April 30). *Nurses have a deep distrust of AI – but transparency and training could help*. Healthcare IT News. https://www.healthcareitnews.com/news/nurses-have-deep-distrust-ai-transparency-and-training-could-help

Francis, I. (2017). Nursing informatics and the metaparadigms of nursing. *Online Journal of Nursing Informatics, 21*(1), 8–1.

Galy, E., Cariou, M., & Mélan, C. (2012). What is the relationship between mental workload factors and cognitive load types? *International Journal of Psychophysiology: Official Journal of the International Organization of Psychophysiology*, *83*(3), 269–275. https://doi.org/10.1016/j.ijpsycho.2011.09.023

Gephart, S. M., Bristol, A. A., Dye, J. L., Finley, B. A., & Carrington, J. M. (2016). Validity and reliability of a new measure of nursing experience with unintended consequences of electronic health records. *Computers, Informatics, Nursing*, *34*(10), 436–447. https://doi.org/10.1097/CIN.0000000000000285

Gephart, S. M., Carrington, J. M., & Finley, B. (2015). A systematic review of nurses' experiences with unintended consequences when using the electronic health record. *Nursing Administration Quarterly*, *39*(4), 345–356. https://doi.org/10.1097/NAQ.0000000000000119

Gesner, E., Dykes, P. C., Zhang, L., & Gazarian, P. (2022). Documentation burden in nursing and its role in clinician burnout syndrome. *Applied Clinical Informatics*, *13*(5), 983–990. https://doi.org/10.1055/s-0042-1757157

Gimpel, H., Lanzl, J., Regal, C., Urbach, N., Wischniewski, S., Tegtmeier, P., Kreilos, M., Kühlmann, T. M., Becker, J., Eimecke, J., & Derra, N. D. (2019). *Gesund digital arbeiten?!: Eine Studie zu digitalem Stress in Deutschland*. https://doi.org/10.24406/fit-n-562039

Goldman, J. (2022). Continuous glucose monitoring metrics: Interpretation and integrations. *The American Journal of Managed Care*, *28*(4 Suppl), S69-S75. https://doi.org/10.37765/ajmc.2022.89214

Golz, C., Peter, K. A., Müller, T. J., Mutschler, J., Zwakhalen, S. M. G., & Hahn, S. (2021a). Technostress and digital competence among health professionals in Swiss psychiatric hospitals: Cross-sectional study. *JMIR Mental Health, 8*(11), e31408. https://doi.org/10.2196/31408

Golz, C., Peter, K. A., Zwakhalen, S. M. G., & Hahn, S. (2021b). Technostress among health professionals - A multilevel model and group comparisons between settings and professions. *Informatics for Health & Social Care*, *46*(2), 136-147. https://doi.org/10.1080/17538157.2021.1872579

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly, 19*(2), 213-236.

Hall, A., & Walton, G. (2004). Information overload within the health care system: A literature review. *Health Information and Libraries Journal*, *21*(2), 102–108. https://doi.org/10.1111/j.1471-1842.2004.00506.x

Harmon, C. S., Adams, S. A., Davis, J. E., Gephart, S. M., & Donevant, S. B. (2023). Unintended consequences of the electronic health record and cognitive load in emergency department nurses. *Applied Nursing Research*, *73*, 151724–151724. https://doi.org/10.1016/j.apnr.2023.151724

Harris, D. A., Haskell, J., Cooper, E., Crouse, N., & Gardner, R. (2018). Estimating the association between burnout and electronic health record-related stress among advanced practice registered nurses. *Applied Nursing Research: ANR*, *43*, 36–41. https://doi.org/10.1016/j.apnr.2018.06.014

Hart, S. G., & Staveland, L.E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In P .A. Hancock & N. Meshkati (Eds.), *Human mental workload* (pp. 139–183). Amsterdam: North Holland.

