THE INTERSECTION OF HEALTH INFORMATICS AND DISPARITIES: UNDERSTANDING HOW DATA PROMOTES HEALTH EQUITY

by

Kala S. Wilson

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Approved by:

Dr. Michael F. Dulin

Dr. Candace S. Brown

Dr. Yhenneko J. Taylor

Dr. Judith B. Cornelius

ABSTRACT

KALA S. WILSON, MPA. The Intersection of Health Informatics and Disparities: Understanding How Data Promotes Health Equity. (Under the direction of DR. MICHAEL F. DULIN).

In this collection of manuscripts, I developed a deeper understanding and insight into how the Coronavirus Disease 2019 (COVID-19) pandemic and subsequent transition to telehealth impacted 1) clinical electronic health record (EHR) data quality and data entry patterns, 2) provider perceptions of the EHR's influence on care delivery, and 3) patient perceptions on barriers related to pandemic-induced telemedicine.

The COVID-19 public health crisis has disproportionately affected individuals and populations historically marginalized in healthcare and public health, including racial and ethnic minorities and individuals with low-income status. The COVID-19 pandemic has drawn new attention to and compounded the existing health and digital disparities in healthcare, with Black Americans being almost 4 times as likely to die from the virus than White Americans. Racial and ethnic health disparities have been historically unwavering and persistent within the United States. Furthermore, this crisis has ignited rapid implementation of digital healthcare solutions such as virtual healthcare (telehealth and telemedicine capabilities) and health information technology (HIT) accessed via mobile applications or online platforms. When assessing HIT's effectiveness, efficiency, quality, safety, and equity, it is essential to consider the reciprocal relationship between HIT and the COVID-19 pandemic. This is of marked significance, considering that virtual care technologies have been shown to exacerbate the digital divide and worsen disparities in a patient's ability to access high-quality care.

The research in this dissertation is informed by the socio-technical and complex systems perspectives of improved human health via high-quality, safe, HIT-driven care, which maintains

two central concepts: 1) multiple levels of influence affect a patient's health outcomes, such as care quality, costs, and patient safety; and 2) complex adaptive systems occur when many agents work together within an organization and patterns materialize as the agents adopt, "simple rules" that optimize outcomes, such as the patient experience and the clinical team's performance. Understanding how these HIT-related behaviors and perceptions multidimensionally affect care delivery is imperative to maximizing the potential benefits of technology and data in healthcare and promoting the need for a concerted effort to ensure safe, high-quality, and equitable care delivery.

Chapter 1 reviewed literature on the relationships between HIT and care quality, patient safety, health equity, biases, and discrimination. In Chapter 2, we assessed the influence of external, societal factors on disparities in data quality and data entry patterns. We found that an external change to healthcare operations – which modifies clinical practice – was correlated with clinical data entry patterns. Also, we found significant differences between departments within the healthcare organization, suggesting data entry differences based on distinct care goals housed within different units. These findings underscore some of the conclusions found in Chapter 3 where we determined the multidimensional relationship between HIT processes and patient safety and quality by exploring how healthcare provider demographic and health system-related characteristics were associated with their perception of the EHR's impact on care delivery.

Perception disparities were present by providers based on sex, age, race, ethnicity, board certification, telemedicine utilization, and years of EHR experience. The results from this research are striking - we uncovered that providers using the EHR and telemedicine were roughly 20 times more likely to perceive the EHR as beneficial for patient safety ($OR=20.25$; $p<0.001$), compared to approximately only 4 times more likely for care quality ($OR=4.48$; $p<0.05$). Despite providers reporting that they found the EHR more beneficial for patient safety than care quality – we found conflicting practical evidence when assessing patient perceptions of telemedicine barriers and their reported outcomes.

Chapter 4 assessed the effect of demographic and healthcare-related factors on patient perceptions of telemedicine barriers. We found that 76% of patients reported facing at least one telemedicine barrier, and 66% reported experiencing a medical error via telemedicine during the pandemic. Similarly, we uncovered patients were more likely to report experiencing a telemedicine barrier if they utilized the patient-facing EHR (OR=27.72), had been diagnosed with 1 to 2 chronic conditions (OR=10.06), and experienced a medical error (OR=1.22). Interestingly, patients were less likely to report experiencing a telemedicine barrier if they identified as Black (OR=0.10; $p<0.001$), Female (OR=0.06; $p<0.05$), and reported 3 to 4 diagnosed chronic conditions (OR=0.10; $p<0.01$). These findings align with prior literature indicating the historically pervasive inequities and disparities amongst these subpopulations. This has been shown to lead to less patient engagement and activation, specifically in Black women and those considered as "super-utilizers" of the healthcare system, often due to complex physical, behavioral, and social needs.

Collectively, these studies advance our understanding of how external factors such as COVID-19, modified workflows, demographic, health system, and healthcare-related characteristics impact health information technology and data perceptions and behaviors. Our findings suggest that these perceptions influence diagnostic EHR data entry, technological utilization, digital care barriers, and corresponding patient outcomes. This dissertation contributes to the public health and healthcare literature by providing practical implications for health systems, clinicians, care teams, and patients interacting with technology and data in healthcare settings. This contribution is significant to better understanding how their interactions with data and technology affect the efficiency, safety, quality, and equity of care delivery, as well as generated clinical and population health data. Our findings underscore the need for further analysis to understand the interactions between the environment, processes, workflows, technological designs, patients, and the core operative nature of the system itself. Health administrators, policymakers, and researchers must acknowledge that technology and data can act as a roadblock to achieving health equity throughout this nation's healthcare systems if human and information technology systems continue to co-exist but not co-evolve concurrently.

In policy and practice, we must pull back the curtain and recognize and address the many forms of coded inequity that is present throughout our healthcare systems by becoming more aware of the social dimensions of technology that generate dominant and discriminatory structures encoded in apps, algorithms, and payment data used in health and healthcare.

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This dissertation was made possible by the contributions and support of so many individuals. First and foremost, I would like to thank God for His continued grace in my life and throughout this journey. Without Him, none of this would even be possible.

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But most of all, I want to thank my friends and family that have *always* supported me. It is incredibly satisfying to acknowledge them in the culmination of my work *finally*. My mother, Reesie Wilson, whose unwavering support and love were one of the very few things that kept me together through some of the most challenging years of my life. This included almost seven years of graduate school and living in Memphis and Charlotte on a next-to-nothing budget. Mom, you taught me countless things – but some of the most important of them all are: to love unconditionally – whether that be people or my passions, the meaning of being both strong and gentle, to not live in the past or have regrets, the importance of trust and understanding, how to master my own happiness, and that I am too blessed to be *this* stressed and for that – you are my rock, and I could not have done this without you. Thank you for your endless strength and support, Mom, even during your own fight against cancer. You are such a warrior!

My father, Ken Wilson, who always tells me how proud he is to be my dad, and has always encouraged me to be fiercely independent, bet on myself, and pursue all my dreams in life, even the things that scare me. Dad, you have filled many roles in my life – my chauffeur, my financial support, a listener, a life mentor, and a friend, but most of all, you are my hero, and I am forever indebted that you have always been there for me when I needed you most. Thank you for everything you have done or ever sacrificed for me to stand here today, as Dr. Kala S. Wilson (aka Dr. K–Dub).

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DEDICATION

"Of all forms of inequality, injustice in healthcare is the most shocking and inhumane."

Dr. Martin Luther King, Jr.

This doctorate degree is dedicated to the countless number of Black and Brown Americans killed or treated senselessly and unjustly. Whether by the overt transgressions displayed by members of the police force or covert discriminatory structures, behaviors, and patterns embedded and entrenched in systems throughout the United States. These systems include our healthcare, educational, research and development, innovation and technology, criminal justice, employment, housing, voting, and financial and banking systems. To that end, this is honoring the unfortunate and unbeknownst contributions to medicine by Black Americans, including the *victims of the Tuskegee experiment in 1932* – who were 600 rural black men, 399 with syphilis – and were not offered available treatments or did not give informed consent to be a part of a study; and *Henrietta Lacks*, whose cells were taken from her body without her knowledge, but most importantly, her permission in *1951*.

This is also honoring the significant and merited achievements and contributions to medicine and healthcare by Black Americans, including *James McCune Smith, MD.*, who became the first Black American to practice in the United States with a medical degree in *1837*, after having to attend medical school in Scotland due to segregated admission practices; *Rebecca Lee Crumpler, MD.*, who became the first Black woman physician in *1864*, and was dedicated to women and children's health research; *Daniel Hale Williams, MD.*, who opened the first Black-owned and first interracial hospital in Chicago, Illinois, in *1891* and performed the world's first successful heart surgery in *1893; Alfred Dey Hershey, PhD.*, who became the first Black American to earn a Nobel Prize in

Physiology or Medicine in *1969* for his research on the replication and genetic structure of viruses; *Lonnie Bristow, MD.,* who was sworn in as the first Black president of the American Medical Association in *1995*; *Michelle Obama, JD.,* who became the first Black First Lady of the United States in *2008,* and brought massive attention to the childhood obesity epidemic and championed healthcare funding for underprivileged children; *Camara Phyllis Jones, MD., MPH., PhD.,* who was elected as president of the American Public Health Association (APHA) in *2014*; and *Marcella Nunez-Smith, MD., MHS.,* who was selected and appointed as Co-Chair of the coronavirus task force by President Joe Biden in *2020*.

Thank you to you all – we are forever indebted as a community, society, and as a nation. Your contributions will never be forgotten, and this dissertation symbolizes *solidarity*. I stand with you all.

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ACRONYMS AND ABBREVIATIONS

AHRQ	Agency for Healthcare Research and Quality
AI	Artificial Intelligence
CDI	Clinical Documentation Integrity
CHIP	Children’s Health Insurance Plan
CMS	The Centers for Medicare & Medicaid Services
CNP	Clinical Nurse Practitioner
COVID-19	Coronavirus Disease of 2019
DO	Doctor of Osteopathic Medicine
DX	Diagnosis
EHR	Electronic Health Record
EMR	Electronic Medical Record
HbA1c	Hemoglobin A1C
HCO	Healthcare Organization
HCP	Healthcare Provider
HIT	Health Information Technology
HITECH Act	Health Information Technology for Economic and Clinical Health Act
IT	Information Technology
MD	Medical Doctor
NCATS	National Center for Advancing Translational Sciences
NC HIEA	North Carolina Health Information Exchange Authority
NCHS	National Center for Health Statistics
NEHRS	National Electronic Health Record Survey
NLP	Natural Language Processing
ONC	Office of the National Coordinator for Health Information Technology
PA	Physician Assistant
PAM	Patient Activation Measure
PHR	Personal Health Record
PREOS-PC	Patient-Reported Experiences of Safety in Primary Care
PSQIA	Patient Safety and Quality Improvement Act of 2005
RN	Registered Nurse
STEEEP	Safe, Timely, Efficient, Effective, Equitable, and Patient-Centered
STST	Sociotechnical Systems Theory
U.S.	United States
VA	The United States Department of Veteran Affairs

CHAPTER ONE. INTRODUCTION

1.1 BACKGROUND

1.1.1 IMPORTANCE OF INFORMATICS TO HEALTH DISPARITIES

The connection between disparities, inequities, and health is well-established and historically persistent.[1–9] One approach to address this nation's long-standing history with disparities and inequities in health and healthcare is for healthcare systems to implement and rely on Health Information Technology (HIT) and data to standardize care delivery and overcome inequities in care quality.[10] Unfortunately, many studies [11–30] have demonstrated that this dependency neglects these emerging technologies' ability to reinforce discrimination, biases, barriers, and inequities in healthcare quality. Despite decades of mounting evidence and political recommendations, deep-seated institutional, interpersonal, and individual-level inequities and disparities continue to exist in health and healthcare in the United States (U.S.). The current healthcare quality and data infrastructure does not address the observed systematic differences in clinical practice patterns or corresponding patient outcomes, although equity, efficiency, safety, and patient-centeredness have been identified as core domains of quality.[31,32] Individuals within the U.S. healthcare system must consider the potential for HIT to address health inequities by better understanding why technology and tools may replicate or exacerbate existing problems.[10,33,34]

1.1.2 BIOMEDICAL AND HEALTH INFORMATICS

Biomedical informatics is the study of using information and information technology (IT) to improve the health of individuals and populations, and healthcare. The overarching field encompasses other sub-disciplines such as public health-, population health-, community health-, consumer health-, and clinical informatics.[35] Informatics, on its own, refers to the general study, design, and development of IT for the greater good of people, organizations, and society. Biomedical informatics differs in that the research and innovation of IT occur at the intersection of mathematics, computational science, social sciences, and health and life sciences. These fields contribute to the primary roles of biomedical informatics, which involves the employment of big data and novel ways of presenting it, coupled with conventional scientific research to span disciplines providing clinical insights, disease exposure, treatment and response patterns, and directing innovative lines of scientific and medical inquiry.[36] Of the many informatics questions posited, the relationship between health and information, or *health informatics*, is fundamental. Questions on health informatics are central to many disciplines, such as medicine,[35,37] pharmacoepidemiology,[38,39] public health and policy,[13,14,28,40–44] government,[45,46] economics,[47] as well as business and administration,[48] but are specific to none. Instead, health informatics is a complex system of information that can be widely applied to support clinical and patient decision-making and evaluate the strength of current healthcare practices and societal goals for better health, quality, safety, and cost.[15,17]

1.1.3 CARE QUALITY

The study of health informatics is often explored using numerous modern data collection methods, analysis, and transmission to improve every part of the healthcare system, public health, and the quality and safety of individual patient care. However, quality within healthcare is latent and hardly observable, and further considerations are needed. The current gold-standard measurement for healthcare quality improvement is the patient experience, given that patient-centeredness is a familiar concept that drives quality improvement.[49] In 2002, the Centers for Medicare and Medicaid Services (CMS) partnered with the Agency for Healthcare Research and

Quality (AHRQ) to develop and test The Hospital Consumer Assessment of Healthcare Providers and Systems (HCAPHS). HCAPHS is the first national, standardized, and publicly reported survey instrument and data collection methodology designed to measure patients' perception of their hospital experience.[50]

Despite organizations developing and utilizing this survey for almost two decades, there are gaps in effectively capturing its primary purpose, *patient perception.* The survey misrepresents its development as a sound conceptual and theoretical measurement. For example, the design of the HCAPHS survey neglects the patient's *perceptions* as a *psychological* concept, being contained within the *quality of healthcare* as a *commercial* construct. Perceived service quality is the outcome of an evaluation process – the consumer compares their expectations with the service they have received (i.e., they compare the perceived service against the expected service).[51]

Furthermore, this process signifies what is known to be the *perceived quality of service* (i.e., patients' perception of the quality of care received). Perceived quality is a form of attitude, associated but not parallel to satisfaction, and results from comparing expectations with perceptions of performance.[51] Therefore, the HCAPHS survey is inadequately measuring the patient experience as a quality improvement metric, given it was designed as though you can measure the *perception* of experience and *experience* of care without the element of *consumer satisfaction.* Thereby inadequately measuring and sharply hindering the potential of healthcare quality improvement. This demonstrates an increased need for the use of informatics in quality improvement, such as the use of electronic clinical quality measures (eCQMs) from electronic health records (EHRs) and gathering insight into the association between the perceptions of clinical team members and HIT.[33,34,52]

1.1.4 PATIENT SAFETY

This failure of quality measurement further uncovers some inherent weaknesses in U.S. healthcare systems, such as economic deficiencies, poor policy implementation, increasing disparities and inequities, and rising mortality and morbidity rates. Although there have been technological advancements and a stark increase in patient safety and quality research since 1999, medical errors, otherwise known as preventable adverse medical care events, are the third leading cause of death in the U.S., claiming up to 440,000 lives each year.[53,54] Moreover, patients are experiencing harm at ten times the rate as in the 1990s, with more Americans dying from preventable adverse events than car accidents or breast cancer.[55,56] Research on the relationship between patient safety and EHRs and telehealth is conflicting. Some researchers [57–60] maintain that EHRs can help improve patient safety and produce measurable improvements through easier record management, centralized record storage, and more straightforward record transfers. Other researchers [61–63] suggest that EHRs and telehealth add an additional layer of complexity, leading to unintended adverse effects such as misdiagnosis, delays in treatment, poor data quality, and medication errors.

Commonly, healthcare providers, administrators, and policymakers, among other stakeholders, agree that patient safety is at the cornerstone of high-quality care, and HIT and tools can help prevent many different patient safety errors.[55] However, we know less about the exact nature of the digitalization of society to expand capacity and infrastructure within healthcare and its unintended consequences on health and healthcare disparities and inequities.

1.1.5 DATA TO UNDERSTAND THE ROLE OF EQUITY, EFFICIENCY, AND SAFETY IN QUALITY IMPROVEMENT

Considering the limitations of the HCAPHS survey and conflicting research on the relationship between health informatics and improving patient safety, other forms of quality measurement should be considered. For example, administrative data, structured clinical data, and electronic patient health records can all be utilized to measure healthcare quality. However, these methods bring an entirely new set of challenges and assumptions concerning data quality and technological design, implementation, and utilization. Moreover, these methods are intended to provide high data validity and reliability to support data-driven clinical decision-making and solve some of healthcare's most prevalent issues, including medical errors, health disparities, structural injustices, and data transparency and interoperability. Prior studies on the persistent deficiencies within healthcare have demonstrated that poorly structured health systems exacerbate poor patient and population health outcomes.[64–66] Therefore, there is a need to further investigate "good-intentioned" individual and system-level factors affecting improved equity, quality, and safety, such as the relationship between health informatics and disparities.

1.2 SIGNIFICANCE OF PROPOSED RESEARCH

When assessing the quality of healthcare – mortality, the safety of care, readmissions, and the patient experience are studied and cited as the most critical measures,[67] neglecting the pervasive inequalities and inequities that exist within these outcomes.[17] Despite the noteworthy and directed governmental ventures in the U.S. over the past several decades, alarming and significant health disparities and inequities persist and, in some cases, even worsen.[15] The issues of poor healthcare quality and safety, and the increasing rates of medical errors and health disparities, are indicators of a broader concern and result partly due to the lack of consideration and comprehension of data and technology in health and healthcare.[15,17] The crisis of disparities, poor healthcare quality, and patient safety in health systems is complex, multifaceted, and often exacerbated by using HIT and tools. For example, electronic health record (EHR) information data reuse [68,69] is repeatedly employed, aimed at selecting patients for electronic cohort development in clinical practice,[57,70] automated disease surveillance, and clinical audits for quality improvement [61] despite data quality limitations that have been identified such as incomplete or inaccurate data, as well as different data formats and data transformation errors.[71–74] Furthermore, a recent medical malpractice study found that provider documentation was recognized as the most common risk management subcategory for EHRs, expressing 72% of all EHR-related risk concerns,[75] and affecting the reliability of diagnosis in the EHR by inaccurate documentation and burdensome documentation requirements.[76] In addition, over 12 million outpatients in the U.S. experience a diagnostic error every year, as well as roughly 6 to 17% of all hospitalized patients.[77]

Prior studies [78–81] suggest that including the patient's perspective can uncover the underlying causes of medical errors that may be otherwise difficult to ascertain. The complexity of neglecting technology's role in improving equity, disparities, quality, and safety poses significant risks to health systems, communities, providers, and patients. Yet, the interactions between data, technology, and healthcare ecosystems are challenging to explain accurately and meaningfully, given that the relationships have not been well-acknowledged nor studied comprehensively. A critical step to improving care and reducing healthcare challenges is acknowledging the need to understand the existing disparities and inequities. This does not only include across socioeconomic boundaries such as race, ethnicity, age, and gender, but also the bias that is produced by disparities in data quality and clinical documentation, the impact of policies, the design and use of technology information systems, and a patient's lack of awareness, knowledge, or access to their health information.

This dissertation demonstrates that differences in HIT clinical data practices using EHR data, utilization patterns, access, and perceptions among subgroups can lead to differential health benefits and outcomes when they are not widely investigated or understood. The methods put forth in this dissertation are novel contributions to the breadth of public health research that already exists. This research represents bridging the gap between patient data, health information and insights healthcare providers get from that data, and the collective intelligence health systems develop from that information. In addition, it provides a fresh look at how data and technology permeate health and healthcare at multiple levels, potentially resulting in exacerbated health, healthcare, and digital disparities and inequities.

1.3 OVERALL PROBLEM STATEMENT AND DESCRIPTION OF THE RESEARCH STUDIES

There is an evident gap in our knowledge considering ways to use data and technology to improve and promote health equity and patient and community health outcomes. Patient safety is a public health crisis, not only within the U.S. but globally as well, and it is likely to affect every one of us at least once in our lifetime.[53,82] There is a need to address the multidimensional and multilevel factors contributing to patient preventable harm through an equitable and technological lens.[64,65,82,83] Research on care quality and safety must bridge the gap between comprehensive informatics utilization and improved patient population health outcomes. My dissertation bridged this gap through the following research efforts. The initial study consisted of a secondary data analysis examining the influence of pandemic-induced telemedicine on disparities in data quality and data entry patterns. The second study was a pilot cross-national quantitative survey and expanded on study one by exploring and determining the multidimensional relationship between telemedicine utilization and board certification on healthcare providers' perceptions of the EHR's impact on care quality and patient safety. Lastly, the third study also entailed a pilot cross-national quantitative survey, which provided the patient perspective by assessing which factors influence the odds of patient-reported telemedicine barriers during the COVID-19 pandemic.

1.4 PURPOSE OF THE RESEARCH STUDIES

This dissertation investigated the impact of the pandemic and subsequent transition to telehealth on (1) clinical data quality within the EHR, (2) provider perceptions of the EHR's impact on care quality, and (3) patient perceptions of barriers related to pandemic-induced telemedicine. In Objective 1, the influence of external, societal factors on disparities in data quality and data entry patterns will be examined. This variation will be characterized and quantified if changes are present to better understand the impact of modified clinical practices. In Objective 2, the multidimensional relationship between pandemic-induced telemedicine and the EHR's impact on care quality and patient safety will be determined. In Objective 3 of this dissertation, the effect of demographic and healthcare-related characteristics on patient perceptions of telemedicine barriers will be assessed. Research questions, hypotheses, and specific aims can be found in the following sections.

1.5 RESEARCH QUESTIONS, HYPOTHESES, AND SPECIFIC AIMS

MANUSCRIPT ONE

OBJECTIVE 1. Examine the influence of external, societal factors on disparities in data quality and data entry patterns.
AIM 1.1. Understand how the COVID-19 pandemic impacted clinical processes and data entry patterns within the EHR in North Carolina.

Research Question	Are there disparities in clinical data entry patterns due to the COVID-19 pandemic across EHR data entry segments?
Hypothesis	An external societal change (i.e., pandemic-induced telemedicine) influences clinical data entry patterns and varies across EHR data entry segments (i.e., problem list, billing DX, etc.), likely due to modified clinical practices.

MANUSCRIPT TWO

OBJECTIVE 2. Determine the multidimensional relationship between HIT processes and patient safety and care quality.

AIM 2.1. Explore and understand the relationship between healthcare provider demographics and health system characteristics on healthcare providers' perceptions concerning EHR impact and care delivery.

Research Question	What is the relationship between healthcare provider demographic and health system-related characteristics (pandemic-induced telemedicine) on perceived EHR impact on care delivery?
Hypothesis	Providers who report using telemedicine and have a board certification are more likely to perceive the EHR's impact as beneficial or highly beneficial on their ability to provide quality healthcare and advance patient safety compared to non-telemedicine providers with no board certification.

MANUSCRIPT THREE

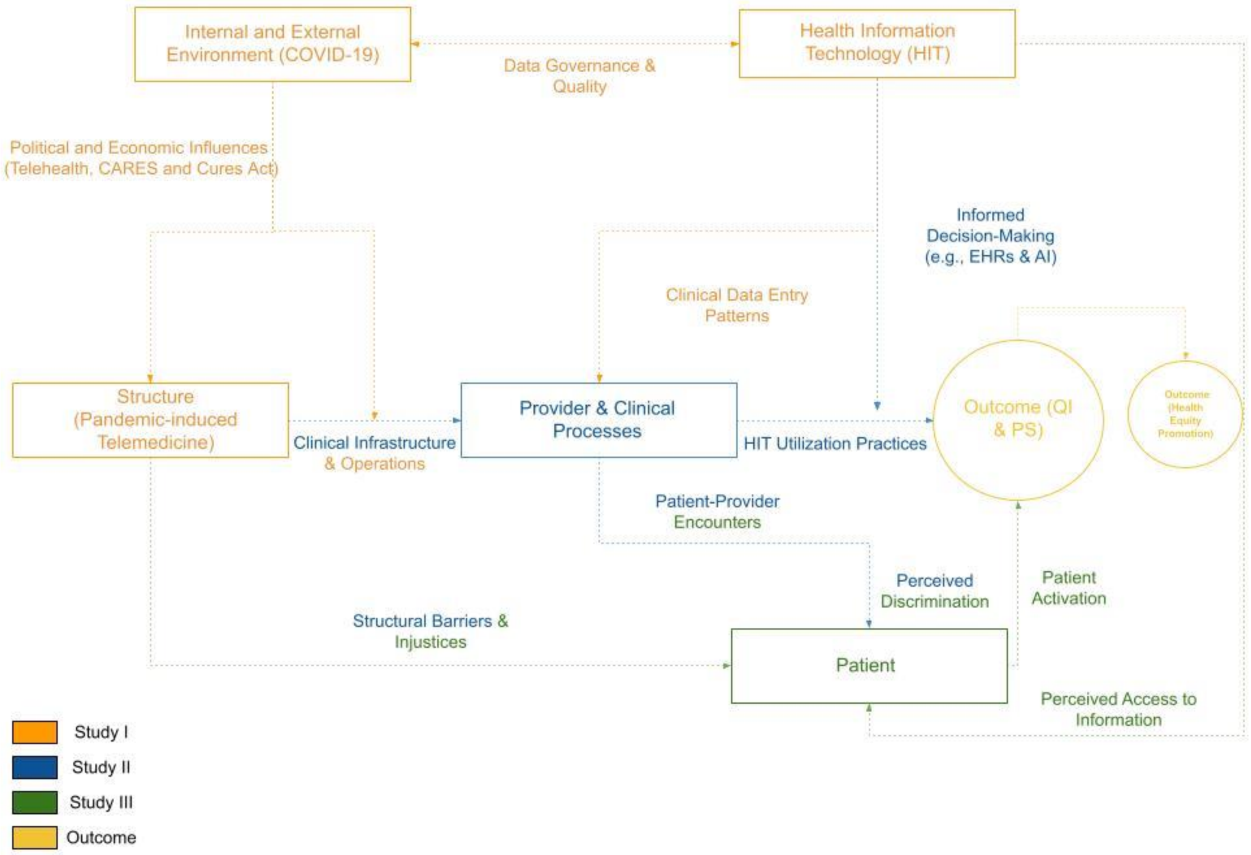
OBJECTIVE 3. Assess the effect of demographic and healthcare-related factors on patient perceptions of telemedicine barriers.

AIM 3.1. Identify which factors impact perceived telemedicine utilization barriers during the COVID-19 pandemic.

Research Question	What is the relationship between patient demographic and healthcare-related characteristics on perceived telemedicine barriers during the pandemic?
Hypothesis	Patients who report experiencing a medical error, have a high activation level (i.e., three or four), and use the patient-facing EHR are more likely to report facing at least one perceived telemedicine barrier with the healthcare system.

1.6 CONCEPTUAL AND THEORETICAL FRAMEWORK

Figure 1: The Interaction Between Health Systems, Health Information Technology, and Health Outcomes



The conceptual and theoretical framework of the interactions between health systems, health information technology (HIT), and patient health outcomes.[84-99]

1.6.1 THE INTERACTIONS BETWEEN HEALTH SYSTEMS, HEALTH INFORMATION TECHNOLOGY, AND HEALTH OUTCOMES

This research operates under the development of an integration between the Donabedian Model, STEEEP Model, Complexity Theory, and Sociotechnical Systems Theory **(Figure 1)**. Many elements are present in this model, but they are all interconnected and interdependent. This model conceptualizes health systems in which the internal and external environment influence the overall healthcare structure [84] and, in turn, shape and are shaped by HIT.[85] Health information technology,[86,87] the internal and external environment,[88–90] and the healthcare structure [91] all influence provider and clinical processes. Furthermore, HIT,[92,93] the environment,[94] the healthcare structure,[95] and provider processes[96–99] affect the patient and the outcome. At the same time, the patient also has independent effects on the outcome.[100] These interactions demonstrate how factors external to the clinical infrastructure (e.g., COVID-19 and increased patient demand for telemedicine), patient HIT utilization, and other demographic and health system factors affect health outcomes and influence inequities in care delivery.

1.6.2 COMPLEXITY THEORY (CT)

Stephen Wolfram developed the term "complex systems" in 1987.[100] This theory attempts to discover how the many disparate elements of a system work with each other to shape the system and its outcomes, as well as how each component within a system changes over time.[100,101] The basic premise of complexity theory is that there is a hidden order to the behavior and evolution of complex systems. This relates to the study's objectives by adding a unique perspective of how the goal and outcome of utilizing health information technology and data feed back into how public and population health interventions and policies are developed.[26,102] As well as how concepts such as data quality and governance affect future clinical research and infrastructures,[75,103–106] how EHR systems are redesigned and utilized despite limited knowledge of their impact,[57,61,107,108] how structural barriers and injustices can be easily perpetuated throughout public and population health.[109–113]

1.6.3 DONABEDIAN MODEL

The Donabedian model was developed in 1966 by Dr. Avedis Donabedian, also commonly referred to as the founder of healthcare quality. This framework is arguably one of the most referenced models in healthcare and public health and focuses on quality measurement as the foundation of improvement.[114] Donabedian not only contributed to the significance of assessing the structural elements, processes, and outcomes of an organization to evaluate quality;[115] but also to the importance of prioritizing governance and management that is supported by measurement to guide all healthcare professionals and researchers to determine the causes of the effectiveness and efficiency of delivering healthcare services.[114,116,117]

Donabedian argues:

> System awareness and systems design are important for health professionals, but they are not enough. They are enabling mechanisms only and it is the ethical dimension of an individual that is essential to the system's success. The secret of quality is love. You must love your patient, you must love your profession, and you must love your God. If you have love, you can work backwards to monitor and improve the system.[115,116,118(p472)]

As significant as the Donabedian model and some of his lasting words are to the field, his work concluded with various research gaps. The first gap worth noting is the current importance of patient-centeredness. This dynamic power shift between providers and patients went well beyond Donabedian's scope and range of interest. The second gap is regarding what some refer to as the information revolution or the information age.[119,120] The information revolution has overwhelmingly impacted health and healthcare. For example, one in three adult Americans use the internet to self-diagnose or educate themselves on health concerns, and there continues to be an increase in online health-seeking behaviors.[121–123] Lastly, the third gap is not fully recognizing healthcare as a system. Donabedian's work did not account for the complexity within healthcare we see today and the value and importance of better understanding the system of healthcare through redesign of those structures and processes.[64,114,124]

1.6.4 STEEEP MODEL

Given these gaps, the STEEEP (Safe, Timely, Effective, Efficient, Equitable, and Patient-Centeredness) Model and Sociotechnical Systems Theory (STST) were utilized to steer this research dissertation. The STEEEP model was developed by the Institute of Medicine in 2001 and is often referred to as the six quality domains. The STEEEP model fills the first gap in Donabedian's work by expanding and acknowledging the importance of having patient-centeredness as a measure to improve quality. Although the Donabedian model referenced the patient's preference, it did not focus on *patients* as a specific element, especially in terms of being a driving force in their care. The STEEEP model established these six aims to guide measurement development for quality improvement.[125]

1.6.5 SOCIOTECHNICAL SYSTEMS THEORY (STST)

Moreover, the sociotechnical systems theory addresses the final two gaps in Donabedian's work by focusing on the information age, or in this case, health information technology's impact on health and healthcare.[119,121] As well as understanding healthcare as a complex system influenced by the multifaceted interaction between individuals, technology, and their environment.[64,65,126] The term "socio-technical system" was coined by Emery and Trist in 1960 and was used to describe the complex socio-technical interactions within organizations intended to enrich systems' organizational performance.[65,127]

1.7 REVIEW OF THE LITERATURE

1.7.1 INTRODUCTION

Health informatics is the study of IT utilization to improve individual, population, community, and system health. The need for public health and healthcare systems to more profoundly engage and integrate health informatics into the fabric and infrastructure of providing and promoting equitable health and healthcare is documented by healthcare system leaders, clinicians, policymakers, governments, and the research community.[16] This review focuses on the emergence of health informatics, how it is conceptualized concerning health equity and quality, and how healthcare systems, clinicians, and patients are impacted by health informatics at varying levels and magnitudes. Throughout this review, I will detail how the concept of health informatics and IT emerged and progressed, as well as the discourses that have contributed to its development, utilization, and unintended consequences on health equity, care quality, and patient safety in healthcare systems throughout the U.S. At the end of this review is a section dedicated to the conceptual framework under which this research operates. It focuses on the Donabedian and STEEEP models and Complexity and Sociotechnical Systems Theory as they relate to the use of HIT during the COVID-19 pandemic for quality improvement and patient safety in the current literature.

1.7.2 THE DIGITAL DIVIDE

Over the past decade, health information technology (HIT) has significantly transformed clinical practice within the U.S., although it was introduced into the healthcare industry in the

1960s.[30] Health information technology is electronic systems that healthcare professionals and patients use to store, share, and analyze health information, data, and knowledge for communication and decision-making. Various forms of health information technology are used throughout healthcare today, such as electronic health records and medical records, patient portals, telehealth, and clinical decision support.[14,28,61,83,93,105,128–133] Despite the suggested promises of HIT,[126,134] widening and troubling disparities persist and are often exacerbated using HIT within clinical settings.[15,29] Disparities are defined as "differences in treatment between racial, ethnic or other demographic groups that are not directly attributable to variation in clinical needs or patient preferences and continue even after adjustment for socioeconomic factors".[32]

Although HIT has been cited for offering the potential ability to increase access to healthcare, improve clinical outcomes, and advance care quality, the promise and capacity that HIT offers have not been materialized, and a "digital divide" remains, in which technology and digital utilization patterns differ across racial, ethnic, and socioeconomic boundaries.[21,29] Some studies suggest that many novel health information technologies and practices such as artificial intelligence (AI),[135] big data,[136] 5G mobile networks,[137] mobile health applications,[138,139] telehealth,[140,141] telemedicine,[142,143] and health information exchange (HIE) services [144,145] contribute to the digital divide we continue to see.[43] However, despite these findings, the reliance on HIT to reduce inequitable health outcomes and disparities continue to accelerate at an unprecedented pace.[22]

A recent systematic review conducted in 2018 [134] reported that roughly 81% of the medical studies assessed demonstrated improved medical outcomes in terms of efficiency and effectiveness resulting from HIT implementation. The authors also maintain that the one common theme between their review and other systemic reviews conducted since the 1990s is the limited knowledge and research correlated with HIE services. Despite this being an influential factor in HIT implementation, most data quality-focused HIT policies are poorly implemented throughout health systems.[41,42,146] Quality improvement has been suggested as a significant area for strategic policy development and initiatives to decrease or eradicate healthcare disparities.[29] Given the increase of HIT utilization in clinical settings and radical debates on its usefulness, researchers [15] argue that it is essential to investigate the interactions between health technology and disparities to improve care quality and delivery.

1.7.3 HEALTH INFORMATION TECHNOLOGY AND CARE QUALITY

The investigation of health technology and disparities is critical. Some researchers argue that the rapid adoption of digital technologies and tools has resulted in unintended consequences on clinical practices, such as provider documentation and data entry quality.[15,17,26,27,59,62,147–149] Provider documentation is fundamental to care quality, facilitating patient diagnosis and treatment plans, reducing medical errors, and keeping costs down for organizational efficiency.[6,10–12] Additionally, comprehensive literature on quality provider documentation factors is needed to improve the fundamental aspects of care quality and foster learning health systems. The demand to foster learning health systems dates to one of the most notorious cases in medical history in 1984. An illustration of the consequences of clinical documentation errors and systemic failures is demonstrated in the excerpt below.[59,153] This case strongly implies that a flawed patient record can have the same catastrophic consequences today as it did almost forty years ago[153]:

> In 1984, a college student in New York, NY named Libby Zion was admitted to a Manhattan emergency room (ER) with a high fever and agitation. After consulting with her family physician, the residents who evaluated Zion in the ER administered a sedative

> and painkiller. None of the caregivers knew—because Zion didn't disclose the information at the point of care—that she was taking an anti-depressant that was dangerously contraindicated with the drugs the physicians gave her in the ER. The drug combination ultimately proved fatal, and Zion died from cardiac arrest.[153(p18)]

Multiple studies [153–156] have recognized that although poor quality of provider documentation and data recorded in patient records have been well-known, medical students, incoming residents, and clinicians' training on documentation is relatively nonexistent.[156] This is concerning since prior research [157] has found that documentation errors related to medication appear in patient charts 43% of the time, and 37% of those errors are related to prescribing. In comparison, 53% are attributed to transcription errors. Given limitations such as these, clinical documentation integrity (CDI) programs were developed to foster high-quality provider documentation to support reimbursement and quality of care by ensuring all data in the health record is accurate to support clinical decision-making practices.[60,150,151] Furthermore, provider documentation impacts the patient's entire care journey.[60,150,151] It should follow essential data quality characteristics (such as the documentation being clear, consistent, complete, reliable, legible, precise, and timely) to ensure the information flowing through numerous care settings within the healthcare matrix is of high quality.[60,152]

1.7.4 HEALTH INFORMATION TECHNOLOGY AND PATIENT SAFETY

Numerous healthcare professionals maintain that inaccurate and incomplete data in one's health record due to poor documentation practices can intensify inadequate patient safety and is a significant barrier to providing coordinated, patient-centric care.[148] Many legislative efforts have been made to improve care quality and patient safety. This was illustrated on July 29th, 2005, when President George W. Bush signed Public Law (PL) 109-41, the Patient Safety and Quality Improvement Act of 2005 (PSQIA), in response to the IOM's report, "To Err is Human".[158] Although it has been nearly twenty years since this act was implemented and there have been numerous technological advancements and a stark increase in patient safety and quality research since 1999, medical errors, otherwise known as preventable adverse events, are the third leading cause of death in the U.S., claiming up to 440,000 lives each year.[54] Moreover, patients are experiencing harm at ten times the rate as in the 1990s, with more Americans dying from preventable adverse events than car accidents or breast cancer. [56,82]

Prior research [53,64–66] indicates that the U.S. health system is inefficient, and without a data-driven systems approach to patient safety, history will continue to repeat itself. Data on the impact of HIT, patient safety, and care quality are conflicting. Prior studies [159] maintain that HIT tools like machine learning can improve patient outcomes. Whereas other researchers [11,12] suggest that HIT tools are not associated with a higher quality of care and may even exacerbate poor health outcomes and disparities, offering a flaw in our understanding of HIT utilization, usability, and usefulness. To this end, Sivashanker & Gandhi [160] argue that numerous patient safety lessons and strategies have evolved over the past twenty years that can be applied to generate informed strategic efforts for improved health equity. For example, it is of great concern to ensure that health systems prioritize having an infrastructure to lead equity efforts within healthcare and that the step is not siloed but instead aligned with other quality and safety efforts.[160]

With growing concerns such as these and the digital transformation within healthcare, there has been a concerted effort by healthcare professionals, policymakers, researchers, and other stakeholders to move toward digital health equity as well.[13,21,22] As digital solutions have continued to increase, especially during the pandemic, it has been imperative to shift our focus from solely assessing social determinants of health as they relate to patient safety and quality to digital determinants of health, such as digital access and literacy.[16,21,29,160,161] These arguments demonstrate a demand to explore further and understand how we can achieve zero inequity, the same way we aspire to achieve zero harm – because there is no such thing as improved health technology and safe, high-quality care that is inequitable.[10,160]

1.7.5 HEALTH INFORMATION TECHNOLOGY AND HEALTH EQUITY

Health *equality* is defined as all individuals being given the same resources and opportunities to attain and sustain their highest degree of health. In contrast, health *equity* ensures that - from those same resources and opportunities, all individuals have the access, knowledge, confidence, and skills to attain and sustain their highest degree of health, both within and outside healthcare.[4,162] Although these two concepts are frequently used interchangeably, it is essential to note that *equality* is not equivalent to *equity*, as *equity* is a process. E*quality* is an outcome of that process.[4] There is an urgent need to advance knowledge between health informatics and inequities. We exist in an era of widespread inequality globally, especially regarding income and wealth.[15] And while various political and economic investments have been made over the past several decades, there are justifiable concerns about how informatics and technological advancements can lead to unintended consequences such as persistent health and healthcare disparities.[15,21]

This is particularly true for artificial intelligence (AI) and algorithms, which are quantitative models that make statistical inferences from large datasets.[135] Various researchers [11,12,18,135] argue that haphazardly deploying AI risks amplifying and exacerbating health inequities. For example, a recent study [11] found that a widely used commercial algorithm to identify high-risk patients was significantly biased against Blacks by using healthcare spending as an unbiased proxy to detect disease burden. The problem with this was that the algorithm did not account for systemic inequalities and inequities created by poorer access to healthcare. This has been the case during a time of normalcy but also the global COVID-19 pandemic crisis.

Prior research [18,135] argues that the combination of the unequal impact of COVID-19 on vulnerable communities and the socio-technical determinants of algorithmic bias and discrimination might produce adverse effects despite their promise. These adverse effects arise from embedded patterns of health inequality and inequity throughout AI systems when bias and discrimination become entrenched in these systems' conception, design, and utilization. Research has demonstrated that bias and discrimination develop across three segments in AI systems. The first is discriminatory structures in datasets used to train systems (e.g., exclusion of data from under-resourced populations due to their lack of access to healthcare). Second are deficiencies in data representativeness (e.g., under-sampling of vulnerable groups), and third, biases across the development and implementation lifecycle (e.g., failure to include demographic variables which are clinically relevant).[163]

1.7.6 DISCRIMINATION IN DATASETS

Many healthcare technologies, such as AI, depend on big data fostered from large datasets. Producing inequities generated from algorithmic models places patients at risk when biases from existing practices and institutional policies affect datasets.[135] Research demonstrates that biased judgment and decision-making, inequitable healthcare processes, policies, and governance regimens can affect EHRs, visit notes, clinical training programs, clinical trials, and public health monitoring systems.[135,164] As datasets are the basis of data-driven AI and machine learning models; we must understand that they will replicate the multifaceted and historically placed practices, customs, and attitudes that extend throughout every healthcare system within the United States. Thus, igniting the risk of reinforcing or augmenting latent discriminatory structures.[135] Prior studies [165–167] argue that as health systems increase their use of natural language processing (NLP) technologies to extract diagnostic information from clinical reports and notes, there is a need to address unreliable and incomplete data in EHRs that mirror inequities in care quality and access. Failure to address data quality issues within EHRs will result in AI systems' ability to potentially reproduce, reiterate, and reinforce preexisting structural barriers and injustices.[135]

1.7.7 DATA REPRESENTATIVENESS

The datasets used to train, analyze, and validate AI models frequently and inadequately represent the public. Studies [19,168] have found that big data are often under-sampled and hinder inferences about individuals with limited or low access to healthcare services, including minorities and those of low-socioeconomic status. Mobile health or social media interventions also may exclude or under-represent people without digital access or low digital literacy, hence the demand for improved digital health equity.[21,22] Part of the effort in enhancing data representativeness and equity is acknowledging the limitations in dataset quality and integrity. For example, further analyses are needed to address the problems around discriminatory design and utilization fostered by biases and a lack of accountability within healthcare systems.

1.7.8 BIASES IN DESIGN AND UTILIZATION PRACTICES

The first step to improving health technology biases and equity unaccountability in healthcare systems is recognizing that limited representativeness and patterns of discrimination are not the only sources of bias in health technology and tools. Recent ethical debates have focused on the responsibilities of computer science professionals (e.g., AI developers) and technology companies for the impact of the technologies they create, which encompass legacies of institutional racism and implicit biases, leading to the integration of discrimination and injustices into both technology innovation processes and services.[15,135,169,170] Health technology innovation projects and interventions must consider any latent biases of those involved in the conception, design, and development, which might allow for the introduction of structural health inequalities and inequities. These biases have been reported in previous studies,[11,163], thus validating the discriminatory patterns that can pass into clinical processes and practices and hinder the improvement of health equity and quality in health and healthcare.