Hendrich, A., Chow, M. P., Skierczynski, B. A., & Lu, Z. (2008). A 36-hospital time and motion study: How do medical-surgical nurses spend their time? *Permanente Journal*, *12*(3), 25–34. https://doi.org/10.7812/tpp/08-021

Hertzum, M. (2021). Reference values and subscale patterns for the task load index (TLX): A meta-analytic review. *Ergonomics*, *64*(7), 869–878. https://doi.org/10.1080/00140139.2021.1876927

Higgins, L. W., Shovel, J. A., Bilderback, A. L., Lorenz, H. L., Martin, S. C., Rogers, D. J., & Minnier, T. E. (2017). Hospital nurses' work activity in a technology-rich environment: A triangulated quality improvement assessment. *Journal of Nursing Care Quality*, *32*(3), 208–217. https://doi.org/10.1097/NCQ.0000000000000237

Hoonakker, P., Carayon, P., Gurses, A. P., Brown, R., Khunlertkit, A., McGuire, K., & Walker, J. M. (2011). Measuring workload of ICU nurses with a questionnaire survey: The NASA Task Load Index (TLX). *IIE Transactions on Healthcare Systems Engineering*, *1*(2), 131–143. https://doi.org/10.1080/19488300.2011.609524

Howe, J. L., Adams, K. T., Hettinger, A. Z., & Ratwani, R. M. (2018). Electronic health record usability issues and potential contribution to patient harm. *JAMA*, *319*(12), 1276–1278. https://doi.org/10.1001/jama.2018.1171

Howell, D. C. (2016). *Fundamental statistics for the behavioral sciences*. (9th ed.). Cengage.

Iduye, S. (2023). Application of Fawcett's criteria in theory evaluation. *Nursing Science Quarterly*, *36*(1), 58–63. https://doi.org/10.1177/08943184221131966

Institute of Medicine. (IOM). (2000). *To err is human: Building a safer health system*. Washington, DC: The National Academies Press. https://doi.org/10.17226/9728

International Organization for Standardization. (2018). *Ergonomics of human-system interaction — Part 11: Usability: Definitions and concepts* (ISO Standard No. 9241-11:2018). https://www.iso.org/obp/ui/#iso:std:iso:9241:-11:ed-2:v1:en

Kaihlanen, A. M., Gluschkoff, K., Laukka, E., & Heponiemi, T. (2021). The information system stress, informatics competence and well-being of newly graduated and experienced nurses: A cross-sectional study. *BMC Health Services Research*, *21*(1), 1096. https://doi.org/10.1186/s12913-021-07132-6

Kaltenegger, H. C., Becker, L., Rohleder, N., Nowak, D., Quartucci, C., & Weigl, M. (2023). Associations of technostressors at work with burnout symptoms and chronic low-grade inflammation: A cross-sectional analysis in hospital employees. *International Archives of Occupational and Environmental Health*, *96*(6), 839-856. https://doi.org/10.1007/s00420-023-01967-8

Kaltenegger, H. C., Marques, M. D., Becker, L., Rohleder, N., Nowak, D., Wright, B. J., & Weigl, M. (2024). Prospective associations of technostress at work, burnout symptoms, hair cortisol, and chronic low-grade inflammation. *Brain, Behavior, and Immunity*, *117*, 320-329. https://doi.org/10.1016/j.bbi.2024.01.222

Kang, H. (2021). Sample size determination and power analysis using the G*Power software. *Journal of Educational Evaluation for Health Professions*, *18*, 17. https://doi.org/10.3352/jeehp.2021.18.17

Kazdin, A. E. (2022). *Research design in clinical psychology* (5th ed.). Cambridge University Press. https://doi.org/10.1017/9781108993647

Kim, M. O., Coiera, E., & Magrabi, F. (2017). Problems with health information technology and their effects on care delivery and patient outcomes: A systematic review. *Journal of the American Medical Informatics Association: JAMIA*, *24*(2), 246–250. https://doi.org/10.1093/jamia/ocw154

Koon, S. (2021). Physician well-being and the future of health information technology. *Mayo Clinic Proceedings. Innovations, Quality & Outcomes*, *5*(4), 753–761. https://doi.org/10.1016/j.mayocpiqo.2021.06.001

Kremer, L., Leeser, L., & Breil, B. (2019). Mental workload relating health information system - A literature review. *Studies in Health Technology and Informatics*, *267*, 289–296. https://doi.org/10.3233/SHTI190840

Kroth, P. J., Morioka-Douglas, N., Veres, S., Babbott, S., Poplau, S., Qeadan, F., Parshall, C., Corrigan, K., & Linzer, M. (2019). Association of electronic health record design and use factors with clinician stress and burnout. *JAMA Network Open*, *2*(8), e199609. https://doi.org/10.1001/jamanetworkopen.2019.9609