1.7.9 THE EQUITY BURDEN

Outside of clinical domains, AI systems are rapidly being repurposed to address public health concerns.[18,135] A noteworthy example is jails, prisons, and mass incarceration. As many sectors attempt to curb the spread of COVID-19, U.S. prison systems have introduced an algorithmic tool developed for measuring the risk of recidivism to decide which inmates will be released to home confinement. As this tool has been shown to display racial biases, repurposing it is dangerous and discriminatory for health risk management. Black inmates are more likely to remain incarcerated and subsequently subjected to increased risk of exposure to COVID-19 and disease-related death.[171] Furthermore, at the beginning of the second wave of the pandemic in the United States (June 2020), this algorithm was repurposed, and the five most significant known clusters of COVID-19 in the U.S. were in prisons and jails, which were framed by mass incarceration based on historic and systemic racism.[171] Although AI and other health technology tools can make a valuable contribution to healthcare, public health, and research; there is a significant need to consider the existing inequalities and inequities, socio-technical determinants of algorithmic bias and discrimination, and the adverse outcomes of clinical and epidemiological HIT applications. This need is particularly and currently imperative in medicine and public health to combat COVID-19 safely and responsibly.

1.7.10 HEALTH INFORMATION TECHNOLOGY AND THE COVID-19 PANDEMIC

The COVID-19 public health crisis has disproportionately affected individuals and populations historically marginalized in healthcare and public health, including minorities and those with low-income status.[16] For example, the COVID-19 pandemic has drawn new attention to and compounded the existing health and digital disparities in healthcare, with Black individuals being almost 4 times more likely to die from the virus than White individuals.[3] This gap is concerning, given that racial and ethnic health disparities have been historically unwavering and persistent within the United States.[2,5] Furthermore, this crisis has ignited rapid implementation of digital healthcare solutions such as virtual healthcare (telehealth and telemedicine capabilities) and health information accessed via mobile applications or online platforms.[22] When assessing the effectiveness and efficiency of HIT, we must consider the reciprocal relationship between HIT and the COVID-19 pandemic. This is of great concern, considering the amount of research [16,18,21,22,43,75,172] that maintains the importance of acknowledging that virtual care technologies do have the ability to exacerbate the digital divide and disparities in access to adequate care quality and safety. Researchers [16] have continued to recommend tackling health equity in virtual care delivery in the context of the COVID-19 pandemic at three critical levels: 1) policy and government, 2) organization and health system, and 3) community and patient.

Promoting health equity using strategies at these three levels will support healthcare professionals, funders, policymakers, and researchers to enable access to both the infrastructure necessary for patients to engage in a virtual care world (e.g., broadband internet and inclusive design standards and practices) [18,135,173–175] and the availability of digital services to all populations (e.g., properly reimbursing virtual care services).[9,13,16,23,28,161,176–178] In addition, health systems must continue to focus on quality improvement initiatives for vulnerable and marginalized populations and advocate for inclusive design strategies involving diverse user perceptions in the design of the technology to enhance digital literacy, access, and equity.[16,22,23,177,179,180] In doing so, the healthcare and public health communities can improve efforts to understand the association between inequities and information technologies.[181]

Furthermore, comprehending the three "levels" of the digital divide is fundamental to gaining understanding. The "first-level divide" refers to the gap between those who have access to technologies compared to those who do not, followed by the "second-level divide," which includes disparities in technology and digital literacy, and the "third-level divide," which is related to technology utilization.[179] Particularly, the second-level divide refers to the notion that despite some individuals having access to the internet and digital services, they may not have attained the skills and knowledge required to utilize these health technologies successfully. Moreover, the third-level divide suggests that even when some individuals have an adequate understanding of how to utilize these health technologies, they may not be able to convert their use into outcomes that advance their health and well-being.[15,16,182] Prior research indicates that care quality and safety improvement, especially during the COVID-19 pandemic, should incorporate strategies that focus on patient-centric care, health and digital health equity, systemic racism and oppression, and other root causes of health disparities and inequities to counter exacerbations driven by HIT and tools within the United States.

1.7.11 SUSTAINABILITY OF EQUITABLE CARE AND HIT PRACTICES AT THE HEALTH SYSTEM LEVEL

This review demonstrates that health systems must address disparities and inequities at varying levels and dimensions. This includes differences in data quality and clinical processes, HIT design, implementation, and utilization practices, risky and discriminatory application of HIT, repurposing of biased datasets and AI systems, and inequities in patient's ability, willingness, knowledge, confidence, skills, and access to health information technology and tools. To that end, this dissertation research works within the socio-technical and complex systems perspective of improved human health via high-quality, safe, HIT-driven care, which maintains two central concepts: 1) multiple levels of influence affect a patient's health outcomes, such as care quality, costs, and patient safety; and 2) complex adaptive systems occur when many agents work together within an organization and patterns materialize as the agents adopt, "simple rules" that optimize outcomes, such as the patient experience and the clinical team's performance.[124]

As existing research has shown that further inquiry is needed, this dissertation addresses some of the *missing* contextual forces, such as information technologies affecting the improvement of data and care quality, patient safety, and inequities within health systems in the United States. Providing more empirical evidence of the relationship between health informatics and disparities by examining differences in data quality, clinical processes, and patient health outcomes in the context of COVID-19 will express a significant and comprehensive call to action for preventing worsening health disparities and promoting equitable care and health technology practices for all individuals and patients alike **(Table 1a).**

Table 1a: Summary of Dissertation Aims

Objective 1. Examine the influence of external, societal factors on disparities in data quality and data entry patterns.
• Understand how the COVID-19 pandemic has impacted clinical processes and data entry patterns within the EHR in North Carolina.
Objective 2. Determine the multidimensional relationship between HIT processes and patient safety and care quality.
• Explore and understand the relationship between healthcare provider demographics and health system characteristics on healthcare providers' perceptions concerning EHR impact and care delivery.
Objective 3. Assess the effect of telehealth, HIT, and structural boundaries on patient perceptions and health outcomes.
• Identify which factors impact perceived telemedicine utilization barriers during the COVID-19 pandemic.

CHAPTER TWO. IMPACT OF THE COVID-19 PANDEMIC ON ELECTRONIC HEALTH RECORD DATA QUALITY

2.1 INTRODUCTION

Generating evidence from real-world data generated within health systems requires a clear understanding of their inner workings and factors influencing data production during clinical care.[1] These systems are a conjunction of dynamic, adaptive, and interdependent components such as individuals (healthcare providers, administration staff, and patients), infrastructure (policies, processes, and protocols), and technology (treatments and diagnostics).[1] The promotion of health information technology (HIT) through changes in national health policy was based on the argument that electronic health records (EHRs) could advance the U.S. healthcare system and aid in consistently improving care quality.[2] Existing EHR systems are designed to provide patient-level data, and provider-level documentation and are primarily clinically and financially focused,[3,4] and can be employed to inform evidence-based policy decisions and solutions.[5,6] The consistency and validity of secondary analyses of EHR-derived data are directly reliant on the accuracy of data entry.[7] Thus, correctly entering structured clinical data in the EHR is fundamental to ensuring reliable and appropriate actions based on insights derived from this data.[8]

Diagnosis (DX) data accuracy is essential to EHR information data reuse [9,10] as it is frequently utilized to select patients for electronic cohort development in clinical practice,[11,12] automated disease surveillance, and clinical audits for quality improvement [13] despite evidenced data quality limitations.[14-17] Existing informatics research has given the most attention to imparting evidence of DX data unreliability and emerging methods to moderate dependence on structured DX data alone.[18-20] However, the amount of published work dedicated to identifying the root causes of poor data quality, the multidimensionality between clinical processes generating the resulting data, and how to dependably use imperfect data consistently within the state of North Carolina is limited.[21]

Our previous works revealed that clinical workflows and human-computer interaction features of data entry (i.e., EHR segment of data entry (which signifies different segments of the user interface regarding the mindset and workflow of when clinicians entered DX data into the EHR), such as problem list or encounter DX) influence clinical data entry patterns and EHR data quality.[22-26] Although this has been investigated almost exclusively in oncological DX data, we uncovered similar patterns in endocrinology DX data entry.[27] Distinctively, we discovered that a hemoglobin A1c (HbA1c) lab above 9% increases the likelihood of DX entry reporting uncontrolled diabetes at statistically detectable levels in EHR data,[27] which differed across EHR segments. These findings strengthen the idea that EHR-wide, disease-independent DX data entry practices are impacted by the EHR segment and clinical workflows. Nevertheless, numerous external influences beyond clinical considerations may modify practice,[28] and it is unclear whether factors influencing clinical practice and workflows impact data entry patterns.

In this manuscript, we investigate the influence of external, population-level factors impacting clinical practice on EHR data entry. Based on the literature,[28] we hypothesized that an external societal change (e.g., pandemic-induced telemedicine) would not only modify clinical practice but would also influence the effects of clinical data entry patterns, which would vary across EHR segments (i.e., problem list, order DX, billing DX, etc.). We examined DX data reporting rates preceding and subsequent to a lab-based indication of uncontrolled diabetes during normal clinical operations and during the North Carolina Stay at Home orders of 2020 (i.e., March 2020). This analysis offers new data describing how clinical data entry and quality can be influenced by external factors that affect clinical processes. Our work provides evidence of the generalizability of previous findings [23-25] and develops the scope of influences that may affect clinical data generation, which must be considered when utilizing clinical data for secondary analysis.[5,6,29] We tested our hypothesis using diabetes-related DX data given its chronic, varying nature over time (e.g., glucose level flow, controlled vs. uncontrolled levels, complex comorbidities) and its significance to public health.[30,31] Our findings emphasize the need to give particular attention to factors impacting clinical practice and data entry on the clinical side of EHR systems and the significance of including clinicians in secondary analyses to supply knowledge of clinical data recording practices.[7]

2.2 METHODS

Structured DX information across five intra-EHR information data segments was extracted from Wake Forest Baptist Medical Center's Translational Data Warehouse. We gathered data on patients treated for diabetes, including HbA1c laboratory values and DX descriptions chosen by clinicians during charting. We uncovered diabetes DX descriptions indicating uncontrolled diabetes by employing string matching and natural language processing practices. We tested our hypothesis by evaluating the differences in patterns of diabetes DX for a cohort of patients with uncontrolled diabetes between two distinct timeframes (i.e., ICD-10 and COVID-19 months) using statistical models built for predicting the association of relevant variables with a post-HbA1c lab value. Logistic regression models were used to predict the presence of the number of DX reporting uncontrolled diabetes after a high HbA1c value for each timeframe. Descriptive and summary statistics for our EHR-phenotyped cohort [11,32] of patients are presented, along with statistical modeling results for hypothesis testing. Approval for this study was obtained by Wake Forest University School of Medicine’s Institutional Review Board (IRB: IRB00062976).

The patient cohort for this study included adults (i.e., 18 years of age or older at the time the data was recorded) who had at least one HbA1c value exceeding 9%, an average measure of blood sugar levels over the course of 3 months that indicates uncontrolled diabetes. Diagnosis code and description information were collected for these patients. The final inclusion criteria were formed on a phenotyping algorithm feature established by the New York City Health Department. This phenotype has a reported positive predictive value of 0.97 at the 6.7% level for both types of diabetes after validation with a gold standard.[32] Patients were excluded from the study if they only had one clinical interaction within 90 days prior to or after their first elevated HbA1c. This measure was used to screen charts that did not contain enough DX data after the HbA1c results were returned to reduce potential noise that would weaken statistical effects in our raw data.

The DX dataset contained 4,160 diabetes descriptions that could be chosen by clinicians at the time a DX was entered into the EHR. We uncovered descriptions of uncontrolled diabetes using a multi-stage process. To begin with, string matching methods were used to discover the terms “uncontrolled,” “inadequately controlled,” “out of control,” “poorly controlled,” “hyperglycemia,” or “not at goal” according to former and existing DX coding guidelines. Second, natural language processing was utilized to reveal other concepts describing uncontrolled diabetes. All clinical concepts in these descriptions were pulled using NOBLE Coder,[33] an NLP named system, which is a recognition tool for biomedical content utilized for traversing different medical domains (e.g., clinical care and research). At that point, subsequent concepts were explored, including similar terms referred to for string matching. Third, we analyzed concepts discovered by employing direct string matching and concept extraction, uncovering the comparative number of DX descriptions returned (755 and 715 for string matching and content extraction). The percent agreement among the two techniques was 99.3%. Likewise, all concepts that were distinguished through concept extraction were found to be contained in the set discovered via string matching. We proceeded to calculate the two rater Cohen's Kappa [34] to confirm inter-rater reliability across strategies utilizing the irr R package. We discovered high agreement between the two methodologies (Kappa=0.977, p<.0001). Finally, 10% of all DX specifications were considered by a clinician to approximate the accuracy of classification. The percent agreement between the highest-performing technique and our expert was 98.1%, and the inter-rater reliability Kappa (0.931, p<.0001) indicated high accuracy of our DX extraction measure.

The data used consisted of laboratory measures and DX descriptions the occurred between November 1st, 2015, and January 1st, 2020. This period was specified to guarantee ICD coding design consistency (i.e., included DX after ICD-10 went into effect). 158,660 diabetes DX recordings for 11,179 patients were included from our EHR for the final dataset. Our preliminary dataset contained DX records with the corresponding timestamp and patient identifier. Every DX had a specific DX description and was correlated with an ICD-10 code (i.e., E10.* and E11.* codes parallel to type 1 and type 2 diabetes). Each patient's original HbA1c result higher than 9% recorded to date was added to each DX record with the 'PostHbA1c' indicator that served as the dichotomous independent variable for our regressions.

Supplementary variables were analyzed to differentiate sequences of DX recorded 90 days preceding and following the initial elevated HbA1c value. These variables included the number of DXs entered in each sequence, the number of distinct DX descriptions, the DX sequence length in days (i.e., the maximum number of days between DX entry and the HbA1c), the number of distinct visit providers they saw during each timeframe, the number of departments or clinical units treating the patient (i.e., care units involved in patient management such as internal medicine, family medicine, and endocrinology), and the number of DX referring to uncontrolled diabetes. We screened data for outliers, missing values, and inaccurate input through examination of summary statistics. Dates were also evaluated for possible errors, such as values outside the study's timeframe.

To test our hypothesis, patient DX sequences were collected (i.e., a chain of chronologically ordered DX records in a patient's EHR), including all diabetes DX in 90 days preceding or subsequent to an elevated HbA1c laboratory (>9%), in concurrence with current care guiding principles for those diagnosed with diabetes. Every DX sequence contained specific ICD-10 codes for Type 1 or 2 diabetes (i.e., ICD-10 DX code, E10.* and E11.*) that indicated lack of control (e.g., "uncontrolled diabetes" or "diabetes with hyperglycemia"). Data was gathered during regular clinical practice (i.e., 2019) and during North Carolina's Stay at home orders (i.e., March 2020). We built binomial statistical models predicting the odds that a 90-day DX sequence would occur preceding or following an elevated HbA1c based on the number of DX records reporting uncontrolled diabetes and to compare the effects during these two time periods. Both datasets from the two timeframes were stacked, and a new variable was created to indicate from which dataset (i.e., ICD10 [Dataset 1] or COVID [Dataset 2]) the patients' data originated. Next, we generated ten different samples with a matched number of patients from both datasets using Stata's random tag function.[35] Statistical significance was set at p=0.05 for all models, and adjustments for multiple comparisons were made using Stata's p-adjust function (Holm's correction method).[36] We refer to the odds ratios as OR and the adjusted p values as adj-p.

Data extraction and preprocessing were executed using a DataGrip software client (version 2019.1, JetBrains s.r.o., Prague, Czech Republic). Visual exploration and analyses were performed using Tableau (version 2020.1, Tableau Software, Inc., Seattle, WA). All statistical analyses and data manipulation, such as scrubbing and reshaping, were done in StataCorp (version 2019.16.1, Stata Statistical Software, College Station, TX).

2.3 RESULTS

Our datasets contained 107,167 diabetes DX recordings for 12,620 patients across five clinical EHR segments and 6,574 diabetes DX recordings for 1,187 patients across five clinical EHR segments for regular operations and confinement operations during the pandemic, respectively **(Table 1b)**. The dataset contained 1,748 distinct DX descriptions entered by 1,246 providers across 633 departments or clinical units for regular operations and 430 distinct DX descriptions entered by 430 providers across 212 departments or clinical units for pandemic operations. The average number of days from the HbA1c result was 9±39 (Mean±Std.Dev.) and 1±11 (Mean±Std.Dev.) for regular and confinement operations.

We found differences in the regressions built for regular clinical operations and clinical operations during confinement **(Table 2b)**. Our model revealed changes in the number of DX reporting uncontrolled diabetes between the two timeframes. During regular operations, a 90-day DX sequence was roughly 7% more likely to appear in the post-HbA1c timeframe for each uncontrolled diabetes DX included (adj-p<.0001). For operations during confinement, a 90-day DX was about 16% more likely to appear in the post-HbA1c timeframe for uncontrolled diabetes (adj-p=.0094), likely secondary to better follow-up. Our models (i.e., regular and confinement) controlled for the total number of DX entries (OR=.963, adj-p<.0001; OR=.919, adj-p=.0135), the number of distinct DX descriptions per patient (OR=1.14,adj-p<.0001; OR=.967, adj-p=0.6825), the number of providers (OR=1.30, adj-p<.0001; OR=1.72, adj-p=0.010), the number of departments/units (OR=2.40; OR=4.10, adj-p<.0001), and length of DX sequence (i.e., pre/post, max number of days from HbA1c) (OR=.973;OR=.928, adj-p <.0001).

We found statistically significant differences in the number of providers between normal (OR=1.309, adj=p<.0001) and confinement (OR=1.722, adj-p=.0101) clinical operations. Our model also uncovered that the number of departments/units had the largest odds ratio (OR=2.405, adj-p<.0001) for regular operations and (OR=4.108, adj-p<.0001) for operations during confinement. Controlling for EHR data provenance, we found statistically significant differences between effects. Specifically, all segments (excluding billing for confinement operations) had statistically significant odds ratios ranging between 0.545 and 1.25 (0.001<p-value<.0001) **(Table 3b).**

Assessing differences between regular and confinement operations, we found statistically significant differences between data entry patterns. A DX sequence was less likely to appear after a high HbA1c during confinement (OR=.839, p<.0001) compared to normal operations. This model also uncovered statistically significant differences after controlling for EHR segment. We found that uncontrolled diabetes was more likely to be reported during normal operations (OR=1.090, p=.004) compared to confinement operations (OR=0.917, p=.004). This indicates a significant difference in the data entry patterns when controlling for when the data was entered (i.e., during normal operations or confinement). We found a slight uptick in the odds ratio for the number of uncontrolled diabetes records (OR=1.08, adj-p<.0001) compared to the regular operations odds ratio (OR=1.07, adj-p<.0001), indicating that the effect from that dataset was stronger, likely due to the larger number of patients. To address this and confirm the robustness of our findings, we developed ten different regressions with a matched number of patients.

The results found in prior regressions could be replicated with randomly matched datasets containing a balanced number of patients **(Table 4b),** indicating robust results. The odds ratio for the number of uncontrolled diabetes DX predicting if our DX sequence appeared before or after the high HbA1c value remained above 1, ranging between 1.08<OR<1.17 (0.001<adj-p>0.03). Time of operation also remained statistically significant (adj-p=0.001), with odd ratios remaining above or below 1 and ranging between 1.23<OR<1.27 and .721<OR<.808, showing that the effect was robust. Controlling for provenance also showed a robust effect. The odds ratio for the number of uncontrolled diabetes DX predicting if our DX sequence appeared before or after the high HbA1c value remained above 1, ranging between 1.07 and 1.16 (0.001<adj-p>0.025).

2.4 DISCUSSION

We compared data entry patterns during regular and confinement operations with respect to the COVID-19 pandemic. Changes were detected in the number of DX reporting uncontrolled diabetes between normal (OR=1.07, adj-p<.001) and confinement (OR=1.16, adj-p=.009) operations for patients with an HbA1c lab results above 9%. Statistically significant differences were found between data entry segments within our EHR database during both regular and confinement operations, confirming prior findings.[27] A sensitivity analysis confirmed changes in DX entry remained consistent throughout ten iterations of randomly matched datasets. These findings reveal that an external change affecting operations in healthcare organizations modifying clinical practice (e.g., COVID-19 and increased telemedicine) is correlated with clinical data entry patterns.[37,38]

Our findings underscore the idea that the variation in data entry across EHR segments during different units of time potentially reflects systematic changes within clinical documentation processes.[39,40] In understanding the secondary use of these data entry processes, this study supports prior findings and a need to systematically explore the complex adaptive nature of the micro-systems (e.g., having disparate providers and clinical departments) and macro-processes (e.g., clinical data entry patterns and ordering of diagnostics tests) in place.[41] In clinical practice, these macro-processes span multiple micro-systems within a healthcare organization. Congruent with that, our data show that clinical data entry may be fragmented [42] and exacerbated by complex high-level system factors outside clinical practice.[4,43,44] For example, our analysis uncovered that the number of departments had the most significant odds ratio (OR=2.405, adj-p<.0001) for regular operations and (OR=4.108, adj-p<.0001) during confinement.

However, these marked differences may suggest that some of the variability in data recording can be explained by providers from different units with different goals contributing to patient care as a team, which is likely to increase the heterogeneity in data entry.[45] In addition, it is important to consider that since many providers were using telemedicine, data were likely coded differently. This consideration gives insight into why our findings revealed changes in the likelihood of DX reporting uncontrolled diabetes after controlling for the number of departments and units.[46,47] Furthermore, our findings align with the argument that one must acknowledge the foundational aspect of diagnosis documentation for improved quality and organizational efficiency to implement behavior change to transform clinical practice.[39,40,48-50]

This study offers insight into the dynamic nature of clinical data entry and its potential impact on secondary use and, by proxy, evidence-based health policy development. Clinical data reuse is a useful tool for care quality improvement, and a deep understanding of its pitfalls and limitations is crucial to improve policies such as cost and payment policies as well as policies concerning EHRs and telehealth.[4,50-52] The goal to control spending in healthcare has led to budget cuts in fundamental areas of clinical practice. For example, randomized laboratory financial reductions are prevalent within healthcare. Laboratory expenses are only 3% of all clinical budgets, and nearly 70% of all medical errors result from diagnostic errors. Thus, inadequate testing often leads to inappropriate care delivery and misdiagnosis, supporting the idea that adequate lab results and testing have a noteworthy role in diagnostics.[50] Furthermore, given that our models revealed that an external societal change is correlated with modified clinical practice and data entry patterns, there is a need to investigate the interactions between the environment, processes, workflows, technological designs, patients, and the core operative nature of the system itself.[28,40,54] Although some researchers [55,56] maintain that quality and safety have improved due to healthcare digitization, resolving the "productivity paradox of health information technology" remains a challenge, and clinical IT and human systems must not only co-exist but co-evolve concurrently.[2,41,57,58]

In the context of healthcare policy within North Carolina, identifying how to seamlessly integrate clinical data while reducing waste and care costs remains largely untapped. Hence, the call in 2015 by the North Carolina General Assembly for a statewide health information exchange (HIE).[59] This act was partly developed to tackle one of the most challenging aspects of HIT, otherwise known as *"interoperability."* It was designed to cultivate a centralized database of health data to strengthen the use of analytics for improved quality of care.[59] Although this is a remarkable effort, the purpose of the NC Health Information Exchange Authority (NC HIEA), which is to bridge all systems of care across North Carolina to accelerate better-quality and timely data sharing, is at risk of being diminished by data quality issues that may be unacknowledged and unaccounted for.[42] Such multi-site integrations are likely to increase the heterogeneity in databases and present a clear threat to secondary data analysis and the reliability of the evidence generated for downstream decision-making.[60,61] In acknowledging this risk, policy changes must be made to encourage and demand improved interoperability and EHR design in the effort to drive better care quality for all patients, communities, and populations across North Carolina.[21,43,62]

Limitations

Our analysis presents several limitations. First, our study was dependent on an EHR-phenotype cohort of patients rather than a hand-curated patient cohort. We used a validated phenotyping algorithm developed by the New York City Health Department [63] to inform our EHR phenotyping techniques for our patient population since we did not have a clinician-developed cohort available. Second, the odds ratios of the number of DX indicating uncontrolled diabetes for pre-pandemic and confinement operations were rather small (i.e., $1.07<OR<1.16$) compared to other predictors. Third, we utilized clinical data from only one healthcare system. However, our future work will use data from multiple health systems to increase generalizability and external validity. Finally, given that we evaluated data from two different timeframes, the volume of both datasets was incongruent. To account for this, we developed ten different samples with an equal number of matched patients and replicated all regression models. Future work will focus on addressing these limitations and verifying our findings through the development of further EHR-based clinical and informatics research.

CONCLUSION

We consistently found changes in the number of DX reporting uncontrolled diabetes between normal and confinement operations. Our results support prior evidence [64] that external factors outside of clinical practice may affect data entry patterns. This evidence highlights the need for innovative approaches to understanding complexities related to EHRs, clinical documentation, and diagnostics, which result in the third most common EHR-related adverse safety event (e.g., timely follow-ups for abnormal lab results).[1] If we effectively capture and utilize clinical data and knowledge, we will have an improved chance of meeting our collective ambitions to ensure safe, high-quality, and sustainable learning health systems.[65,66] In uncovering the digital infrastructure and data captured by providers in EHRs, it is particularly important to explore the emerging opportunities in how EHRs impact adverse safety events and errors, as well as providers' and patients’ perceptions of quality care within healthcare systems. With the evolution of patient-focused HIT policy,[53] the pervasive disparities and inequities that exist within healthcare systems must be evaluated to achieve more equitable data practices and decision-making.

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Table 1b: Dataset Descriptive Statistics

	Regular Operations			Confinement Operations		
Measures/Timeframe	Overall	Pre-HbA1c	Post-HbA1c	Overall	Pre-HbA1c	Post-HbA1c
Distinct Patients	12,620	6,042	11,515	1,187	415	1,067
Number of DX Records	107,167	28,593	78,574	6,574	1,463	5,111
Distinct DX Descriptions	1,748	1,135	1,524	430	226	363
Number of Uncontrolled Diabetes DX Records	31,377	7,738	23,639	2,287	409	1,878
Distinct Providers	1,246	1,015	1,193	430	253	394
Distinct Hospital Department/Unit	633	472	584	212	126	192
Days from HbA1c Result (Mean±Std.Dev.)	9±39	-33±31	24±29	1±11	-9±11	4±9

Table 2b: Overall Regression Results. During regular operations, a 90-day DX sequence was about 7% more likely to appear in the post-HbA1c timeframe for each uncontrolled diabetes DX included (adj-p<.0001). Whereas, for operations during confinement, a 90-day DX was 16% more likely to appear in the post-HbA1c timeframe for uncontrolled diabetes (adj-p=.009).

Model	Term	Odds Ratio (exp(B))	Confidence Interval (95%)		Std. Error	p-value	Adjusted p-value
Overall Regular Operations	Number of Uncontrolled Diabetes DX	1.07	1.05	1.08	.009	<.0001	<.0001
	Number of DX	.963	.955	.972	.004	<.0001	<.0001
	Number of Distinct DX	1.14	1.10	1.19	.023	<.0001	<.0001
	Number of Providers	1.30	1.23	1.39	.041	<.0001	<.0001
	Number of Departments/Units	2.40	2.26	2.55	.072	<.0001	<.0001
	DX Sequence Length (Days)	.973	.973	.974	.000	<.0001	<.0001
Overall Confinement Operations	Number of Uncontrolled Diabetes DX	1.16	1.05	1.27	.056	0.002	0.009
	Number of DX	.919	.865	.977	.028	0.007	0.013
	Number of Distinct DX	.967	.823	1.13	.079	0.682	0.682
	Number of Providers	1.722	1.19	2.47	.319	0.003	0.010
	Number of Departments/Units	4.10	2.87	5.86	.746	<.0001	<.0001
	DX Sequence Length (Days)	.928	.918	.937	.004	<.0001	<.0001
Regular Operations	Number of Uncontrolled Diabetes DX	1.07	1.04	1.08	.009	<.0001	<.0001
	Number of DX	.965	.957	.974	.004	<.0001	<.0001
	Number of Distinct DX	1.15	1.10	1.20	.023	<.0001	<.0001

	Number of Providers	1.25	1.17	1.34	.041	<.0001	<.0001
	Number of Departments/Units	2.76	2.60	2.94	.087	<.0001	<.0001
	DX Sequence Length (Days)	.973	.972	.974	.000	<.0001	<.0001
	Provenance – Primary Encounter DX (Ref.)	1	Ref	Ref	Ref	Ref	Ref
	Encounter DX	.721	.690	.754	.016	<.0001	<.0001
	Order DX	.672	.642	.703	.015	<.0001	<.0001
	Problem List DX	1.25	1.19	1.30	.026	<.0001	<.0001
	Billing DX	.812	.776	.847	.018	<.0001	<.0001
Confinement Operations Controlling for EHR Segment	Number of Uncontrolled Diabetes DX	1.17	1.05	1.28	.058	0.002	0.01
	Number of DX	.958	.899	1.02	.030	0.182	0.546
	Number of Distinct DX	.897	.761	1.05	.075	0.198	0.546
	Number of Providers	1.56	1.08	2.26	.294	0.018	0.07
	Number of Departments/Units	4.93	3.42	7.08	.911	0.000	0.001
	DX Sequence Length (Days)	.926	.916	.935	.004	0.000	0.001
	Provenance – Primary Encounter DX (Ref.)	1	Ref	Ref	Ref	Ref	Ref
	Encounter DX	.718	.608	.847	.060	0.000	0.001
	Order DX	.545	.457	.649	.048	0.000	0.001
	Billing DX	.916	.779	1.07	.075	0.290	0.546

Table 3b: Regression Results Controlling for Confinement vs. Normal Operation Timeframes. A DX sequence was less likely to appear after a high HbA1c during confinement (OR=.839, p<.0001) compared to normal operations.

Model	Term	Odds Ratio (exp(B))	Confidence Interval (95%)		p-value
Confinement	Number of Uncontrolled Diabetes DX	1.08	1.06	1.09	<.0001
	Number of DX	.961	.952	.969	<.0001
	Number of Distinct DX	1.14	1.09	1.18	<.0001
	Number of Providers	1.32	1.24	1.40	<.0001
	Number of Departments/Units	2.47	2.33	2.62	<.0001
	DX Sequence Length (Days)	.973	.972	.974	<.0001
	Dataset- Normal Operations (Ref.)	1	Reference	Reference	Reference
	Confinement Operations	.838	.787	.883	<.0001
Confinement and EHR	Number of Uncontrolled Diabetes DX	1.07	1.05	1.09	<.0001
	Number of DX	.963	.954	.972	<.0001
	Number of Distinct DX	1.14	1.10	1.19	<.0001
	Number of Providers	1.26	1.18	1.35	<.0001
	Number of Departments/Units	2.86	2.69	3.04	<.0001
	DX Sequence Length (Days)	.973	.972	.973	<.0001
	Dataset- Normal Operations (Ref.)	1	Reference	Reference	Reference
	Confinement Operations	.917	.865	.972	0.004
	Provenance – Primary Encounter DX (Ref.)	1	Reference	Reference	Reference
	Encounter DX	.819	.691	.753	<.0001
	Order DX	.721	.638	.697	<.0001

	Problem List DX	.667	1.20	1.30	<.0001
	Billing DX	1.25	.785	.855	<.0001
Normal	Number of Uncontrolled Diabetes DX	1.07	1.06	1.09	<.0001
	Number of DX	.961	.952	.969	<.0001
	Number of Distinct DX	1.14	1.09	1.18	<.0001
	Number of Providers	1.32	1.24	1.40	<.0001
	Number of Departments/Units	2.47	2.33	2.62	<.0001
	DX Sequence Length (Days)	.973	.972	.974	<.0001
	Dataset- Confinement Operations (Ref.)	1	Reference	Reference	Reference
	Normal Operations	1.20	1.13	1.27	<.0001
Normal and EHR	Number of Uncontrolled Diabetes DX	1.07	1.05	1.08	<.0001
	Number of DX	.963	.954	.972	<.0001
	Number of Distinct DX	1.14	1.10	1.19	<.0001
	Number of Providers	1.26	1.18	1.35	<.0001
	Number of Departments/Units	2.86	2.69	3.04	<.0001
	DX Sequence Length (Days)	.973	.972	.973	<.0001
	Dataset- Confinement Operations (Ref.)	1	Reference	Reference	Reference
	Normal Operations	1.10	1.03	1.16	0.004
	Provenance – Primary Encounter DX (Ref.)	1	Reference	Reference	Reference
	Encounter DX	.721	.691	.753	<.0001
	Order DX	.667	.638	.697	<.0001
	Problem List DX	1.25	1.20	1.31	<.0001
	Billing DX	.819	.785	.855	<.0001

Table 4b: Ranges of Odds Ratios and P-values for the Ten Matched-Patient Regressions. The odds ratio for the number of uncontrolled diabetes DX predicting if our DX sequence appeared before or after the high HbA1c value remained above 1, ranging between 1.08<OR<1.17 and (0.001<Adj-p>0.03).

Model	**Term**	**Odds Ratios Mean (Min-Max)**	**Confidence Interval (95%) (Min-Max)**	**P-value Range (Min-Max)**	**Adjusted P-value Range (Min-Max)**
Overall Normal Operations	**Number of Uncontrolled Diabetes DX**	**1.13 (1.08-1.17)**	**1.02-1.23**	**<.0001-0.006**	**0.001-0.03**
	Dataset – Confinement Operations (Ref).	1	Reference	Reference	Reference
	Normal Operations	1.25 (1.23-1.27)	1.14-1.37	<.0001	0.001
Overall Confinement Operations	**Number of Uncontrolled Diabetes DX**	**1.13 (1.08-1.17)**	**1.02-1.23**	**<.0001-0.006**	**0.001-0.03**
	Dataset – Normal Operations (Ref).	1	Reference	Reference	Reference
	Confinement Operations	.794 (.786-.808)	.721-.874	<.0001	0.001
Regular Operations Controlling for EHR Segment	**Number of Uncontrolled Diabetes DX**	**1.12 (1.07-1.16)**	**1.02-1.24**	**<.0001-0.006**	**0.001-0.03**
Confinement Operations Controlling for EHR Segment	**Number of Uncontrolled Diabetes DX**	**1.12 (1.07-1.16)**	**1.02-1.22**	**<.0001-0.004**	**0.001-0.025**

2.5 REFERENCES

1. Roosan D, Law AV, Karim M, Roosan M. Improving Team-Based Decision Making Using Data Analytics and Informatics: Protocol for a Collaborative Decision Support Design. *JMIR Res Protoc*. 2019;8(11). doi:10.2196/16047

2. Bowman S. Impact of electronic health record systems on information integrity: quality and safety implications. *Perspect Health Inf Manag*. 2013;10:1c.

3. Kukafka R, Ancker JS, Chan C, et al. Redesigning electronic health record systems to support public health. *J Biomed Inform*. 2007;40(4):398-409. doi:10.1016/j.jbi.2007.07.001

4. Basch P, Smith JRL. CMS Payment Policy, E&M Guideline Reform, and the Prospect of Electronic Health Record Optimization. *Appl Clin Inform*. 2018;9(4):914-918. doi:10.1055/s-0038-1676337

5. Safran C. Reuse Of Clinical Data. *IMIA Yearb*. 2014;9(1):52-54. doi:10.15265/IY-2014-0013

6. Safran C. Using routinely collected data for clinical research. *Stat Med*. 1991;10(4):559-564.

7. de Lusignan S, Mimnagh C. Breaking the first law of informatics: the Quality and Outcomes Framework (QOF) in the dock. *Inform Prim Care*. 2006;14(3):153-156. doi:10.14236/jhi.v14i3.625

8. Doremus HD, Michenzi EM. Data Quality: An Illustration of Its Potential Impact upon a Diagnosis-Related Group’s Case Mix Index and Reimbursement. *Med Care*. 1983;21(10):1001-1011.

9. Köpcke F, Prokosch HU. Employing Computers for the Recruitment into Clinical Trials: A Comprehensive Systematic Review. *J Med Internet Res*. 2014;16(7). doi:10.2196/jmir.3446

10. Moskowitz A, Chen K. Defining the Patient Cohort. In: *Secondary Analysis of Electronic Health Records*. Springer International Publishing; 2016:93-100. doi:10.1007/978-3-319-43742-2_10

11. Shivade C, Raghavan P, Fosler-Lussier E, et al. A review of approaches to identifying patient phenotype cohorts using electronic health records. *J Am Med Inform Assoc*. 2014;21(2):221-230. doi:10.1136/amiajnl-2013-001935

12. Kreuzthaler M, Schulz S, Berghold A. Secondary use of electronic health records for building cohort studies through top-down information extraction. *J Biomed Inform*. 2015;53:188-195. doi:10.1016/j.jbi.2014.10.010

13. Shah SM, Khan RA. Secondary Use of Electronic Health Record: Opportunities and Challenges. *ArXiv200109479 Cs*. Published online January 26, 2020. doi:10.1109/ACCESS.2020.3011099

14. Farzandipour M, Sheikhtaheri A, Sadoughi F. Effective factors on accuracy of principal DX coding based on International Classification of Diseases, the 10th revision (ICD-10). *Int J Inf Manag*. 2010;30(1):78-84. doi:10.1016/j.ijinfomgt.2009.07.002

15. McDonald CJ, Huff SM, Suico JG, et al. LOINC, a Universal Standard for Identifying Laboratory Observations: A 5-Year Update. *Clin Chem*. 2003;49(4):624-633. doi:10.1373/49.4.624

16. O'Malley KJ, Cook KF, Price MD, Wildes KR, Hurdle JF, Ashton CM. Measuring Diagnoses: ICD Code Accuracy. *Health Serv Res*. 2005;40(5p2):1620-1639. doi:10.1111/j.1475-6773.2005.00444.x

17. Hsia DC, Krushat WM, Fagan AB, Tebbutt JA, Kusserow RP. Accuracy of Diagnostic Coding for Medicare Patients under the Prospective-Payment System. http://DX.doi.org/10.1056/NEJM198802113180604. doi:10.1056/NEJM198802113180604
18. Conway M, Berg RL, Carrell D, et al. Analyzing the Heterogeneity and Complexity of Electronic Health Record Oriented Phenotyping Algorithms. *AMIA Annu Symp Proc*. 2011;2011:274-283.

19. Wei WQ, Teixeira PL, Mo H, Cronin RM, Warner JL, Denny JC. Combining billing codes, clinical notes, and medications from electronic health records provides superior phenotyping performance. *J Am Med Inform Assoc*. 2016;23(e1):e20-e27. doi:10.1093/jamia/ocv130

20. Sarmiento RF, Dernoncourt F. Improving Patient Cohort Identification Using Natural Language Processing. In: *Secondary Analysis of Electronic Health Records*. Springer International Publishing; 2016:405-417. doi:10.1007/978-3-319-43742-2_28

21. Thompson ME, Dulin MF. Leveraging Data Analytics to Advance Personal, Population, and System Health: Moving Beyond Merely Capturing Services Provided. *N C Med J*. 2019;80(4):214-218. doi:10.18043/ncm.80.4.214

22. Botsis T, Hartvigsen G, Chen F, Weng C. Secondary Use of EHR: Data Quality Issues and Informatics Opportunities. *AMIA Summits Transl Sci Proc*. 2010;2010:1.

23. Diaz-Garelli JF, Strowd R, Wells BJ, Ahmed T, Merrill R, Topaloglu U. Lost in Translation: Diagnosis Records Show More Inaccuracies After Biopsy in Oncology Care EHRs. *AMIA Summits Transl Sci Proc*. 2019;2019:325-334.

24. Diaz-Garelli JF, Wells BJ, Yelton C, Strowd R, Topaloglu U. Biopsy Records Do Not Reduce Diagnosis Variability in Cancer Patient EHRs: Are We More Uncertain After Knowing? In: ; 2018.

25. Diaz-Garelli JF, Strowd R, Ahmed T, et al. A tale of three subspecialties: Diagnosis recording patterns are internally consistent but Specialty-Dependent. *JAMIA Open*. Published online August 5, 2019. doi:10.1093/jamiaopen/ooz020

26. Diaz-Garelli F, Strowd R, Ahmed T, et al. What Oncologists Want: Identifying Challenges and Preferences on Diagnosis Data Entry to Reduce EHR-Induced Burden and Improve Clinical Data Quality. *JCO Clin Cancer Inform*. 2021;(5):527-540. doi:10.1200/CCI.20.00174

27. Diaz-Garelli F, Lenoir KM, Wells BJ. Catch Me if You Can: Acute Events Hidden in Structured Chronic Disease Diagnosis Descriptions Show Detectable Recording Patterns in EHR. *AMIA Annu Symp Proc*. 2021;2020:373-382.

28. Kruse CS, Stein A, Thomas H, Kaur H. The use of Electronic Health Records to Support Population Health: A Systematic Review of the Literature. *J Med Syst*. 2018;42(11):214. doi:10.1007/s10916-018-1075-6

29. Hersh WR, Weiner MG, Embi PJ, et al. Caveats for the use of operational electronic health record data in comparative effectiveness research. *Med Care*. 2013;51(8 Suppl 3):S30-37. doi:10.1097/MLR.0b013e31829b1dbd

30. Centers for Medicare and Medicaid. DM-2 (NQF 0059): Diabetes: Hemoglobin A1c (HbA1c) Poor Control (>9%). Published online 2019:18.