Kutney-Lee, A., Brooks Carthon, M., Sloane, D. M., Bowles, K. H., McHugh, M. D., & Aiken, L. H. (2021). Electronic health record usability: Associations with nurse and patient outcomes in hospitals. *Medical Care*, *59*(7), 625–631. https://doi.org/10.1097/MLR.0000000000001536

Laukka, E., Hammarén, M., Pölkki, T., & Kanste, O. (2023). Hospital nurse leaders' experiences with digital technologies: A qualitative descriptive study. *Journal of Advanced Nursing*, *79*(1), 297–308. https://doi.org/10.1111/jan.15481

Lazarus, R. S. (1966). *Psychological stress and the coping process.* McGraw-Hill.

Lazarus, R. S., & Folkman S. (1984). *Stress, appraisal and coping*. New York, NY: Springer.

Lee, S. B., Lee, S. C., and Suh, Y. H. (2016). Technostress from mobile communication and its impact on quality of life and productivity. *Total Quality Management & Business Excellence*, *27*(7-8), 775–790. https://doi.org/10.1080/14783363.2016.1187998

Lewis, J. R., & Sauro, J. (2018). Item benchmarks for the system usability scale. *Journal of Usability Studies*, *13*(3). 158-167. https://uxpajournal.org/item-benchmarks-system-usability-scale-sus/

Liehr, P. R., & Smith, M. J. (2017). Middle range theory: A perspective on development and use. *Advances in Nursing Science*, *40*(1), 51–63. https://doi.org/10.1097/ANS.0000000000000162

Lindsay, M. R., & Lytle, K. (2022). Implementing best practices to redesign workflow and optimize nursing documentation in the electronic health record. *Applied Clinical Informatics*, *13*(3), 711–719. https://doi.org/10.1055/a-1868-6431

Liu, C.-F., Cheng, T.-J., & Chen, C.-T. (2019). Exploring the factors that influence physician technostress from using mobile electronic medical records. *Informatics for Health & Social Care*, *44*(1), 92-104. https://doi.org/10.1080/17538157.2017.1364250

Lucena, J. C.-R., Carvalho, C., Santos-Costa, P., Mónico, L., & Parreira, P. (2021). Nurses' strategies to prevent and/or decrease work-related technostress: A scoping review. *CIN: Computers, Informatics, Nursing*, *39*(12), 916-920. https://doi.org/10.1097/CIN.0000000000000771

Marsh, E., Vallejos, E. P., & Spence, A. (2022). The digital workplace and its dark side: An integrative review. *Computers in Human Behavior*, *128*, 107118. https://doi.org/10.1016/j.chb.2021.107118

McBride, S. & Tietze, M. (2019). *Nursing informatics for the advanced practice nurse* (2nd ed.). Springer Publishing Company. https://doi.org/10.1891/9780826140555

McBride, S., Alexander, G. L., Baernholdt, M., Vugrin, M., & Epstein, B. (2023). Scoping review: Positive and negative impact of technology on clinicians. *Nursing Outlook, 71*(2), 101918. https://doi.org/10.1016/j.outlook.2023.101918

Meehan, E., R. (1985). [Review of *Technostress: The human cost of the computer revolution*]. *Journal of Broadcasting & Electronic Media*, *29*(2), 226–228. Broadcast Education Association.

Melnick, E. R., Dyrbye, L. N., Sinsky, C. A., Trockel, M., West, C. P., Nedelec, L., Tutty, M. A., & Shanafelt, T. (2020). The association between perceived electronic health record usability and professional burnout among US physicians. *Mayo Clinic Proceedings*, *95*(3), 476–487. https://doi.org/10.1016/j.mayocp.2019.09.024

Minda, S., & Brundage, D. J. (1994). Time differences in handwritten and computer documentation of nursing assessment. *Computers in Nursing*, *12*(6), 277–279.

Mirzaei, A., Carter, S. R., Patanwala, A. E., & Schneider, C. R. (2022). Missing data in surveys: Key concepts, approaches, and applications. *Research in Social and Administrative Pharmacy*, *18*(2), 2308–2316. https://doi.org/10.1016/j.sapharm.2021.03.009

Mohammadnejad, F., Freeman, S., Klassen-Ross, T., Hemingway, D., & Banner, D. (2023). Impacts of technology use on the workload of registered nurses: A scoping review. *Journal of Rehabilitation and Assistive Technologies Engineering*, *10*, 20556683231180189. https://doi.org/10.1177/20556683231180189

Momenipour, A., & Pennathur, P. R. (2019). Balancing documentation and direct patient care activities: A study of a mature electronic health record system. *International Journal of Industrial Ergonomics, 72*, 338–346. https://doi.org/10.1016/j.ergon.2019.06.012

Mortensen, K., & Hughes, T. L. (2018). Comparing Amazon's mechanical Turk platform to conventional data collection methods in the health and medical research Literature. *Journal of General Internal Medicine*, *33*(4), 533–538. https://doi.org/10.1007/s11606-017-4246-0

Moy, A. J., Aaron, L., Cato, K. D., Schwartz, J. M., Elias, J., Trepp, R., & Rossetti, S. C. (2021b). Characterizing multitasking and workflow fragmentation in electronic health records among emergency department clinicians: Using time-motion data to understand documentation burden. *Applied Clinical Informatics*, *12*(5), 1002–1013. https://doi.org/10.1055/s-0041-1736625

Moy, A. J., Hobensack, M., Marshall, K., Vawdrey, D. K., Kim, E. Y., Cato, K. D., & Rossetti, S. C. (2023). Understanding the perceived role of electronic health records and workflow fragmentation on clinician documentation burden in emergency departments. *Journal of the American Medical Informatics Association: JAMIA*, *30*(5), 797–808. https://doi.org/10.1093/jamia/ocad038

Moy, A. J., Schwartz, J. M., Chen, R., Sadri, S., Lucas, E., Cato, K. D., & Rossetti, S. C. (2021a). Measurement of clinical documentation burden among physicians and nurses using electronic health records: A scoping review. *Journal of the American Medical Informatics Association: JAMIA*, *28*(5), 998–1008. https://doi.org/10.1093/jamia/ocaa325

Moy, A. J., Schwartz, J. M., Withall, J., Lucas, E., Cato, K. D., Rosenbloom, S. T., Johnson, K., Murphy, J., Detmer, D. E., & Rossetti, S. C. (2021c). Clinician and health care leaders' experiences with and perceptions of COVID-19 documentation reduction policies and practices. *Applied Clinical Informatics*, *12*(5), 1061–1073. https://doi.org/10.1055/s-0041-1739518

National Academies of Science, Engineering, and Medicine. (2019). *Taking action against clinician burnout: A systems approach to professional well-being*. The National Academies Press.

National Nurses United. (2024, May 15). *National Nurses United survey finds AI technology degrades and undermines patient safety*. https://www.nationalnursesunited.org/press/national-nurses-united-survey-finds-ai-technology-undermines-patient-safety

Nguyen, O. T., Jenkins, N. J., Khanna, N., Shah, S., Gartland, A. J., Turner, K., & Merlo, L. J. (2021a). A systematic review of contributing factors of and solutions to electronic health record-related impacts on physician well-being. *Journal of the American Medical Informatics Association: JAMIA*, *28*(5), 974–984. https://doi.org/10.1093/jamia/ocaa339

Nguyen, O. T., Shah, S., Gartland, A. J., Parekh, A., Turner, K., Feldman, S. S., & Merlo, L. J. (2021b). Factors associated with nurse well-being in relation to electronic health record use: A systematic review. *Journal of the American Medical Informatics Association: JAMIA*, *28*(6), 1288–1297. https://doi.org/10.1093/jamia/ocaa289

Nielson, J. (2012, January 3). *Usability 101: Introduction to usability.* Nielsen Norman Group. https://www.nngroup.com/articles/usability-101-introduction-to-usability/

O'Brien, A., Weaver, C., Settergren, T. T., Hook, M. L., & Ivory, C. H. (2015). EHR documentation: The hype and the hope for improving nursing satisfaction and quality outcomes. *Nursing Administration Quarterly, 39*(4), 333–339. https://doi.org/10.1097/NAQ.0000000000000132

O'Connor, O'Reilly, P., & O'Donoghue, J. (2013). M-health infusion by healthcare practitioners in the national health services (NHS). *Health Policy and Technology, 2*(1), 26–35. https://doi.org/10.1016/j.hlpt.2012.12.002

Office of the Surgeon General. (2022). *Addressing health worker burnout–The US Surgeon General's advisory on building a thriving health workforce. Current Priorities of the US Surgeon General*. U.S. Department of Health and Human Services. https://www.hhs.gov/sites/default/files/health-worker-wellbeing-advisory.pdf

Pailaha, A. D. (2023). The impact and issues of artificial intelligence in nursing science and healthcare settings. *Sage Open Nursing, 9*, 23779608231196847. https://doi.org/10.1177/23779608231196847

Parse, R. R. (1987). *Nursing science: Major paradigms, theories, and critiques.* W. B. Saunders.