31. Susan van D, Beulens JWJ, Yvonne T. van der S, Grobbee DE, Nealb B. The global burden of diabetes and its complications: an emerging pandemic. *Eur J Cardiovasc Prev Rehabil*. 2010;17(1_suppl):s3-s8. doi:10.1097/01.hjr.0000368191.86614.5a

32. Spratt SE, Pereira K, Granger BB, et al. Assessing electronic health record phenotypes against gold-standard diagnostic criteria for diabetes mellitus. *J Am Med Inform Assoc JAMIA*. 2017;24(e1):e121-e128. doi:10.1093/jamia/ocw123

33. Tseytlin E, Mitchell K, Legowski E, Corrigan J, Chavan G, Jacobson RS. NOBLE – Flexible concept recognition for large-scale biomedical natural language processing. *BMC Bioinformatics*. 2016;17(1):32. doi:10.1186/s12859-015-0871-y

34. McHugh ML. Interrater reliability: the kappa statistic. *Biochem Medica*. 2012;22(3):276-282.

35. Higgins S. *RANDOMSELECT: Stata Module to Randomly Select and Tag Observations*. Boston College Department of Economics; 2017. Accessed April 14, 2021. https://ideas.repec.org/c/boc/bocode/s458200.html

36. M A, H G. Adjusting for multiple testing when reporting research results: the Bonferroni vs Holm methods. *Am J Public Health*. 1996;86(5):726-728. doi:10.2105/ajph.86.5.726

37. Sturmberg JP, O’Halloran DM, Martin CM. Understanding health system reform - a complex adaptive systems perspective: Understanding health system reform. *J Eval Clin Pract*. 2012;18(1):202-208. doi:10.1111/j.1365-2753.2011.01792.x

38. Westerlund A, Garvare R, Höög E, Nyström ME. Facilitating system-wide organizational change in healthcare. *Int J Qual Serv Sci*. 2015;7(1):72-89. doi:10.1108/IJQSS-01-2015-0004

39. Butler TJ, Firestone KS, Grow JL, Kantak AD. Standardizing documentation and the clinical approach to apnea of prematurity reduces length of stay, improves staff satisfaction, and decreases hospital cost. *Jt Comm J Qual Patient Saf*. 2014;40(6):263-269. doi:10.1016/s1553-7250(14)40035-7

40. Ommaya AK, Cipriano PF, Hoyt DB, et al. Care-Centered Clinical Documentation in the Digital Environment: Solutions to Alleviate Burnout. *NAM Perspect*. Published online January 29, 2018. doi:10.31478/201801c

41. Rothschild AS, Dietrich L, Ball MJ, Wurtz H, Farish-Hunt H, Cortes-Comerer N. Leveraging systems thinking to design patient-centered clinical documentation systems. *Int J Med Inf*. 2005;74(5):395-398. doi:10.1016/j.ijmedinf.2005.03.011

42. Anderson L. Realizing the Future We Want: Leveraging Technology to Achieve a Better Healthcare Experience for All. *N C Med J*. 2019;80(4):224-228. doi:10.18043/ncm.80.4.224

43. Gold R, Cottrell E, Bunce A, et al. Developing Electronic Health Record (EHR) Strategies Related to Health Center Patients' Social Determinants of Health. *J Am Board Fam Med JABFM*. 2017;30(4):428-447. doi:10.3122/jabfm.2017.04.170046

44. Cottrell EK, Dambrun K, Cowburn S, et al. Variation in Electronic Health Record Documentation of Social Determinants of Health Across a National Network of Community Health Centers. *Am J Prev Med*. 2019;57(6 Suppl 1):S65-S73. doi:10.1016/j.amepre.2019.07.014

45. Diaz-Garelli F, Strowd R, Lawson VL, et al. Workflow Differences Affect Data Accuracy in Oncologic EHRs: A First Step Toward Detangling the Diagnosis Data Babel. *JCO Clin Cancer Inform*. 2020;(4):529-538. doi:10.1200/CCI.19.00114

46. Önmez A, Gamsızkan Z, Özdemir Ş, et al. The effect of COVID-19 lockdown on glycemic control in patients with type 2 diabetes mellitus in Turkey. *Diabetes Metab Syndr*. 2020;14(6):1963-1966. doi:10.1016/j.dsx.2020.10.007

47. Misra A, Ghosh A, Gupta R. Heterogeneity in presentation of hyperglycaemia during COVID-19 pandemic: A proposed classification. *Diabetes Metab Syndr*. 2021;15(1):403-406. doi:10.1016/j.dsx.2021.01.018

48. Combs T. The Importance of High-Quality Clinical Documentation Across the Healthcare Continuum | Journal Of AHIMA. Published April 1, 2020. Accessed May 4, 2021. https://journal.ahima.org/the-importance-of-high-quality-clinical-documentation-across-the-healthcare-continuum/

49. Rowlands S, Coverdale S, Callen J. Documentation of clinical care in hospital patients' medical records: A qualitative study of medical students' perspectives on clinical documentation education. *Health Inf Manag J*. 2016;45(3):99-106. doi:10.1177/1833358316639448

50. Soto CM, Kleinman KP, Simon SR. Quality and correlates of medical record documentation in the ambulatory care setting. *BMC Health Serv Res*. 2002;2(1):22. doi:10.1186/1472-6963-2-22

51. Rissanen M. Translational health technology and system schemes: enhancing the dynamics of health informatics. Published online 2020:11.

52. Biddle S, Milstead JA. The intersection of policy and informatics. *Nurs Manag (Harrow)*. 2016;47(2):12-13. doi:10.1097/01.NUMA.0000479453.73651.89

53. Bell K. Public Policy and Health Informatics. *Semin Oncol Nurs*. 2018;34(2):184-187. doi:10.1016/j.soncn.2018.03.010

54. Kasiri N, Sharda R, Asamoah D. Evaluating Electronic Health Records Systems: A Systems Dynamics Simulation. *Simulation*. 2012;88(6):639-648. doi:10.1177/0037549711416244

55. Casey JA, Schwartz BS, Stewart WF, Adler NE. Using Electronic Health Records for Population Health Research: A Review of Methods and Applications. *Annu Rev Public Health*. 2016;37:61-81. doi:10.1146/annurev-publhealth-032315-021353

56. Kizzier-Carnahan V, Artis KA, Mohan V, Gold JA. Frequency of Passive EHR Alerts in the ICU: Another Form of Alert Fatigue? *J Patient Saf*. 2019;15(3):246-250. doi:10.1097/PTS.0000000000000270

57. Wachter RM, Howell MD. Resolving the Productivity Paradox of Health Information Technology: A Time for Optimism. *JAMA*. 2018;320(1):25-26. doi:10.1001/jama.2018.5605

58. Meigs SL, Solomon M. Electronic Health Record Use a Bitter Pill for Many Physicians. *Perspect Health Inf Manag*. 2016;13:1d.

59. Revels C, Burris C. NC HealthConnex and Value-based Care: Statewide Health Information Exchange as a Technology Tool for All. *N C Med J*. 2019;80(4):229-233. doi:10.18043/ncm.80.4.229

60. Ramanathan T, Schmit C, Menon A, Fox C. The Role of Law in Supporting Secondary Uses of Electronic Health Information. *J Law Med Ethics*. 2015;43(S1):48-51. doi:10.1111/jlme.12215

61. Kosseim P, Brady M. POLICY BY PROCRASTINATION: SECONDARY USE OF ELECTRONIC HEALTH RECORDS FOR HEALTH RESEARCH PURPOSES. 2008;2:41.

62. Mehta A. How Data Will Transform Healthcare: We Just Need It Better, Faster, and Cheaper. *N C Med J*. 2019;80(4):225-226. doi:10.18043/ncm.80.4.225

63. Chamany S, Silver LD, Bassett MT, et al. Tracking Diabetes: New York City's A1C Registry. *Milbank Q*. 2009;87(3):547-570. doi:10.1111/j.1468-0009.2009.00568.x

64. Kroth PJ, Morioka-Douglas N, Veres S, et al. Association of Electronic Health Record Design and Use Factors With Clinician Stress and Burnout. *JAMA Netw Open*. 2019;2(8):e199609. doi:10.1001/jamanetworkopen.2019.9609

65. Veinot TC, Mitchell H, Ancker JS. Good intentions are not enough: how informatics interventions can worsen inequality. *J Am Med Inform Assoc*. 2018;25(8):1080-1088. doi:10.1093/jamia/ocy052

66. Fennelly O, Cunningham C, Grogan L, et al. Successfully implementing a national electronic health record: a rapid umbrella review. *Int J Med Inf*. 2020;144:104281. doi:10.1016/j.ijmedinf.2020.104281

CHAPTER THREE. EXPLORING PROVIDERS' PERCEIVED TELEMEDICINE AND EHR IMPACT ON PATIENT SAFETY AND QUALITY DURING THE COVID-19 PANDEMIC

3.1 INTRODUCTION

Over the past decade, health information technology (HIT) has significantly transformed clinical practice within the United States (US), although it was introduced into the healthcare industry during the 1960s.[1] Health information technology incorporates electronic systems that healthcare professionals and patients use to store, share, and analyze health information, data, and knowledge for communication and decision-making. Despite the suggested promises of HIT,[2,3] widening and troubling disparities persist and are often exacerbated using HIT within clinical settings.[4,5] Disparities are "differences in treatment between racial, ethnic or other demographic groups that are not directly attributable to variation in clinical needs or patient preferences and continue even after adjustment for socioeconomic factors."[6]

Although HIT has been cited for offering the potential ability to increase access to healthcare, improve clinical outcomes, and advance care quality, the promise and capacity that HIT offers have not been materialized, and a "digital divide" remains, in which technology and digital utilization patterns differ across racial, ethnic, and socioeconomic boundaries.[5,7] Some studies suggest that many novel health information technologies and practices such as artificial intelligence (AI),[8] big data,[9] 5G mobile networks,[10] mobile health applications,[11,12] telehealth,[13,14] telemedicine,[15,16] and health information exchange (HIE) services [17,18] contribute to the digital divide we continue to see.[4,3] However, despite these findings, the reliance on HIT to reduce inequitable health outcomes and disparities continue to accelerate at an unprecedented pace.[20]

A recent systematic review conducted in 2018 [3] reported that roughly 81% of the medical studies assessed demonstrated improved medical outcomes in terms of efficiency and effectiveness resulting from HIT implementation. The authors also maintain that the one difference they had in common themes between their systematic review and other systemic reviews conducted since the 1990s is the limited knowledge and research correlated with HIE services. Despite this being a noteworthy factor in HIT implementation, most data quality-focused HIT policies are poorly implemented throughout health systems.[21–23] Quality improvement has been suggested as a significant area for strategic policy development and initiatives to decrease or eradicate healthcare disparities. [5] Given the pandemic-induced increase of HIT utilization in clinical settings and radical debates on its usefulness, researchers [4] argue that it is essential to investigate the interactions between health technology and disparities to improve care quality and delivery.

The effects of pandemic-induced telemedicine and healthcare provider and system characteristics on perceived electronic health record (EHR) documentation have not been assessed in the current population within public health and health services research. The findings of this research can inform future evaluation, policies, and interventions geared toward HIT-related patient error prevention and reduction, as well as reduction of disparities and inequities in patients, populations, and communities. Accurate recording of patient health information, including diagnosis, treatment, prescription, and lab result data in the EHR, is crucial for clinical practice and learning health systems. Adverse events and preventable errors are the third leading cause of death in the U.S.[24] This demonstrates that although the industry has taken steps and conducted research to improve patient safety and quality, little to no progress has been made. Patients today are experiencing ten times the rate of preventable harm as they were in the 1990s, despite the advancements in health information technology and tools.[25]

This paper investigated the multidimensional relationship between pandemic-induced telemedicine, care quality, and patient safety. Based on the current literature,[24, 25] the hypothesis for this study was that healthcare providers (e.g., MDs, DOs, PAs, CNPs, & RNs) who report using telemedicine or having a board certification perceive the EHR's impact on their ability to provide quality healthcare and avoid errors as beneficial or highly beneficial, compared to non-telemedicine providers with no board certification. The findings from this study emphasize the need to give particular attention to demographic and health-system-related characteristics' influence on perceptions of the satisfaction or utility of health information technology tools such as electronic health records.

3.2 METHODS

Data Source

This study was based on a pilot cross-national, cross-sectional research design, which included U.S. healthcare providers (e.g., MDs, DOs, PAs, CNPs, & RNs) who continually practiced from the start of the COVID-19 pandemic in March 2020. This study was conducted using an anonymous web questionnaire to determine the multidimensional relationship between demographic and health system-related characteristics and perceived EHR impact on care delivery through an equitable and sociotechnical lens. The study consisted of adult (18+), English-speaking healthcare providers from various hospitals, health systems, and institutions. Providers were excluded if they did not practice medicine from the start of the pandemic to when the study was conducted. Eligible providers were informed of a 20-question anonymous online questionnaire through an e-listserv (i.e., National Study of Long-Term Care Providers (NSLTCP) and various social media platforms (i.e., Twitter, Facebook, Slack, and LinkedIn). The questionnaire, described in detail **(Appendix A1**), was adapted from the National Electronic Health Records Survey (NEHRS) [26] and The Electronic Health Record End User Survey.[27] The modified survey, designed to be completed in 10 to 15 minutes, was validated based on results from a study conducted by DesRoches et al.,[28] where they employed the NEHRS with the use of a national survey including 2,758 clinicians. Their results indicated that clinicians reported positive effects of these systems on several dimensions of care quality and high levels of satisfaction. However, the DesRoches et al.,[28] study validated the need to investigate healthcare providers' perceptions of HIT and their utilization practices.

Data collection occurred six weeks from March 1st, 2022, to April 11th, 2022. Logistic regression models were used to predict the odds of healthcare providers reporting that the EHR's impact on care delivery was beneficial or highly beneficial during the COVID-19 pandemic, based on telemedicine utilization and board certification. Descriptive and summary statistics for our sample of providers are presented, along with statistical modeling results for hypothesis testing. The descriptive information for the variables was also assessed graphically via histograms. Researchers obtained approval from The University of North Carolina at Charlotte's Institutional Review Board (IRB#: 22-0701). Our final sample consisted of N =159 healthcare providers after 16 providers, who did not practice medicine during the designated timeframe, and 24 providers, who submitted incomplete questionnaires, were excluded (**Table 1c**).

Study Variables and Statistical Analysis

Electronic Health Record (EHR) Measures

Outcome Variables. The dependent variable, *perceived EHR impact*, was binary and measured by the question, "Based on your experience during the pandemic, please indicate whether you believe the effect of the EHR on your clinical practice has been detrimental, beneficial, or neither, using the scale below:" Providers were asked to indicate their perceived level of EHR impact by selecting a response ranging from 1 (highly detrimental) to 5 (highly beneficial). The primary and secondary outcome measures were *perceived EHR impact on quality of healthcare* and *perceived EHR impact on avoiding errors.* Quality of healthcare (herein referred to as "care quality") indicates the increased likelihood of desired health outcomes, and avoiding errors (herein referred to as “patient safety”) entails averting a preventable adverse event of care to the patient. Care quality and patient safety are collectively referred to as “care delivery” throughout this study.

A validated instrument (The Electronic Health Record End User Survey) was utilized to minimize measurement error and internal validity issues. The Electronic Health Record End User Survey is a questionnaire designed in 2011 by the Michigan Public Health Institute for clinical staff in an ambulatory setting.[27] This instrument was designed to measure the existing state of EHRs, and this study used an adapted version of The Electronic Health Record End User Survey, asking questions related to the EHR's impact on care quality, patient safety, diversity, equity, and inclusion efforts, and other aspects of clinical practice (**Appendix A2)**.

Demographic and Health System-Related Measures

Predictor Variables. Based on a review of literature related to EHR satisfaction and utility, the following independent variables were 1) selected as predictor variables, 2) had ordinal and nominal scaling, and 3) constituted two content-related groups: demographics and health system-related factors. The demographic variables were geographic location, age, sex, race, and ethnicity. The health system-related factors were telemedicine utilization, medical credentials, professional experience, weekly patients, EHR experience, practice setting, and type of healthcare organization (HCO). For the multivariable analysis, three variables (i.e., geographic location, race, and board certification) were reduced in the number of categories to produce more meaningful results and avoid multicollinearity. For example, in the variable ‘state of residency,’ various states (n=12) were not represented throughout the sample. Therefore, the states were aggregated into regions labeled 'Geographic Location.' The number of categories was also reduced for 'race’ in the multivariable analyses. The following categories were aggregated into one category labeled 'Other': American Indian or Alaska Native, Asian Indian, Asian, Native Hawaiian, and other or prefer not to answer.

To assess the primary exposure, telemedicine utilization, participants were asked, "During the COVID-19 pandemic, did you deliver care via telemedicine technology?"; "What type(s) of telemedicine tools do you use for your patient visits?”; and "What, if any, issues affected your use of telemedicine during the pandemic?" The validated National Electronic Health Records Survey (NEHRS) was utilized to minimize measurement error and internal validity issues. The NEHRS is an annual survey conducted by the National Center for Health Statistics (NCHS) in partnership with RTI International and sponsored by the Office of the National Coordinator for Health Information Technology (ONC).[26] The survey has been conducted since 2008 and provides information on EHR systems adoption and utilization practices within HCOs in the United States.[26] In addition, results from the NEHRS have been instrumental in providing data to progress toward meeting the policy goals of The Health Information Technology for Economic and Clinical Health (HITECH) Act.[26] The NEHRS was developed with guidance from experts on survey research, health information technology, and healthcare management and policy.[28] This study explored telemedicine utilization during the COVID-19 pandemic using an adapted version of the NEHRS, asking questions related to telemedicine deployment, the types of tools utilized, barriers faced with telemedicine, and telemedicine care quality **(Appendix A3)**.

Statistical Analysis. Summary statistics of providers' demographic and health system characteristics and outcomes were calculated. Univariable logistic regression analyses were conducted to determine whether the variables were statistically independent or correlated with perceived EHR impact on care delivery, estimating the unadjusted odds ratios (ORs). Confounding could be detected by comparing these unadjusted ORs with the adjusted ORs determined in the multivariable analyses. Multivariable logistic regression analyses were utilized to examine the joint explanatory power of the independent variables on perceived EHR impact on care delivery.

One final model included eight of the explanatory variables. The reference categories were picked to allow comparisons of polarized groups. The final model illustrates the statistical probabilities of telemedicine utilization and having a board certification on perceived EHR impact when controlling for demographic and other health system-related factors, including geographic location, age, sex, race, ethnicity, medical credentials, years of EHR experience, and type of healthcare organization. Through a series of collinearity diagnostics, multicollinearity was present for various independent variables. Therefore, not all variables were included in the multivariable analyses.

Variables not showing a statistically significant association with the outcome variable in the univariable analysis were still included in the multivariable analysis to detect any apparent non-associations and account for clinical or biological relevance. These variables were used as control variables. Statistical significance was set at p=0.20 [29] for the univariable and preliminary multivariable models to identify factors for inclusion in the multivariable model. The statistical significance was set to p=0.05 for the final multivariable model. All results are presented as odds ratios (ORs), with the 95% confidence interval (95% CI) listed in the table. All statistical analyses and data manipulation, such as scrubbing and reshaping, were done in StataCorp (version 2019.16.1, Stata Statistical Software, College Station, TX).

3.4 RESULTS

Among healthcare providers (HCPs) who utilized the EHR during the COVID-19 pandemic, perception disparities were present, with significant disparities according to telemedicine utilization, board certification, diversity, equity, and inclusion efforts, sex, race, ethnicity, medical credentials, weekly patients, EHR experience, practice setting, and healthcare organization type.

Demographic and Health System-Related Characteristics

Descriptive Findings

The study sample included 159 adult healthcare providers (**Table 1c**). Majority of the sample identified as White (68.2%), men (52.6%), between the ages of 25 to 40 years (66.9%). Participants were recruited online via an e-mail listserv (i.e., National Study of Long-Term Care Providers (NSLTCP)) and social media platforms (i.e., Twitter, Facebook, Slack, and LinkedIn). A purposive sampling strategy was employed for a geographically diverse sample across the US to identify eligible healthcare providers. All participants were English-speaking and reported that they delivered care during the COVID-19 pandemic. For the study to have 80% power to detect a moderate effect size (f^2=0.15) with a significance level of .05, 87 participants were required.

The final sample satisfied these requirements. Healthcare providers were roughly 35% Physicians, 32% Physician Assistants, 20% Clinical Nurse Practitioners, 6% Registered Nurses, and 7% Other. Most of the providers were board-certified in Anesthesiology (10.8%), Emergency Medicine (10.1%), Dermatology (9.5%), Endocrinology (8.9%), Family Medicine (8.2%), Obstetrics and Gynecology (7.6%), as well as Cardiology and Geriatrics (7%). Most healthcare providers reported using telemedicine (92.9%) and experiencing at least one or two barriers to delivering care via telemedicine (60.3%). Furthermore, providers identified numerous barriers to implementing and adopting telemedicine. The most frequently cited barrier was limited internet access or speed issues (22.8%), followed by patients' access to technology (e.g., smartphone, computer, tablet, or internet) (18.5%).

Perceived EHR Impact on Care Quality (Model 1)

Unadjusted Findings

Table 2c presents the unadjusted probabilities of a beneficial EHR impact on care delivery (i.e., care quality and patient safety) reported by healthcare providers. Telemedicine utilization, board certification, weekly patients, diversity, equity and inclusion efforts, and telemedicine quality were all associated with significantly increased odds of reporting a beneficial perception of the EHR's impact on improved care quality. Providers who reported using telemedicine during the pandemic had significantly increased odds of perceiving the EHR's effect on care quality as beneficial or highly beneficial (hereafter referred to as 'beneficial') (OR=4.48; p<0.05) compared to non-telemedicine providers. Significantly increased odds of perceiving the EHR's impact as beneficial were found for providers who were board certified in emergency medicine (OR=12.00; P<0.01), delivered care to 11 to 15 patients per week (OR=11.00; p<0.01), or perceived the EHR's impact as beneficial for diversity, equity, and inclusion efforts (OR=7.00; p<0.01).In addition, providers who felt they could deliver the same quality of care 'to some extent' had significantly increased odds of perceiving the EHR as beneficial (OR=2.08; p<0.05).

Telemedicine barriers, telemedicine quality, race, ethnicity, medical credentials, practice setting, and type of healthcare organization were all associated with statistically significant decreased odds of reporting a beneficial perception of the EHR's impact on improved care quality. Providers who experienced 3 to 4 telemedicine barriers had significantly lower odds of reporting the EHR's impact as beneficial (OR=0.24; p<0.001) compared to providers reporting more than 5 barriers, all the barriers listed, or none. Similar associations were found for providers who felt 'to a small extent,' they could deliver the same quality care via telemedicine compared to in-person care (OR=0.16; p<0.05). Providers who identified as Asian or Asian Indian had significantly lower odds of reporting the EHR's impact as beneficial (OR=0.26; p<0.05, OR=0.17; p<0.05) than their

White counterparts. Similar associations were present for providers of Hispanic, Latinx, or Spanish origin (OR=0.42; p<0.05), along with providers who reported being Physician Assistants (OR=0.42; p<0.01), practicing in an urban community (OR=0.10; p<0.01), or working for the United States Department of Veteran Affairs (VA) (OR=0.10; p<0.01).

Adjusted Findings

Table 3c presents the adjusted probabilities of a beneficial EHR impact on care delivery (i.e., care quality and patient safety) reported by healthcare providers. Telemedicine barriers, telemedicine quality, professional experience, board certification type, and practice setting were excluded from the model, and all other factors were retained as independent variables associated with beneficial EHR impact on care quality. To account for multicollinearity in the model, board certification type was aggregated into a binary variable (i.e., yes, or no) and labeled "Board Certification." Providers who reported using telemedicine during the pandemic had significantly increased odds of perceiving the EHR's impact on care quality as beneficial or highly beneficial (hereafter referred to as 'beneficial') (OR= 4.79; p<0.05) compared to non-telemedicine providers. Providers who reported having a board certification versus not having a board certification were roughly 37 times more likely to perceive the EHR's impact on care quality as beneficial when controlling for all other demographic and health-system-related variables (OR=36.68; p<0.01). Similarly, healthcare providers who reported perceiving the EHR's impact on diversity, equity, and inclusion efforts as beneficial (OR=19.28; p<0.01) delivered care in the Northeast region of the country (OR=5.86; p<0.05), saw 10 or more patients a week (OR=4.78; p<0.05), and were a Physician Assistant (OR=2.13; p<0.05) had significantly increased odds of perceiving the EHR's impact as beneficial on care quality compared to other providers who saw less than ten patients a week and delivered care in the Midwest, West, or South while holding all other variables constant.

Physicians (OR=0.06; p<0.05) working for the VA (OR=0.10; p<0.001) with 6 to 10 (OR=0.10; p<0.05) or 10 to 15 years of EHR experience (OR=0.05; p<0.05) had significantly lower odds of perceiving the EHR’s impact on care quality as beneficial, compared to their counterparts while holding all other variables constant. Similar associations were found for Hispanic (OR=0.25; p<0.05) providers aged between 25 to 40 years (OR=0.23; p<0.05) and providers who identified as Black (OR=0.02; p<0.05) compared to their counterparts.

Perceived EHR Impact on Patient Safety (Model 2)

Unadjusted Findings

Care quality, telemedicine utilization, board certification type, diversity, equity and inclusion, race, and gender were all associated with statistically significant increased odds of reporting a beneficial perception of the EHR’s impact on increased patient safety. Providers who reported the EHR’s impact as beneficial on care quality had significantly higher odds of perceiving the EHR’s effect on patient safety as beneficial (OR=48.13; p<0.001) compared to providers who reported the EHR’s impact as detrimental or highly detrimental on care quality (see **Table 2c**). Providers who reported using telemedicine during the pandemic had significantly increased odds of perceiving the EHR’s impact on patient safety as beneficial or highly beneficial (hereafter referred to as ‘beneficial’) (OR=20.25; p<0.001) compared to non-telemedicine providers. Providers board certified in Endocrinology (OR=13.33; p<0.05), Pathology (OR=11.67; p<0.05), Emergency Medicine (OR=9.16; p<0.01), Family Medicine (OR=6.66; p<0.05), or Geriatrics (OR=3.88; p<0.01) had significantly increased odds of reporting the EHR’s impact on patient safety as beneficial. Similar associations were found for providers who reported a beneficial EHR impact on diversity, equity, and inclusion efforts (OR=8.86; p<0.001), Black providers (OR=2.88;

p<0.05), and those who identified as female (OR=2.32; p<0.05) compared to HCPs who identified as White and male.

Telemedicine barriers, practice setting, weekly patients, EHR experience, healthcare organization type, and race were all associated with statistically significant decreased odds of reporting a beneficial perception of the EHR's impact on increased patient safety. Providers had significantly lower odds of perceiving the EHR's impact as beneficial on patient safety if they reported experiencing 3 or 4 telemedicine barriers (OR=0.38; p<0.05), served a suburban community (OR=0.24; p<0.05), delivered care to 11 to 15 patients a week (OR=0.23; p<0.01), had 3 to 5 (OR=0.20; p<0.05), or 6 to 10 (OR=0.19; p<0.05) years of EHR experience, delivered care to 3 to 5, or 6 to 10 (OR=0.15; p<0.05) patients a week, worked for the VA (OR=0.15; p<0.05), or identified as Asian (OR=0.14; p<0.05).

Adjusted Findings

Providers who reported using telemedicine during the pandemic had significantly increased odds of perceiving the EHR's impact on patient safety as beneficial or highly beneficial (hereafter referred to as 'beneficial') (OR=21.96; p<0.001) compared to non-telemedicine providers (see **Table 3c**). Telemedicine barriers, telemedicine quality, professional experience, board certification type, medical credentials, weekly patients, geographic location, ethnicity, and practice setting were excluded from the model, and all other factors were retained as independent variables associated with beneficial EHR impact on patient safety. To account for multicollinearity in the model, board certification type was aggregated into a binary variable (i.e., yes, or no) and labeled "Board Certification." There was a significant association between providers who reported a beneficial EHR impact on diversity, equity, and inclusion efforts (OR=21.96; p<0.001) and those who reported having a board certification (OR=16.10; p<0.05). Similarly, providers who identified as female (OR=3.72; $p<0.05$) also had significantly increased odds of perceiving the EHR's impact on patient safety as beneficial.

In contrast, providers between 25 and 40 years of age (OR=0.29; $p<0.05$) who identified as Black (OR=0.28; $p<0.05$) or Other (i.e., American Indian or Alaska Native, Asian Indian, Asian, or Native Hawaiian) (OR=0.27; $p<0.05$), and worked for the VA (OR=0.04; $p<0.01$) had significantly lower odds of perceiving the EHR's impact on patient safety as beneficial, compared to their counterparts and holding all of the variables constant.

Perceived Impact on Care Delivery (Model 3)

Adjusted Findings

Providers who reported the EHR's impact as beneficial on care quality had significantly higher odds of perceiving the EHR's impact on patient safety as beneficial (OR=81.19; $p<0.001$) compared to providers who reported the EHR's impact as detrimental or highly detrimental on care quality while holding all other variables constant (see **Table 3c**). Telemedicine barriers, telemedicine quality, professional experience, board certification type, medical credentials, EHR experience, weekly patients, geographic location, ethnicity, and practice setting were excluded from the model, and all other factors were retained as independent variables associated with beneficial EHR impact on care delivery. To account for multicollinearity in the model, board certification type was aggregated into a binary variable (i.e., yes, or no) and labeled "Board Certification." There was no significant association between providers who reported using telemedicine during the pandemic and perceiving the EHR's impact on care delivery as beneficial or highly beneficial (hereafter referred to as 'beneficial') compared to non-telemedicine providers while holding all other variables constant.

Although no significant association was found between telemedicine providers and beneficial EHR impact on care delivery; providers aged between 41 to 56 years (OR=49.87; $p<0.05$) and 25 to 40 years (OR=20.34; $p<0.05$) had significantly increased odds of reporting the EHR's impact on care delivery as beneficial compared to providers aged between 18 to 24 years, while holding all other variables constant. Similar associations were found for providers who reported a beneficial EHR impact on diversity, equity, and inclusion efforts (OR=32.64; $P<0.05$) and identified as female (OR=2.77; $P<0.05$).

In contrast, providers had significantly lower odds of perceiving the EHR's impact as beneficial on care delivery if they identified as Black (OR=0.03; $p<0.05$) and worked for the VA (OR=0.01; $p<0.05$).

3.4 DISCUSSION

We employed quantitative research methods to explore and understand the relationship between healthcare provider demographics and health system-related characteristics on how providers perceive the EHR's impact on care delivery. Our findings align with existing literature and extend it in two ways. First, we found that not only are providers who use telemedicine more likely to perceive the EHR's impact as beneficial for care quality and patient safety independently, but they are also more likely to perceive the EHR as beneficial given the type of board certification they hold. Providers board certified in endocrinology,[30] dermatology,[31] geriatrics,[32] emergency medicine,[33] family medicine,[34] and pathology[35] had positive perceptions of the EHR for patient safety, but not care quality. This is concerning considering quality improvement is one of the most widely cited benefits of EHRs from organizations such as the Agency for Healthcare Quality and Research (AHRQ),[36] and the Office of the National Coordinator for Health Information

Technology (ONC).[37] Few studies to date [38–40] have highlighted that various healthcare specialists have diverse needs and, therefore, differing perspectives.

Second, we found that perceptions of the EHR differed by the provider's race, age, gender, geographic location, and practice setting for both care quality and patient safety. The COVID-19 pandemic ignited further use of telehealth and telemedicine services; and engendered a heightened call of action for safe, equitable, high-quality care that cannot be simply ignored. The potentially significant impact of a provider's characteristics on developing and promoting an efficient and robust safety culture to improve care and reduce harm should be highlighted.[41] Future policy efforts need a focus on developing or augmenting telehealth clinical guidelines and standards, as well as value-based care, not just telemedicine reimbursement or incentivizing increased utilization of telemedicine without addressing barriers to safe, equitable delivery of care.[41,42] Prior research [41] has found that safety culture is associated with how healthcare providers perceive diversity and equity. Therefore, to acknowledge the unintended consequences of HIT and avoid worsening disparities and inequities, we must emphasize equity being at the heart of technological design and all efforts to achieve the promising future of health information technology.

Limitations

This study had several limitations. First, considering this study had a pilot cross-national design, our sample size was relatively small, likely due to the limited timeframe. Future studies will conduct this work on a larger scale and extend the length of recruitment to increase the generalizability of the findings. Second, the study focused on providers who delivered care between March 2020 and April 2022; perceptions of the EHR's impact on care delivery for providers who delivered telemedicine services before then may differ. Third, the data was limited to a six-week timeframe. Changes in telemedicine volume, as well as recent policy updates (for example, The 21st Century Cures Act and Cures 2.0), which focused on policies to advance the delivery of treatments and innovations to patients via telehealth across the U.S. and provides federal guidance to CMS to extend telehealth access and coverage to beneficiaries of Medicare, Medicaid, and Children's Health Insurance Program (CHIP),[43] may cause the findings to change over time, signifying a need for continued assessment of the evolution of healthcare perceptions. Future work will focus on addressing these limitations and verifying our findings through the development of further equity and health information technology-based qualitative research.

Future Directions

Our findings underscore the complex relationship between providers, technology, and their environments. Current policies and initiatives focused on telemedicine and HIT practices must consider the multidimensional factors outside the clinical setting that impact how providers perceive and deploy digital tools. This is of particular importance, the federal government has spent almost $36 billion over the past decade on the transition to EHRs.[44] Our findings are a necessary first step toward acknowledging that we must not ignore the factors influencing providers' perceptions regarding the EHR's impact because research suggests that EHRs provide an opportunity to achieve health equity.[45]

To achieve health equity through the lens of digital transformation, providers must value digital tools such as the EHR in all aspects of care. If not, researchers, public health officials, policymakers, health administrators, and care teams must find strategies to dissolve barriers that often obstruct the path to health equity, such as poor data documentation and quality; increased medical errors, morbidity, mortality, and disparities; and interpersonal and institutional level biases. To further enable learning health systems, we propose for further investigation to be conducted on the patient's perspective and experience with pandemic-induced telemedicine and the corresponding patient health outcomes. We also suggest more qualitative efforts to better understand and frame the impact of health information technology on patient outcomes, disparities, and inequities.

CONCLUSION

Secondary use of EHR data is repeatedly employed for comparative effectiveness research,[46] cohort development,[47–49], and building artificial intelligence and machine learning models.[50] Efforts to attain the promised benefits of tools such as the EHR among healthcare providers are essential to promoting equitable, safe, high-quality care. Our findings suggest that demographic and health system-related factors influence the extent to which healthcare providers perceive the EHR's impact to benefit care delivery. This study aligns with and extends the current literature by demonstrating that differences in provider characteristics such as race, ethnicity, age, and board certification influence their perceptions.[39,40,51,51–53] Thus, there are massive practical implications for patients, considering the quality and safety of care are being influenced by their providers' understanding and interpretation of the EHR's impact on their care delivery, often not accounting for their own perspectives.[38,54–56]

Table 1c: Demographic and Health System-Related Characteristics of Healthcare Providers Reporting EHR Impact on Care Delivery (**N=159**)

Demographic and Health System-Related Characteristics	Frequency (n)	Percent (%)
Perceived EHR Impact on Care Delivery		
Quality of healthcare		
Highly Detrimental or Detrimental Overall	29	24.79
Highly Beneficial or Beneficial Overall	88	75.21
Avoiding Errors		
Highly Detrimental or Detrimental Overall	28	25.23
Highly Beneficial or Beneficial Overall	83	74.77
Diversity, Equity, and Inclusion		
Highly Detrimental or Detrimental Overall	72	45.28
Highly Beneficial or Beneficial Overall	87	54.72
Telemedicine Utilization		
Telemedicine Use		
No	11	7.14
Yes	143	92.86
Telemedicine Barriers		
One to Two	91	60.26
Three to Four	42	27.81
More than five	6	3.97

All	7	4.64
None	5	3.31
Telemedicine Quality		
Fully	29	18.24
To a great extent	62	38.99
To some extent	58	36.48
To a small extent	9	5.66
Not at all	1	0.63
Demographic and Health System-Related Characteristics		
Geographic Region		
Northeast	65	41.14
Midwest	24	15.19
West	37	23.42
South	32	20.25
Age		
18-24	15	9.55
25-40	105	66.88
41-56	35	22.29
57-64	1	0.64
65 or older	1	0.64
Sex		
Male	82	52.56
Female	71	45.51
Non-binary/Other	3	1.92
Race		
White or Caucasian	107	68.15

Black or African American	15	9.55
American Indian or Alaska Native	15	9.55
Asian Indian	7	4.46
Asian	9	5.73
Native Hawaiian	2	1.27
Other or prefer not to answer	2	1.27
Ethnicity		
No	75	50.34
Hispanic, Latinx, or Spanish Origin	64	42.95
Other or prefer not to answer	10	6.71
Medical Credentials		
Physician (MD, DO)	54	34.39
Physician's Assistant (PA)	51	32.48
Certified Nurse Practitioner (CNP)	31	19.75
Registered Nurse (RN)	10	6.37
Other	11	7.01
Professional Years of Experience		
Less than 2	9	5.81
3-5	72	46.45
6-10	53	34.19
11-15	15	9.68
More than 15	6	3.87
Average Number of Patients/Week		
Less than 2	8	5.19

3-5	35	22.73
6-10	58	37.66
11-15	26	16.88
More than 15	27	17.53
Board Certification (Binary)		
No	10	6.33
Yes	148	93.67
Board Certification		
Anesthesiology	17	10.76
Cardiology	11	6.96
Endocrinology	14	8.86
Dermatology	15	9.49
Geriatrics	11	6.96
Emergency medicine	16	10.13
Family medicine	13	8.23
Radiology	7	4.43
Neurology	6	3.80
Obstetrics and Gynecology	12	7.59
Pathology	4	2.53
Psychiatry	3	1.90
Infectious Disease	2	1.27
Internal medicine	3	1.90
Pediatrics	4	2.53
General surgery	5	3.16
Oncology	3	1.90
Orthopedics	2	1.27
None	10	6.33
EHR Experience		

Less than 2	30	20.00
3-5	63	42.00
6-10	39	26.00
11-15	16	10.67
More than 15	2	1.33
Practice Setting		
Rural	23	14.74
Suburban	61	39.10
Urban	72	46.15
Type of HCO		
Academic	60	38.96
Community	76	49.35
VA	13	8.44
Other	5	3.25

Abbreviations: EHR, Electronic Health Record; HCO, Healthcare Organization; VA, Veteran Affairs

Table 2c: Unadjusted Odds Ratios and 95% Confidence Intervals for the Association between Demographic and Health System Characteristics and Perceived EHR Impact on Care Delivery

Demographic and Health System Characteristics	Care Quality[a]		Patient Safety[b]	
	OR	95% CI	OR	95% CI
Perceived EHR Impact on Care Delivery				
Quality of healthcare				
Highly Detrimental or Detrimental Overall	1.00	Referent	1.00	Referent
Highly Beneficial or Beneficial Overall	–[c]	–[c]	**48.13***	10.47 – 221.08
Avoiding Errors				
Highly Detrimental or Detrimental Overall	1.00	Referent	1.00	Referent
Highly Beneficial or Beneficial Overall	**48.13***	10.45 – 221.08	–[c]	–[c]
Diversity, Equity, and Inclusion				
Highly Detrimental or Detrimental Overall	1.00	Referent	1.00	Referent
Highly Beneficial or Beneficial Overall	**7.00***	2.73 – 17.92	**8.86***	3.29 – 23.79
Telemedicine Utilization				
Telemedicine Use				
No	1.00	Referent	1.00	Referent
Yes	**4.48***	0.93 – 21.36	**20.25***	2.23 – 183.14
Telemedicine Barriers				
One to Two	1.00	Referent	1.00	Referent
Three to Four	**0.24***	0.20 – 0.73	**0.38***	0.12 – 0.93
More than five	0.24	0.56 – 7.80	0.83	0.08 – 8.26
All	0.39	0.02 – 1.12	0.52	0.08 – 3.07
None	0.47			
Telemedicine Quality				
Fully	1.00	Referent	1.00	Referent

To a great extent	0.67	0.21 - 2.19	0.44	0.10 – 1.81
To some extent	**2.08***	1.56 – 7.80	1.03	0.23 – 4.51
To a small extent	**0.16***	0.02 – 1.12	0.46	0.05 – 3.81
Not at all	–[c]	–[c]	–[c]	–[c]
Demographic and Health System-Related Characteristics				
Geographic Region				
Northeast	1.00	Referent	1.00	Referent
Midwest	1.33	0.37 – 4.77	1.02	0.27 – 3.83
West	1.40	0.43 – 4.52	0.69	0.23 – 2.06
South	0.71	0.24 – 2.16	0.78	0.24 – 2.53
Age				
18-24	1.00	Referent	1.00	Referent
25-40	1.31	0.29 – 5.71	0.34	0.04 – 2.96
41-56	3.13	0.54 – 17.84	0.75	0.07 – 7.88
57-64	–[c]	–[c]	–[c]	–[c]
Sex				
Male	1.00	Referent	1.00	Referent
Female	0.59	0.28 – 1.28	**2.32***	1.96 – 5.62
Non-binary/Other	–[c]	–[c]	–[c]	–[c]
Race				
White or Caucasian	1.00	Referent	1.00	Referent
Black or African American	1.04	0.20 – 5.43	**2.88***	1.34 – 24.13
American Indian or Alaska Native	1.04	0.26 – 4.16	1.29	0.25 – 6.58
Asian Indian	**0.17***	0.02 – 1.13	0.28	0.03 – 2.20
Asian	**0.26***	0.06 – 1.16	**0.14***	0.02 – 0.85
Native Hawaiian	–[c]	–[c]	–[c]	–[c]

Ethnicity				
No	1.00	Referent	1.00	Referent
Hispanic, Latinx, or Spanish Origin	**0.42***	0.16 – 1.05	**0.27****	0.10 – 0.72
Medical Credentials				
Physician (MD, DO)	1.59	0.27 – 9.30	0.66	0.07 – 6.25
Physician's Assistant (PA)	**0.42****	0.07 – 2.37	0.26	0.03 – 2.47
Certified Nurse Practitioner (CNP)	1.14	0.17 – 7.76	0.42	0.04 – 4.23
Registered Nurse (RN)	1.42	0.09 – 20.43	–[c]	–[c]
Other	1.00	Referent	1.00	Referent
Professional Years of Experience				
Less than 2	1.00	Referent	1.00	Referent
3-5	0.91	0.15 – 5.21	1.17	0.19 – 7.19
6-10	1.60	0.26 – 9.81	1.45	0.22 – 9.16
11-15	2.40	0.26 – 22.10	2.75	0.28 – 26.61
More than 15	1.20	0.07 – 12.89	–[c]	–[c]
Average Number of Patients/ Week				
Less than 2	2.83	0.44 – 18.04	–[c]	–[c]
3-5	2.7	0.46 – 15.64	**0.15***	0.02 – 0.85
6-10	2.57	0.41 – 15.91	**0.15***	0.03 – 0.75
11-15	**11.00****	1.27 – 95.17	**0.23****	0.04 – 1.31
More than 15	1.00	Referent	1.00	Referent
Board Certification				
Anesthesiology	1.00	Referent	1.00	Referent
Cardiology	1.00	0.15 – 6.41	8.33	0.63 – 110.02
Endocrinology	3.50	0.47 – 25.90	**13.33***	1.06 – 166.37
Dermatology	4.00	0.54 – 29.10	2.66	0.43 – 16.38

Geriatrics	–^{c}	–^{c}	**3.88****	1.54 – 27.86
Emergency medicine	**12.00****	1.10 – 130.58	**9.16****	1.14 – 73.23
Family medicine	3.00	0.49 – 18.16	**6.66***	0.98 – 54.95
Radiology	4.00	0.32 – 49.59	5.00	0.34 – 72.66
Neurology	4.00	0.32 – 49.59	3.33	0.36 – 30.71
Obstetrics and Gynecology	1.75	0.30 – 10.02	10.00	0.77 – 128.77
Pathology	3.50	0.47 – 25.90	**11.67***	1.14 – 128.81
Psychiatry	–^{c}	–^{c}	1.66	0.07 – 37.72
Infectious Disease	–^{c}	–^{c}	–^{c}	–^{c}
Internal medicine	–^{c}	–^{c}	–^{c}	–^{c}
Pediatrics	–^{c}	–^{c}	–^{c}	–^{c}
General surgery	–^{c}	–^{c}	–^{c}	–^{c}
Oncology	–^{c}	–^{c}	–^{c}	–^{c}
Orthopedics	–^{c}	–^{c}	1.66	0.07 – 37.72
None	3.09	0.39 – 22.71	8.33	0.63 – 110.02
Years of Experience with EHR				
Less than 2	1.00	Referent	1.00	Referent
3-5	0.25	0.05 – 1.24	**0.20***	0.03 – 0.96
6-10	0.25	0.04 – 1.32	**0.19***	0.04 – 0.99
11-15	0.16	0.02 – 1.10	0.30	0.04 – 2.11
More than 15	–^{c}	–^{c}	–^{c}	–^{c}
Practice Setting				
Rural	1.00	Referent	1.00	Referent
Suburban	0.86	0.33 – 2.24	**0.24***	0.04 – 1.21
Urban	**0.10****	0.01 – 0.64	0.70	0.13 – 3.67
Type of HCO				
Academic	1.00	Referent	1.00	Referent

Community	0.87	0.33 – 2.24	0.55	0.21 – 1.43
VA	**0.10****	0.01 – 0.64	**0.15***	0.02 – 1.06
Other	—[c]	—[c]	—[c]	—[c]

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[a] Model measured the primary outcome: quality of healthcare (care quality)

[b] Model measured the secondary outcome: avoiding errors (patient safety)

[c] Not applicable or omitted due to multicollinearity

Abbreviations: CI, Confidence Interval; EHR, Electronic Health Record; HCO, Healthcare organization; OR, Odds Ratio

P-Values: *p<0.05 **p<0.01 ***p<0.001

Table 3c: Adjusted Odds Ratios and 95% Confidence Intervals for the Association between Demographic and Health System Characteristics and Perceived EHR Impact on Care Delivery