Peart, J., & MacKinnon, K. (2018). Cultivating praxis through Chinn and Kramer's emancipatory knowing. *ANS. Advances in Nursing Science, 41*(4), 351–358. https://doi.org/10.1097/ANS.0000000000000232

Peer, E., Rothschild, D., Gordon, A., Evernden, Z., & Damer, E. (2022). Data quality of platforms and panels for online behavioral research. *Behavior Research Methods, 54*(4), 1643–1662. https://doi.org/10.3758/s13428-021-01694-3

Pepper, S. P. (1948). *World hypotheses: A study in evidence*. Berkeley: University of California Press.

Perpetua, Z., Lennon, J., Shovel, J. A., Appell, K. E., Patterson, L., Martin, S. C., Minnier, T. E., Sackrowitz, R., Zapf, R. L., Kip, P. L., & McLaughlin, M. (2023). A Current state assessment on nursing work activities: An observational study. *Journal of Nursing Care Quality, 38*(4), 381–387. https://doi.org/10.1097/NCQ.0000000000000723

Prolific. (2024, September 15). *About Prolific*. https://www.prolific.com/about

Qualtrics. (2024, September 15). *Fraud detection*. https://www.qualtrics.com/support/survey-platform/survey-module/survey-checker/fraud-detection

Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S., & Tu, Q. (2008). The consequences of technostress for end users in organizations: Conceptual development and empirical validation. *Information Systems Research, 19*(4), 417–433. https://doi.org/10.1287/isre.1070.0165

Ratwani, R. M., Fairbanks, R. J., Hettinger, A. Z., & Benda, N. C. (2015). Electronic health record usability: analysis of the user-centered design processes of eleven electronic health record vendors. *Journal of the American Medical Informatics Association: JAMIA*, *22*(6), 1179–1182. https://doi.org/10.1093/jamia/ocv050

Ratwani, R. M., Savage, E., Will, A., Fong, A., Karavite, D., Muthu, N., Rivera, A. J., Gibson, C., Asmonga, D., Moscovitch, B., Grundmeier, R., & Rising, J. (2018). Identifying electronic health record usability and safety challenges in pediatric settings. *Health Affairs (Project Hope)*, *37*(11), 1752–1759. https://doi.org/10.1377/hlthaff.2018.0699

Reed, P. G. (2019). Intermodernism: A philosophical perspective for development of scientific nursing theory. *Advances in Nursing Science*, *42*(1), 17–27. https://doi-org.ezproxy2.library.arizona.edu/10.1097/ANS.0000000000000249

Reed, P. G. (2020a). *Pam's notes: Nursing metaparadigm views and philosophical worldviews.* [Unpublished manuscript]. University of Arizona College of Nursing, Tucson.

Reed, P. G. (2020b). *Pam's notes: A philosophical perspective (Ism) from and for nursing: Intermodernism (Part 3).* [Unpublished manuscript]. University of Arizona College of Nursing, Tucson.

Reed, P. G., & Shearer, N. B. C. (2017). *Nursing knowledge and theory innovation: Advancing the science of practice.* Springer Publishing Company, LLC.

Reydon, T. A. C., & Ereshefsky, M. (2022). How to incorporate non-epistemic values into a theory of classification. *European Journal for Philosophy of Science, 12*(1). https://doi.org/10.1007/s13194-021-00438-6

Rodziewicz, T. L., Houseman, B., & Hipskind, J. E. (2022). Medical error reduction and prevention. In *StatPearls*. StatPearls Publishing.

Roman, L. C., Ancker, J. S., Johnson, S. B., & Senathirajah, Y. (2017). Navigation in the electronic health record: A review of the safety and usability literature. *Journal of Biomedical Informatics*, *67*, 69–79. https://doi.org/10.1016/j.jbi.2017.01.005

Rony, M. K. K., Numan, S. M., Akter, K., Tushar, H., Debnath, M., Johra, F. T., Akter, F., Mondal, S., Das, M., Uddin, M. J., Begum, J., & Parvin, M. R. (2024). Nurses' perspectives on privacy and ethical concerns regarding artificial intelligence adoption in healthcare. *Heliyon*, *10*(17), e36702. https://doi.org/10.1016/j.heliyon.2024.e36702

Roth, R. (1986). [Review of *Technostress: The human cost of the computer revolution*]. *Social Science Computer Review*, *4*(4), 553–556. Sage Publications. https://doi.org/10.1177/089443938600400428

Sakamoto, M. L. (2018). Nursing knowledge: A middle ground exploration. *Nursing Philosophy, 19*(3), e12209–n/a. https://doi.org/10.1111/nup.12209

Savoy, A., Patel, H., Murphy, D. R., Meyer, A. N. D., Herout, J., & Singh, H. (2023). Electronic health records' support for primary care physicians' situation awareness: A meta-narrative review. *Human Factors*, *65*(2), 237–259. https://doi.org/10.1177/00187208211014300

Schenk, E., Schleyer, R., Jones, C. R., Fincham, S., Daratha, K. B., & Monsen, K. A. (2017). Time motion analysis of nursing work in ICU, telemetry and medical-surgical units. *Journal of Nursing Management, 25*(8), 640–646. https://doi.org/10.1111/jonm.12502

Shanafelt, T. D., Dyrbye, L. N., Sinsky, C., Hasan, O., Satele, D., Sloan, J., & West, C. P. (2016). Relationship between clerical burden and characteristics of the electronic environment with physician burnout and professional satisfaction. *Mayo Clinic Proceedings*, *91*(7), 836–848. https://doi.org/10.1016/j.mayocp.2016.05.007

Sherrill, A. M., Wiese, C. W., Abdullah, S., & Arriaga, R. I. (2022). Overcoming clinician technophobia: What we learned from our mass exposure to telehealth during the COVID-19 pandemic. *Journal of Technology in Behavioral Science*, *7*(4), 547–553. https://doi.org/10.1007/s41347-022-00273-3

Shultz, S. & Hand, M. W. (2015). Usability: A concept analysis. *Journal of Theory Construction & Testing*, *19*(2), 65–70.

Sittig, D. F., & Singh, H. (2010). A new sociotechnical model for studying health information technology in complex adaptive healthcare systems. *Quality & Safety in Health Care, 19 Suppl 3*(Suppl 3), i68–i74. https://doi.org/10.1136/qshc.2010.042085

Smith, J., & Palesy, D. (2020). Technology stress in perioperative nursing: An ongoing concern. *ORNAC Journal*, *38*(1), 41-51.

Smith, M. J., & Liehr, P. R. (2018). *Middle range theory for nursing.* (4th ed.). Springer Publishing.

Sockolow, P. S., Børøsund, E., & Hellesø, R. (2024). Artificial intelligence in nursing: Perspectives from Norwegian nurses. *Studies in Health Technology and Informatics, 315*, 217–222. https://doi.org/10.3233/SHTI240139

Sommer, D., Schmidbauer, L., & Wahl, F. (2024). Nurses' perceptions, experience and knowledge regarding artificial intelligence: Results from a cross-sectional online survey in Germany. *BMC Nursing*, *23*(1), 205. https://doi.org/10.1186/s12912-024-01884-2

Sousa, V. D., Driessnack, M., & Mendes, I. A. (2007). An overview of research designs relevant to nursing: Part 1: Quantitative research designs. *Revista Latino-Americana de Enfermagem*, *15*(3), 502–507. https://doi.org/10.1590/s0104-11692007000300022

Stadin, M., Nordin, M., Fransson, E. I., & Broström, A. (2020). Healthcare managers' experiences of technostress and the actions they take to handle it - A critical incident analysis. *BMC Medical Informatics and Decision Making*, *20*(1), 244. https://doi.org/10.1186/s12911-020-01261-4

Stanton, K., Carpenter, R. W., Nance, M., Sturgeon, T., & Villalongo Andino, M. (2022). A multisample demonstration of using the Prolific platform for repeated assessment and psychometric substance use research. *Experimental and Clinical Psychopharmacology*, *30*(4), 432–443. https://doi.org/10.1037/pha0000545