	Care Quality[a]		Patient Safety[b]		Care Quality & Patient Safety[c]	
	OR	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**
Perceived EHR Impact on Care Delivery						
Quality of healthcare						
Highly Detrimental or Detrimental Overall	1.00	Referent	1.00	Referent	1.00	Referent
Highly Beneficial or Beneficial Overall	–[d]	–[d]	–[d]	–[d]	–[d]	–[d]
Avoiding Errors						
Highly Detrimental or Detrimental Overall	1.00	Referent	1.00	Referent	1.00	Referent
Highly Beneficial or Beneficial Overall	–[d]	–[d]	–[d]	–[d]	81.19***	6.11 – 161.31
Diversity, Equity, and Inclusion						
Highly Detrimental or Detrimental Overall	1.00	Referent	1.00	Referent	1.00	Referent
Highly Beneficial or Beneficial Overall	19.28**	3.26 – 113.76	21.96***	3.93 – 122.63	32.64*	1.44 – 117.18
Telemedicine Utilization						
Telemedicine Use						
No	1.00	Referent	1.00	Referent	1.00	Referent
Yes	4.79*	0.00 – 7.03	4.19*	0.26 – 66.98	1.81	0.02 – 24.30
Demographic and Health System Characteristic						
Board Certification						
No	1.00	Referent	1.00	Referent	1.00	Referent
Yes	36.68**	3.47 – 196.24	16.10*	0.23 – 114.92	0.61	0.00 – 50.12
Medical Credentials						
Physician (MD, DO)	0.06*	0.00 – 0.58	–[d]	–[d]	–[d]	–[d]
Physician's Assistant (PA)	2.13*	0.11 – 38.74	–[d]	–[d]	–[d]	–[d]
Certified Nurse Practitioner (CNP)	0.56	0.00 – 3.75	–[d]	–[d]	–[d]	–[d]
Registered Nurse (RN)	–[d]	–[d]	–[d]	–[d]	–[d]	–[d]
Other	1.00	Referent	1.00	Referent	1.00	Referent

EHR Experience						
Less than 2	1.00	Referent	1.00	Referent	1.00	Referent
3-5	0.19	0.03 – 1.48	0.20	0.02 – 1.60	–[d]	–[d]
6-10	**0.10***	0.01 – 0.94	**0.08***	0.01 – 0.88	–[d]	–[d]
11-15	**0.05***	0.01 – 0.67	0.12	0.00 – 2.24	–[d]	–[d]
More than 15	–[d]	–[d]	–[d]	–[d]	–[d]	–[d]
HCO Type						
Academic	1.00	Referent	1.00	Referent	1.00	Referent
Community	0.74	0.81 – 3.70	0.55	0.14 – 2.16	2.90	0.19 – 42.12
VA	**0.01*****	0.00 – 0.41	**0.01****	0.00 – 0.36	**0.01***	0.00 – 1.07
Weekly Patients						
Less than 10	1.00	Referent	1.00	Referent	1.00	Referent
Ten or more	**4.78***	1.10 – 10.21	–[d]	–[d]	–[d]	–[d]
Geographic Location						
Northeast	**5.86***	1.01 – 63.26	–[d]	–[d]	–[d]	–[d]
Midwest	1.00	Referent	1.00	Referent	1.00	Referent
West	9.23	0.54 – 94.31	–[d]	–[d]	–[d]	–[d]
South	2.65	0.36 – 19.23	–[d]	–[d]	–[d]	–[d]
Age						
18-24	1.00	Referent	1.00	Referent	1.00	Referent
25-40	**0.23***	0.00 – 0.60	**0.29***	0.00 – 2.88	**20.34***	1.29 – 94.33
41-56	0.45	0.00 – 2.02	–[d]	–[d]	**49.87***	1.57 – 158.10
Sex						
Male	1.00	Referent	1.00	Referent	1.00	Referent
Female	**5.02***	0.23 – 37.74	**3.72***	0.97 – 25.29	**2.77***	0.98 – 48.13
Race						
White or Caucasian	1.00	Referent	1.00	Referent	1.00	Referent
Black or African American	**0.02***	0.00 – 0.48	**0.28***	0.00 – 1.93	**0.03***	0.00 – 1.23
Other	0.33	0.05 – 2.24	**0.27***	0.00 – 1.37	1.10	0.08 – 13.73
Ethnicity						
No	1.00	Referent	1.00	Referent	1.00	Referent

Hispanic, Latinx, or Spanish Origin	**0.25***	0.02 – 1.17	–[d]	–[d]	–[d]	–[d]

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[a] Model measured the primary outcome: quality of healthcare (care quality); adjusted for DEI efforts, telemedicine use, board certification, medical credentials, EHR experience, type of healthcare organization, weekly patients, geographic location, age, sex, race, and ethnicity

[b] Model measured the secondary outcome: avoiding errors (patient safety); adjusted for DEI efforts, telemedicine use, board certification, EHR experience, type of healthcare organization, age, sex, and race

[c] Model measured the primary and secondary outcomes: care quality and patient safety; adjusted for adjusted for DEI efforts, telemedicine use, board certification, type of healthcare organization, age, sex, and race

[d] Not applicable or omitted due to multicollinearity

Abbreviations: CI, Confidence Interval; EHR, Electronic Health Record; HCO, Healthcare organization; OR, Odds Ratio

P-Values: *p<0.05 **p<0.01 ***p<0.001

3.5 REFERENCES

1. Zhang X, Hailu B, Tabor DC, et al. Role of Health Information Technology in Addressing Health Disparities: Patient, Clinician, and System Perspectives. *Med Care*. 2019;57(Suppl 2):S115-S120. doi:10.1097/MLR.0000000000001092

2. Singh H, Sittig DF. Measuring and improving patient safety through health information technology: The Health IT Safety Framework. Published online 2002:7.

3. Kruse CS, Beane A. Health Information Technology Continues to Show Positive Effect on Medical Outcomes: Systematic Review. *J Med Internet Res*. 2018;20(2):e41. doi:10.2196/jmir.8793

4. Veinot TC, Ancker JS, Bakken S. Health informatics and health equity: improving our reach and impact. *J Am Med Inform Assoc*. 2019;26(8-9):689-695. doi:10.1093/jamia/ocz132

5. Saeed SA, Masters RM. Disparities in Health Care and the Digital Divide. *Curr Psychiatry Rep*. 2021;23(9):61. doi:10.1007/s11920-021-01274-4

6. Institute of Medicine (IOM). *Unequal Treatment: Confronting Racial and Ethnic Disparities in Health Care (with CD)*. National Academies Press; 2003:12875. doi:10.17226/12875

7. Brewer LC, Fortuna KL, Jones C, et al. Back to the Future: Achieving Health Equity Through Health Informatics and Digital Health. *JMIR MHealth UHealth*. 2020;8(1):e14512. doi:10.2196/14512

8. Leslie D, Mazumder A, Peppin A, Wolters MK, Hagerty A. Does “AI” stand for augmenting inequality in the era of covid-19 healthcare? *BMJ*. Published online March 15, 2021:n304. doi:10.1136/bmj.n304

9. Wang CJ, Ng CY, Brook RH. Response to COVID-19 in Taiwan: Big Data Analytics, New Technology, and Proactive Testing. *JAMA*. 2020;323(14):1341. doi:10.1001/jama.2020.3151

10. Di Ciaula A. Towards 5G communication systems: Are there health implications? *Int J Hyg Environ Health*. 2018;221(3):367-375. doi:10.1016/j.ijheh.2018.01.011

11. Ekong I, Chukwu E, Chukwu M. COVID-19 Mobile Positioning Data Contact Tracing and Patient Privacy Regulations: Exploratory Search of Global Response Strategies and the Use of Digital Tools in Nigeria. *JMIR MHealth UHealth*. 2020;8(4):e19139. doi:10.2196/19139

12. Cho H, Ippolito D, Yu YW. Contact Tracing Mobile Apps for COVID-19: Privacy Considerations and Related Trade-offs. *ArXiv200311511 Cs*. Published online March 30, 2020. Accessed January 6, 2022. http://arxiv.org/abs/2003.11511

13. Dorsey ER, Topol EJ. State of Telehealth. Campion EW, ed. *N Engl J Med*. 2016;375(2):154-161. doi:10.1056/NEJMra1601705

14. Tuckson RV, Edmunds M, Hodgkins ML. Telehealth. *N Engl J Med*. 2017;377(16):1585-1592. doi:10.1056/NEJMsr1503323

15. Hong Z, Li N, Li D, et al. Telemedicine During the COVID-19 Pandemic: Experiences From Western China. *J Med Internet Res*. 2020;22(5):e19577. doi:10.2196/19577

16. Wootton R. Recent advances: Telemedicine. *BMJ*. 2001;323(7312):557-560. doi:10.1136/bmj.323.7312.557

17. Vest JR, Gamm LD. Health information exchange: persistent challenges and new strategies: Table 1. *J Am Med Inform Assoc*. 2010;17(3):288-294. doi:10.1136/jamia.2010.003673

18. Vest JR, Kern LM, Campion TR, Silver MD, Kaushal R. Association between use of a health information exchange system and hospital admissions. *Appl Clin Inform*. 2014;05(01):219-231. doi:10.4338/ACI-2013-10-RA-0083

19. Ye J. The Role of Health Technology and Informatics in a Global Public Health Emergency: Practices and Implications From the COVID-19 Pandemic. *JMIR Med Inform*. 2020;8(7):e19866. doi:10.2196/19866

20. Crawford A, Serhal E. Digital Health Equity and COVID-19: The Innovation Curve Cannot Reinforce the Social Gradient of Health. *J Med Internet Res*. 2020;22(6):e19361. doi:10.2196/19361

21. Kosseim P, Brady M. POLICY BY PROCRASTINATION: SECONDARY USE OF ELECTRONIC HEALTH RECORDS FOR HEALTH RESEARCH PURPOSES. 2008;2:41.

22. Bell K. Public Policy and Health Informatics. *Semin Oncol Nurs*. 2018;34(2):184-187. doi:10.1016/j.soncn.2018.03.010

23. Basch P, Smith JRL. CMS Payment Policy, E&M Guideline Reform, and the Prospect of Electronic Health Record Optimization. *Appl Clin Inform*. 2018;9(4):914-918. doi:10.1055/s-0038-1676337

24. Bates DW, Singh H. Two Decades Since *To Err Is Human* : An Assessment Of Progress And Emerging Priorities In Patient Safety. *Health Aff (Millwood)*. 2018;37(11):1736-1743. doi:10.1377/hlthaff.2018.0738

25. Pestotnik S. How to Use Data to Improve Quality and Patient Safety. *Health Catal*. Published online 2019.

26. Centers for Disease Control and Prevention. NEHRS - National Electronic Health Records Survey Homepage. Published 2021. Accessed January 9, 2022. https://www.cdc.gov/nchs/nehrs/about.htm

27. Michigan Public Health Institute. Electronic Health Record End User Survey | Digital Healthcare Research. Published 2011. Accessed August 3, 2022. https://digital.ahrq.gov/health-it-tools-and-resources/evaluation-resources/health-it-survey-compendium/electronic-health-record-end-user-survey

28. DesRoches CM, Campbell EG, Rao SR, et al. Electronic Health Records in Ambulatory Care — A National Survey of Physicians. *N Engl J Med*. 2008;359(1):50-60. doi:10.1056/NEJMsa0802005

29. Zhang Z. Model building strategy for logistic regression: purposeful selection. *Ann Transl Med*. 2016;4(6):111-111. doi:10.21037/atm.2016.02.15

30. Carhill AA, Cabanillas ME, Jimenez C, et al. The Noninvestigational Use of Tyrosine Kinase Inhibitors in Thyroid Cancer: Establishing a Standard for Patient Safety and Monitoring. *J Clin Endocrinol Metab*. 2013;98(1):31-42. doi:10.1210/jc.2012-2909

31. Patel J, Otto E, Taylor JS, et al. Patient safety in dermatology: a ten-year update. *Dermatol Online J*. 2021;27(3). doi:10.5070/D3273052763

32. Lette M, Ambugo EA, Hagen TP, Nijpels G, Baan CA, de Bruin SR. Addressing safety risks in integrated care programs for older people living at home: a scoping review. *BMC Geriatr*. 2020;20(1):81. doi:10.1186/s12877-020-1482-7

33. Amaniyan S, Faldaas BO, Logan PA, Vaismoradi M. Learning from Patient Safety Incidents in the Emergency Department: A Systematic Review. *J Emerg Med*. 2020;58(2):234-244. doi:10.1016/j.jemermed.2019.11.015

34. Kuriakose R, Aggarwal A, Sohi R, Goel R, Rashmi N, Gambhir R. Patient safety in primary and outpatient health care. *J Fam Med Prim Care*. 2020;9(1):7. doi:10.4103/jfmpc.jfmpc_837_19

35. Becich MJ, Gilbertson JR, Gupta D, Patel A, Grzybicki DM, Raab SS. Pathology and patient safety: the critical role of pathology informatics in error reduction and quality initiatives. *Clin Lab Med*. 2004;24(4):913-943. doi:10.1016/j.cll.2004.05.019

36. Agency for Healthcare Research and Quality (AHRQ). Use of Electronic Health Records | Agency for Healthcare Research and Quality. Chartbook on Care Coordination. Published 2018. Accessed August 3, 2022. https://www.ahrq.gov/research/findings/nhqrdr/chartbooks/carecoordination/measure5.html

37. Atasoy H, Greenwood BN, McCullough JS. The Digitization of Patient Care: A Review of the Effects of Electronic Health Records on Health Care Quality and Utilization. *Annu Rev Public Health*. 2019;40(1):487-500. doi:10.1146/annurev-publhealth-040218-044206

38. Frimpong JA, Myers CG, Sutcliffe KM, Lu-Myers Y. When Health Care Providers Look at Problems from Multiple Perspectives, Patients Benefit. *Harv Bus Rev*. Published online June 23, 2017. Accessed August 3, 2022. https://hbr.org/2017/06/when-health-care-providers-look-at-problems-from-multiple-perspectives-patients-benefit

39. Bascom E. Survey: Clinicians' perceptions of telehealth vary based on specialty. Published 2022. Accessed August 3, 2022. https://www.healio.com/news/primary-care/20220610/survey-clinicians-perceptions-of-telehealth-vary-based-on-specialty

40. Fox DA, Hauser JM. Exploring perception and usage of narrative medicine by physician specialty: a qualitative analysis. *Philos Ethics Humanit Med*. 2021;16(1):7. doi:10.1186/s13010-021-00106-w

41. Gandhi T. How Workforce Perceptions of Safety Culture Differ by Race, Ethnicity, and Gender. Published 2022. Accessed August 3, 2022. https://info.pressganey.com/press-ganey-blog-healthcare-experience-insights/how-workforce-perceptions-of-safety-culture-differ-by-race-ethnicity-and-gender

42. Lau J, Knudsen J. Reducing Disparities In Telemedicine: An Equity-Focused, Public Health Approach: Perspective examines ways to reduce disparities in telemedicine. *Health Aff (Millwood)*. 2022;41(5):647-650. doi:10.1377/hlthaff.2022.00314

43. Office of the Commissioner. 21st Century Cures Act. FDA. Published January 31, 2020. Accessed August 17, 2022. https://www.fda.gov/regulatory-information/selected-amendments-fdc-act/21st-century-cures-act

44. Schulte F. As coronavirus strikes, crucial data in electronic health records hard to harvest. Fierce Healthcare. Published April 30, 2020. Accessed August 3, 2022. https://www.fiercehealthcare.com/tech/as-coronavirus-strikes-crucial-data-electronic-health-records-hard-to-harvest

45. Sherin KM, Burroughs-Girardi E. Promoting Health Equity with Electronic Health Records. Published online 2014:2.

46. Food and Drug Administration (FDA). Use of Electronic Health Record Data in Clinical Investigations Guidance for Industry. Published online 2018:15.

47. Diaz-Garelli JF, Strowd R, Ahmed T, et al. A tale of three subspecialties: Diagnosis recording patterns are internally consistent but Specialty-Dependent. *JAMIA Open*. 2019;2(3):369-377. doi:10.1093/jamiaopen/ooz020

48. Diaz-Garelli F, Strowd R, Lawson VL, et al. Workflow Differences Affect Data Accuracy in Oncologic EHRs: A First Step Toward Detangling the Diagnosis Data Babel. *JCO Clin Cancer Inform*. 2020;(4):529-538. doi:10.1200/CCI.19.00114

49. Diaz-Garelli F, Lenoir KM, Wells BJ. Catch Me if You Can: Acute Events Hidden in Structured Chronic Disease Diagnosis Descriptions Show Detectable Recording Patterns in EHR. *AMIA Annu Symp Proc*. 2021;2020:373-382.

50. Lin WC, Chen JS, Chiang MF, Hribar MR. Applications of Artificial Intelligence to Electronic Health Record Data in Ophthalmology. *Transl Vis Sci Technol*. 9(2):13. doi:10.1167/tvst.9.2.13

51. Saman DM, Walton KM, Harry ML, et al. Understanding primary care providers' perceptions of cancer prevention and screening in a predominantly rural healthcare system in the upper Midwest. *BMC Health Serv Res*. 2019;19(1):1019-1019. doi:10.1186/s12913-019-4872-9

52. andhi T. How Workforce Perceptions of Safety Culture Differ by Race, Ethnicity, and Gender. Published 2022. Accessed August 3, 2022. https://info.pressganey.com/press-ganey-blog-healthcare-experience-insights/how-workforce-perceptions-of-safety-culture-differ-by-race-ethnicity-and-gender

53. Connolly SL, Miller CJ, Gifford AL, Charness ME. Perceptions and Use of Telehealth Among Mental Health, Primary, and Specialty Care Clinicians During the COVID-19 Pandemic. *JAMA Netw Open*. 2022;5(6):e2216401. doi:10.1001/jamanetworkopen.2022.16401

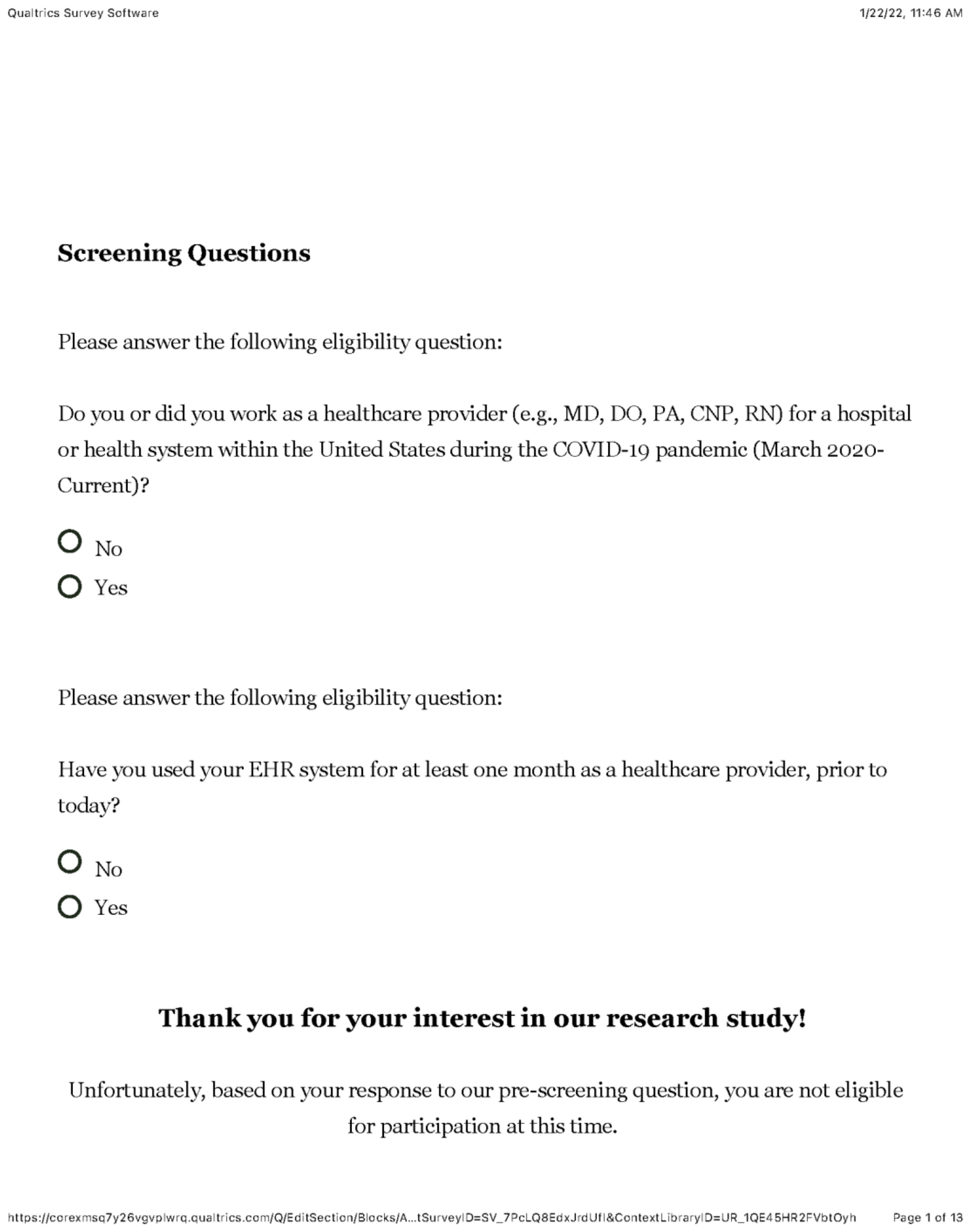
54. Haldane V, Tan YG, Teo KWQ, et al. Perspectives on Acceptance and Use of a Mobile Health Intervention for the Prevention of Atherosclerotic Cardiovascular Disease in Singapore: Mixed-Methods Study. *JMIR MHealth UHealth*. 2019;7(3):e11108-e11108. doi:10.2196/11108

55. Whitney RL, Ward DH, Marois MT, Schmid CH, Sim I, Kravitz RL. Patient Perceptions of Their Own Data in mHealth Technology-Enabled N-of-1 Trials for Chronic Pain: Qualitative Study. *JMIR MHealth UHealth*. 2018;6(10):e10291-e10291. doi:10.2196/10291

56. Bell SK, Mejilla R, Anselmo M, et al. When doctors share visit notes with patients: a study of patient and doctor perceptions of documentation errors, safety opportunities and the patient–doctor relationship. *BMJ Qual Saf*. 2017;26(4):262-270. doi:10.1136/bmjqs-2015-004697

3.6 APPENDIX A: SUPPLEMENTARY MATERIALS FOR CHAPTER THREE

Appendix A1. Healthcare Provider Screening Questions, Consent, and Questionnaire



Qualtrics Survey Software 1/22/22, 11:46 AM

Screening Questions

Please answer the following eligibility question:

Do you or did you work as a healthcare provider (e.g., MD, DO, PA, CNP, RN) for a hospital or health system within the United States during the COVID-19 pandemic (March 2020-Current)?