Su, C.-Y., & Chao, C.-M. (2022). Investigating factors influencing nurses' behavioral intention to use mobile learning: Using a modified unified theory of acceptance and use of technology model. *Frontiers in Psychology*, *13*, 673350. https://doi.org/10.3389/fpsyg.2022.673350

Swiger, P. A., Vance, D. E., & Patrician, P. A. (2016). Nursing workload in the acute-care setting: A concept analysis of nursing workload. *Nursing Outlook*, *64*(3), 244–254. https://doi.org/10.1016/j.outlook.2016.01.003

Tacy, J. W. (2016). Technostress: A concept analysis. *Online Journal of Nursing Informatics*, *20*(2), 8-8.

Tan, M., Lipman, S., Lee, H., Sie, L., & Carvalho, B. (2019). Evaluation of electronic medical records on nurses' time allocation during cesarean delivery. *Journal of Patient Safety*, *15*(4), e82–e85. https://doi.org/10.1097/PTS.0000000000000467

Tarafdar, M., Cooper, C. L., & Stich, J. (2019). The technostress trifecta - techno eustress, techno distress and design: Theoretical directions and an agenda for research. *Information Systems Journal (Oxford, England)*, *29*(1), 6–42. https://doi.org/10.1111/isj.12169

Tarafdar, M., Tu, Q., Ragu-Nathan, B. S., & Ragu-Nathan, T. S. (2007). The impact of technostress on role stress and productivity. *Journal of Management Information Systems*, *24*(1), 301–328. https://doi.org/10.2753/MIS0742-1222240109

Tarafdar, Tu, Q., & Ragu-Nathan, T. S. (2010). Impact of technostress on end-user satisfaction and performance. *Journal of Management Information Systems*, *27*(3), 303–334. https://doi.org/10.2753/MIS0742-1222270311

Tell, A., Westenhöfer, J., Harth, V., & Mache, S. (2023). Stressors, resources, and strain associated with digitization processes of medical staff working in neurosurgical and vascular surgical hospital wards: A multimethod study. *Healthcare (Basel, Switzerland)*, *11*(14). https://doi.org/10.3390/healthcare11141988

Tolentino, D. A., Patmon, F., & Gephart, S. M. (2021). A descriptive study of nurses' experiences with unintended consequences of the electronic health record in two urban hospitals. *Journal of Nursing Informatics, 6*(2), 6–10.

Trochim, W. M. (2022, February 1). *The research methods knowledge base*. https://conjointly.com/kb/

Tsai, C. H., Eghdam, A., Davoody, N., Wright, G., Flowerday, S., & Koch, S. (2020). Effects of electronic health record implementation and barriers to adoption and use: A scoping review and qualitative analysis of the content. *Life (Basel, Switzerland)*, *10*(12), 327. https://doi.org/10.3390/life10120327

Turner, A. M., Engelsma, T., Taylor, J. O., Sharma, R. K., & Demiris, G. (2021). Recruiting older adult participants through crowdsourcing platforms: Mechanical Turk versus Prolific Academic. *AMIA ... Annual Symposium proceedings. AMIA Symposium*, *2020*, 1230–1238.

von Gerich, H., Moen, H., Block, L. J., Chu, C. H., DeForest, H., Hobensack, M., Michalowski, M., Mitchell, J., Nibber, R., Olalia, M. A., Pruinelli, L., Ronquillo, C. E., Topaz, M., & Peltonen, L. M. (2022). Artificial Intelligence -based technologies in nursing: A scoping literature review of the evidence. *International Journal of Nursing Studies*, *127*, 104153. https://doi.org/10.1016/j.ijnurstu.2021.104153

Wang, J., Calderon, G., Hager, E. R., Edwards, L. V., Berry, A. A., Liu, Y., Dinh, J., Summers, A. C., Connor, K. A., Collins, M. E., Prichett, L., Marshall, B. R., & Johnson, S. B. (2023). Identifying and preventing fraudulent responses in online public health surveys: Lessons learned during the COVID-19 pandemic. *PLOS Global Public Health*, *3*(8), e0001452. https://doi.org/10.1371/journal.pgph.0001452

Wang, X., & Cheng, Z. (2020). Cross-sectional studies: Strengths, weaknesses, and recommendations. *Chest*, *158*(1S), S65–S71. https://doi.org/10.1016/j.chest.2020.03.012

Walker, A. (2024, April 24). *Nurses protest AI use in hospitals, "Trust Nurses, Not AI"*. Nurse.org. https://nurse.org/news/nurses-protest-ai/

Waterson, P., Robertson, M. M., Cooke, N. J., Militello, L., Roth, E., & Stanton, N. A. (2015). Defining the methodological challenges and opportunities for an effective science of sociotechnical systems and safety. *Ergonomics, 58*(4), 565–599. https://doi.org/10.1080/00140139.2015.1015622

Westbrook, J., Duffield, C., Li, L., & Creswick, N. J. (2011). How much time do nurses have for patients? A longitudinal study quantifying hospital nurses' patterns of task time distribution and interactions with health professionals. *BMC Health Services Research, 11*(1), 319–319. https://doi.org/10.1186/1472-6963-11-319

Wilbanks, B. A., & McMullan, S. P. (2018). A review of measuring the cognitive workload of electronic health records. *Computers, Informatics, Nursing*, *36*(12), 579–588. https://doi.org/10.1097/CIN.0000000000000469

Wisner, K, Lyndon, A., & Chesla, C. A. (2019). The electronic health record's impact on nurses' cognitive work: An integrative review. *International Journal of Nursing Studies, 94*, 74–84. https://doi.org/10.1016/j.ijnurstu.2019.03.003

Wu, D., Xu, C., Kim, A., Bindhu, S., Mah, K. E., & Eckman, M. H. (2021). A scoping review of health information technology in clinician burnout. *Applied Clinical Informatics*, *12*(3), 597–620. https://doi.org/10.1055/s-0041-1731399

Wynn, M., Garwood-Cross, L., Vasilica, C., & Davis, D. (2023). Digital nursing practice theory: A scoping review and thematic analysis. *Journal of Advanced Nursing*. 1-12. https://doi.org/10.1111/jan.15660

Xu, Pace, S., Kim, J., Iachini, A., King, L. B., Harrison, T., DeHart, D., Levkoff, S. E., Browne, T. A., Lewis, A. A., Kunz, G. M., Reitmeier, M., Utter, R. K., & Simone, M. (2022). Threats to online surveys: Recognizing, detecting, and preventing survey bots. *Social Work Research*, *46*(4), 343–350. https://doi.org/10.1093/swr/svac023

Yan, Q., Jiang, Z., Harbin, Z., Tolbert, P. H., & Davies, M. G. (2021). Exploring the relationship between electronic health records and provider burnout: A systematic review. *Journal of the American Medical Informatics Association: JAMIA*, *28*(5), 1009–1021. https://doi.org/10.1093/jamia/ocab009

Ye, J. (2021). The impact of electronic health record-integrated patient-generated health data on clinician burnout. *Journal of the American Medical Informatics Association*, *28*(5), 1051-1056. https://doi.org/10.1093/jamia/ocab017

Yee, T., Needleman, J., Pearson, M., Parkerton, P., Parkerton, M., & Wolstein, J. (2012). The influence of integrated electronic medical records and computerized nursing notes on nurses' time spent in documentation. *Computers, Informatics, Nursing*, *30*(6), 287–292. https://doi.org/10.1097/NXN.0b013e31824af835

Yen, P., Kellye, M., Lopetegui, M., Saha, A., Loversidge, J., Chipps, E. M., Gallagher-Ford, L., & Buck, J. (2018). Nurses' time allocation and multitasking of nursing activities: A time motion study. *AMIA ... Annual Symposium Proceedings, 2018*, 1137–1146.

Younas, A., & Quennell, S. (2019). Usefulness of nursing theory-guided practice: An integrative review. *Scandinavian Journal of Caring Sciences*, *33*(3), 540–555. https://doi.org/10.1111/scs.12670

Young, M. S., Brookhuis, K. A., Wickens, C. D., & Hancock, P. A. (2015). State of science: Mental workload in ergonomics. *Ergonomics*, *58*(1), 1–17. https://doi.org/10.1080/00140139.2014.956151

Yuan, Z., Wang, J., Feng, F., Jin, M., Xie, W., He, H., & Teng, M. (2023). The levels and related factors of mental workload among nurses: A systematic review and meta-analysis. *International Journal of Nursing Practice*, *29*(5), e13148. https://doi.org/10.1111/ijn.13148