○ No
○ Yes

Please answer the following eligibility question:

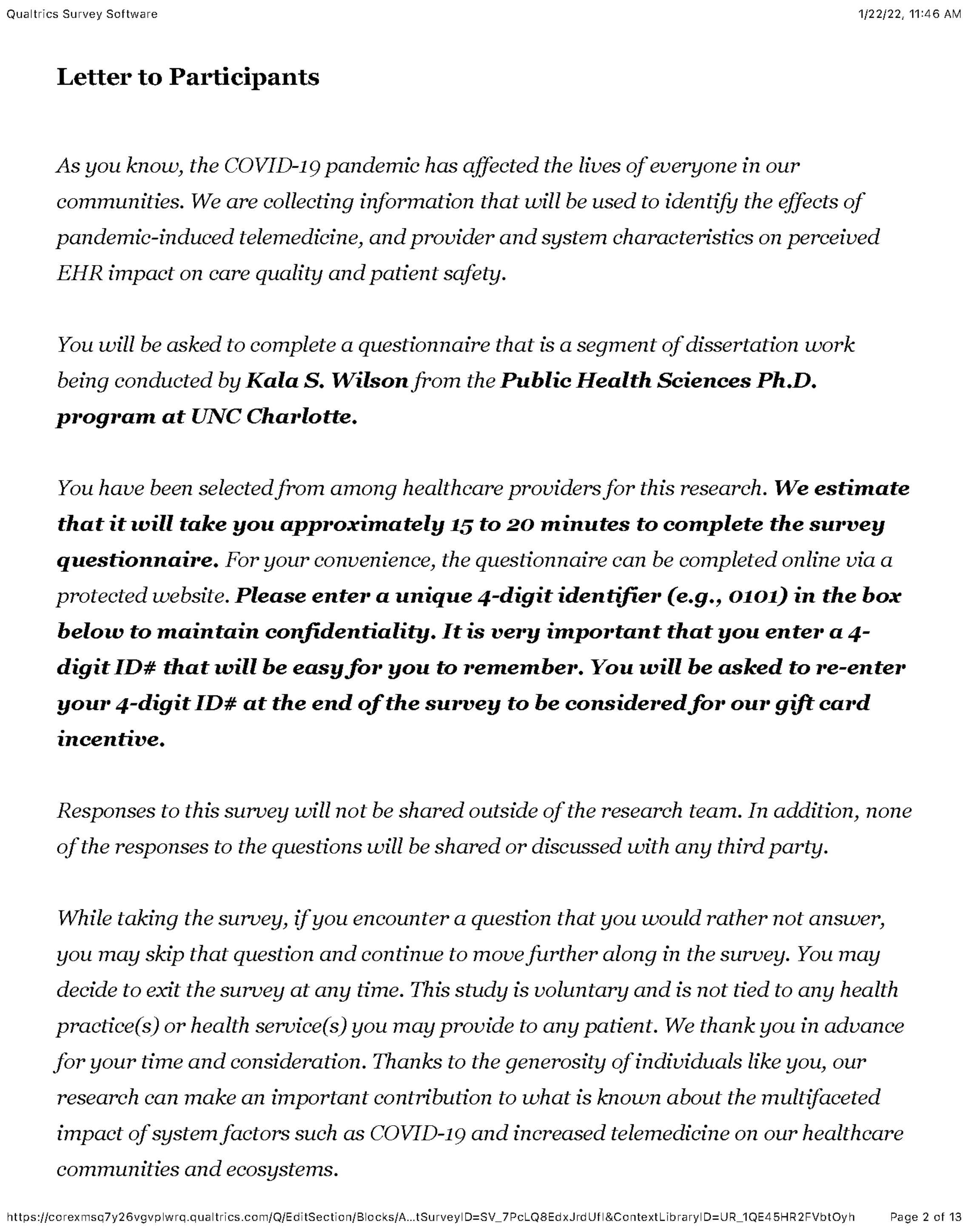
Have you used your EHR system for at least one month as a healthcare provider, prior to today?

○ No
○ Yes

Thank you for your interest in our research study!

Unfortunately, based on your response to our pre-screening question, you are not eligible for participation at this time.

https://corexmsq7y26vgvplwrq.qualtrics.com/Q/EditSection/Blocks/A...tSurveyID=SV_7PcLQ8EdxJrdUfl&ContextLibraryID=UR_1QE45HR2FVbtOyh Page 1 of 13



Letter to Participants

As you know, the COVID-19 pandemic has affected the lives of everyone in our communities. We are collecting information that will be used to identify the effects of pandemic-induced telemedicine, and provider and system characteristics on perceived EHR impact on care quality and patient safety.

You will be asked to complete a questionnaire that is a segment of dissertation work being conducted by ***Kala S. Wilson*** *from the* ***Public Health Sciences Ph.D. program at UNC Charlotte.***

You have been selected from among healthcare providers for this research. ***We estimate that it will take you approximately 15 to 20 minutes to complete the survey questionnaire.*** *For your convenience, the questionnaire can be completed online via a protected website.* ***Please enter a unique 4-digit identifier (e.g., 0101) in the box below to maintain confidentiality. It is very important that you enter a 4-digit ID# that will be easy for you to remember. You will be asked to re-enter your 4-digit ID# at the end of the survey to be considered for our gift card incentive.***

Responses to this survey will not be shared outside of the research team. In addition, none of the responses to the questions will be shared or discussed with any third party.

While taking the survey, if you encounter a question that you would rather not answer, you may skip that question and continue to move further along in the survey. You may decide to exit the survey at any time. This study is voluntary and is not tied to any health practice(s) or health service(s) you may provide to any patient. We thank you in advance for your time and consideration. Thanks to the generosity of individuals like you, our research can make an important contribution to what is known about the multifaceted impact of system factors such as COVID-19 and increased telemedicine on our healthcare communities and ecosystems.

For your voluntary participation and time, you will be asked to provide ***an email address, your 4-digit ID#, and gift card preference*** *to be included in a drawing to receive one of five* ***$25 gift cards*** *to your choice of either Amazon or Starbucks.*

If you have questions about the survey, please feel free to contact ***Kala Wilson*** *at* ***kwils154@uncc.edu,*** *I would be happy to discuss questions or concerns with you.*

Sincerely,

Kala S. Wilson, MPA

Consent

Thank you for taking the time to answer this survey. This survey's purpose is to investigate the impact of pandemic-induced telehealth on healthcare provider EHR impact perceptions.

The results of this survey will be used for dissertation work being completed at the University of North Carolina at Charlotte. All answers are confidential.

To move forward with the survey process, please select either statement below that applies to you. To advance to the survey, you must consent to participate and be at least 18 years of age.

○ **I agree** to take part in the study
○ **I do not agree** to take part in the study

INSTRUCTIONS

INSTRUCTIONS: For each of the following questions, please select or enter the response that best describes you:

TELEMEDICINE UTILIZATION

TELEMEDICINE UTILIZATION: *Understandably, due to the COVID-19 pandemic many healthcare systems have needed to make the transition to provide virtual care to their patients. Questions 1-4 will ask about Telehealth utilization in your practice.*

During the COVID-19 pandemic (Between March 2020-Present), did your practice use telemedicine technology?

○ No
○ Yes
○ I do not know

What type(s) of telemedicine tools do you use for your patient visits? **PLEASE CHECK ALL THAT APPLY.**

☐ Synchronous videoconference software with audio (e.g., Zoom, WebEx, Facetime, or other interactive video connection
☐ Asynchronous videoconference software (e.g., sending images or medical data to your healthcare provider via secure web server, encrypted e-mail, or electronic health record (EHR)
☐ Telephone audio
☐ Secure private messaging (e.g., via web portal such as electronic health record (EHR), encrypted e-mail)

☐ Remote patient monitoring (e.g., wearables such as continuous glucose monitoring device (glucometer), activity trackers, or heart rate device)

What, if any, factors affected your use of telemedicine? **PLEASE CHECK ALL THAT APPLY.**

☐ Limited internet access or speed issues
☐ Telemedicine platform not easy to use or did not meet our needs
☐ Telemedicine is not appropriate for my specialty or type of patients
☐ Improved reimbursement and relaxation of rules related to the use of telemedicine visits
☐ Limitations in patients' access to technology (e.g., smartphone, computer, tablet, internet)
☐ Patients' difficulty using technology or telemedicine platform
☐ All the above
☐ None

To what extent are you able to provide similar quality of care during telemedicine visits as you do during in-person visits?

○ Fully
○ To a great extent
○ To some extent
○ To a small extent
○ Not at all

EHR IMPACT

EHR IMPACT: *Questions 5-7 will ask about your perception of the EHR's impact during the COVID-19 pandemic on high-quality care and patient safety, as well as bias, disparities, and inequities.*

Based on your experience during the pandemic, please indicate whether you believe the effect of the EHR on your clinical practice has been **detrimental, beneficial, or neither,** using the scale below:

	Highly detrimental	Detrimental overall	Neither detrimental nor beneficial	Beneficial overall	Highly beneficial
Quality of healthcare	○	○	○	○	○
Avoiding errors (such as overlooking a drug interaction)	○	○	○	○	○
Clinicians' access to up-to-date knowledge	○	○	○	○	○
Interaction within the healthcare team	○	○	○	○	○
Enjoyment of clinical practice	○	○	○	○	○
Clinicians' stress-level	○	○	○	○	○
Personal and professional privacy	○	○	○	○	○

Diversity and inclusion efforts of clinical practice	○	○	○	○	○
Patients' satisfaction with the quality of care they receive	○	○	○	○	○
The efficiency of clinical practice	○	○	○	○	○

How do you believe the EHR can help healthcare providers decrease bias, disparities, and inequities in patient care?

Please provide your response in the space provided below.

How do you believe the EHR can impact standardization and overcoming bias, disparities, and inequities within the healthcare system?

Please provide your response in the space provided below.

HEALTHCARE PROVIDER DEMOGRPAHIC AND HEALTH SYSTEM CHARACTERISTICS

HEALTHCARE PROVIDER DEMOGRAPHIC AND HEALTH SYSTEM

CHARACTERISTICS: *Questions 8-20 will ask about your demographics and the characteristics of your healthcare system.*

What state did you or do you practice medicine in? **CHOOSE FROM THE DROPDOWN BOX BELOW.** (Responses are listed by region within the United States)

Did you receive care via telemedicine from any of the following health systems within North Carolina? **PLEASE CHECK ALL THAT APPLY.**

☐ Wake Forest Baptist Medical Center
☐ Novant Health
☐ Atrium Health
☐ Duke Health
☐ UNC Health
☐ WakeMed Health

What is your age?

○ 18-24
○ 25-40
○ 41-56
○ 57-64
○ 65 or older

What is your sex?

○ Male
○ Female
○ Non-binary
○ Other or prefer not to answer

What is your race and ethnicity?

○ White or Caucasian
○ Black or African American
○ American Indian or Alaska Native
○ Asian Indian
○ Asian
○ Native Hawaiian
○ Other or prefer not to answer

Are you of Hispanic, Latinx, or Spanish origin?

○ No
○ Yes
○ Prefer not to answer

What are your medical credentials?

○ Physician (MD, DO)
○ Physician's Assistant (PA)
○ Certified Nurse Practitioner (CNP)
○ Registered Nurse (RN)

○ Other

How many years of experience do you have in the profession?

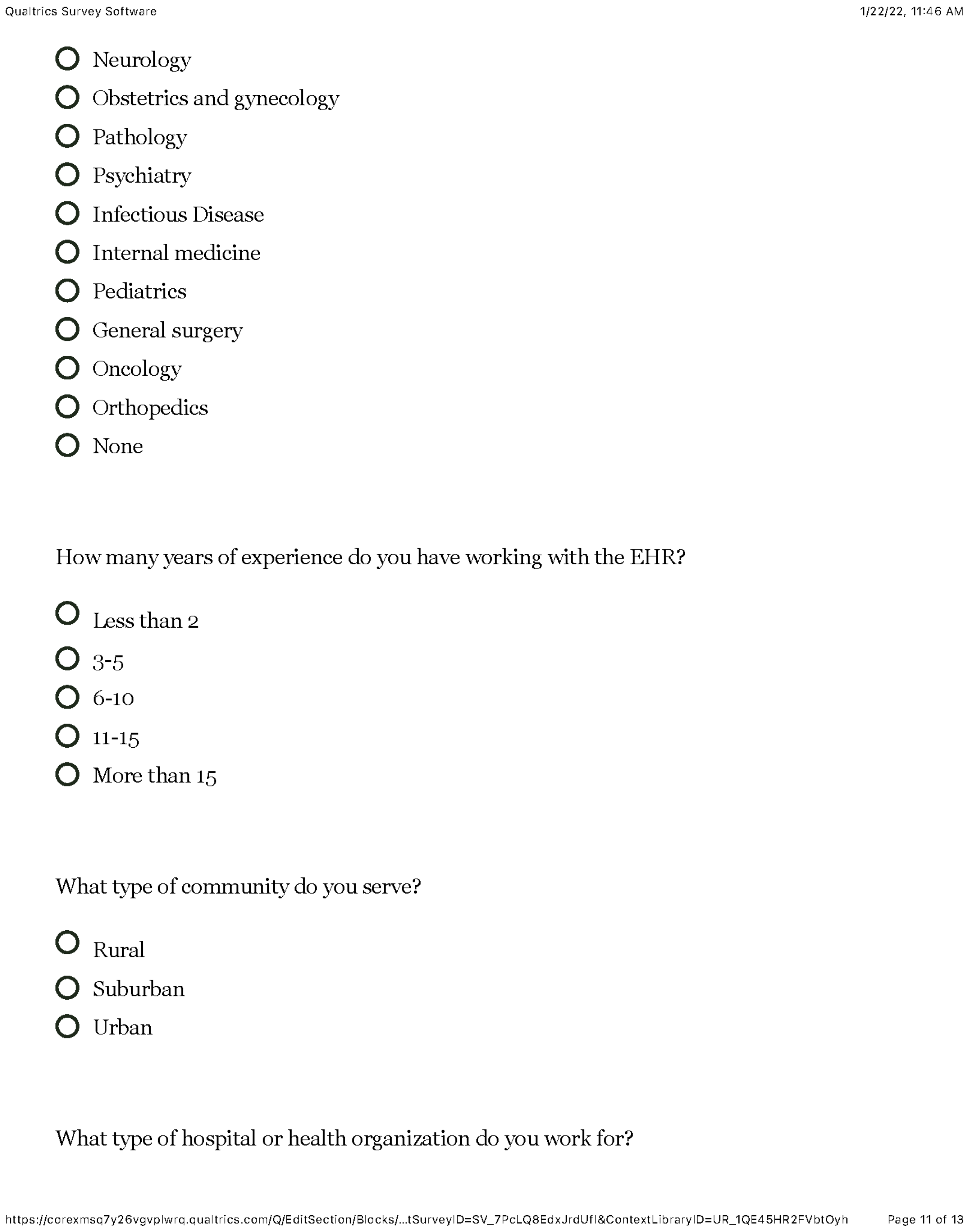
○ Less than 2
○ 3-5
○ 6-10
○ 11-15
○ More than 15

How many patients do you see on average per week?

○ Less than 2
○ 3-5
○ 6-10
○ 11-15
○ More than 15

Do you have a board certification in the profession?

○ Anesthesiology
○ Cardiology
○ Endocrinology
○ Dermatology
○ Geriatrics
○ Emergency medicine
○ Family medicine
○ Radiology



- ○ Neurology
- ○ Obstetrics and gynecology
- ○ Pathology
- ○ Psychiatry
- ○ Infectious Disease
- ○ Internal medicine
- ○ Pediatrics
- ○ General surgery
- ○ Oncology
- ○ Orthopedics
- ○ None

How many years of experience do you have working with the EHR?

- ○ Less than 2
- ○ 3-5
- ○ 6-10
- ○ 11-15
- ○ More than 15

What type of community do you serve?

- ○ Rural
- ○ Suburban
- ○ Urban

What type of hospital or health organization do you work for?

○ Academic
○ Community
○ VA
○ Other

How many beds does your hospital or health facility have?

○ Under 25 beds
○ 26-75 beds
○ 76-150 beds
○ 151-300 beds
○ I do not know
○ 0 (It is a freestanding health facility)

END OF SURVEY

WE THANK YOU FOR TAKING THIS SURVEY.

You have reached the end of the survey. If you have questions or concerns about the study, you may contact **Kala Wilson**, via email at kwils154@uncc.edu.
Thank you again for your feedback and for taking the time to complete this survey.
We really appreciate your time, and we will be in contact if you are selected to receive one of the $25 gift cards!

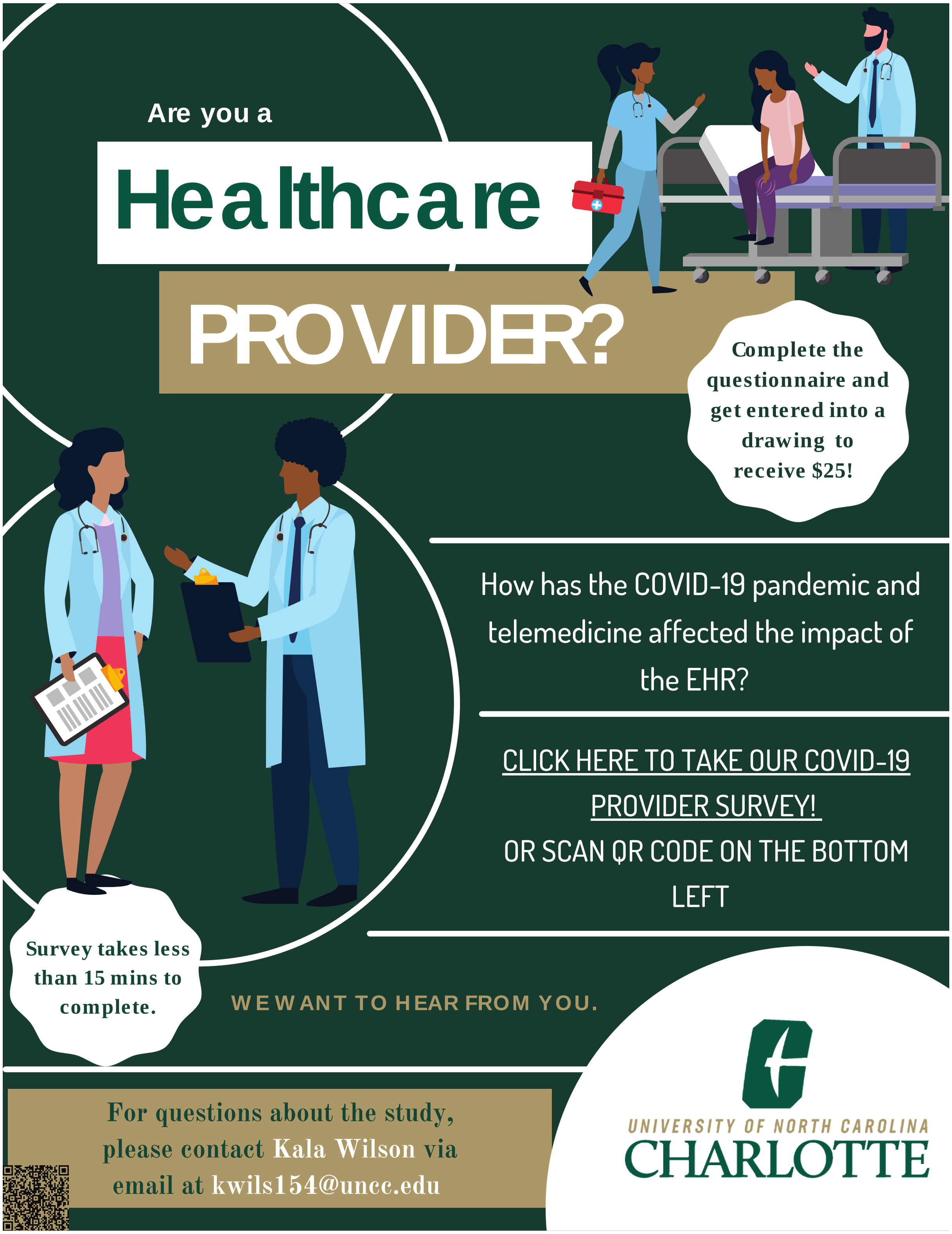
If you are interested in receiving a $25 gift card, please choose Yes or No to enter your email address, 4-digit ID #, and gift card preference.

○ Yes

○ No

Click here to fill out our Gift Card Form!

Appendix A2. Healthcare Provider Recruitment Flyer



Are you a

Healthcare

PROVIDER?

Complete the questionnaire and get entered into a drawing to receive $25!

How has the COVID-19 pandemic and telemedicine affected the impact of the EHR?

CLICK HERE TO TAKE OUR COVID-19 PROVIDER SURVEY!

OR SCAN QR CODE ON THE BOTTOM LEFT

Survey takes less than 15 mins to complete.

WE WANT TO HEAR FROM YOU.

For questions about the study, please contact Kala Wilson via email at kwils154@uncc.edu

UNIVERSITY OF NORTH CAROLINA
CHARLOTTE

Appendix A3. Healthcare Provider Draft Recruitment Email

Dear XX,

As you know, the COVID-19 pandemic has affected the lives of everyone in our communities. This survey is being conducted by UNC Charlotte researchers to collect information that will be used to identify the effects of pandemic-induced telemedicine, and provider and system characteristics on perceived EHR impact on care delivery. For your voluntary participation and time, you will be asked to provide an e-mail address to be included into a drawing to receive one of five $25 gift cards to your choice of either Amazon or Starbucks. If you have questions about the survey, please feel free to contact Kala Wilson at kwils154@uncc.edu, or Michael Dulin at mdulin3@uncc.edu. We would be happy to discuss questions or concerns with you.

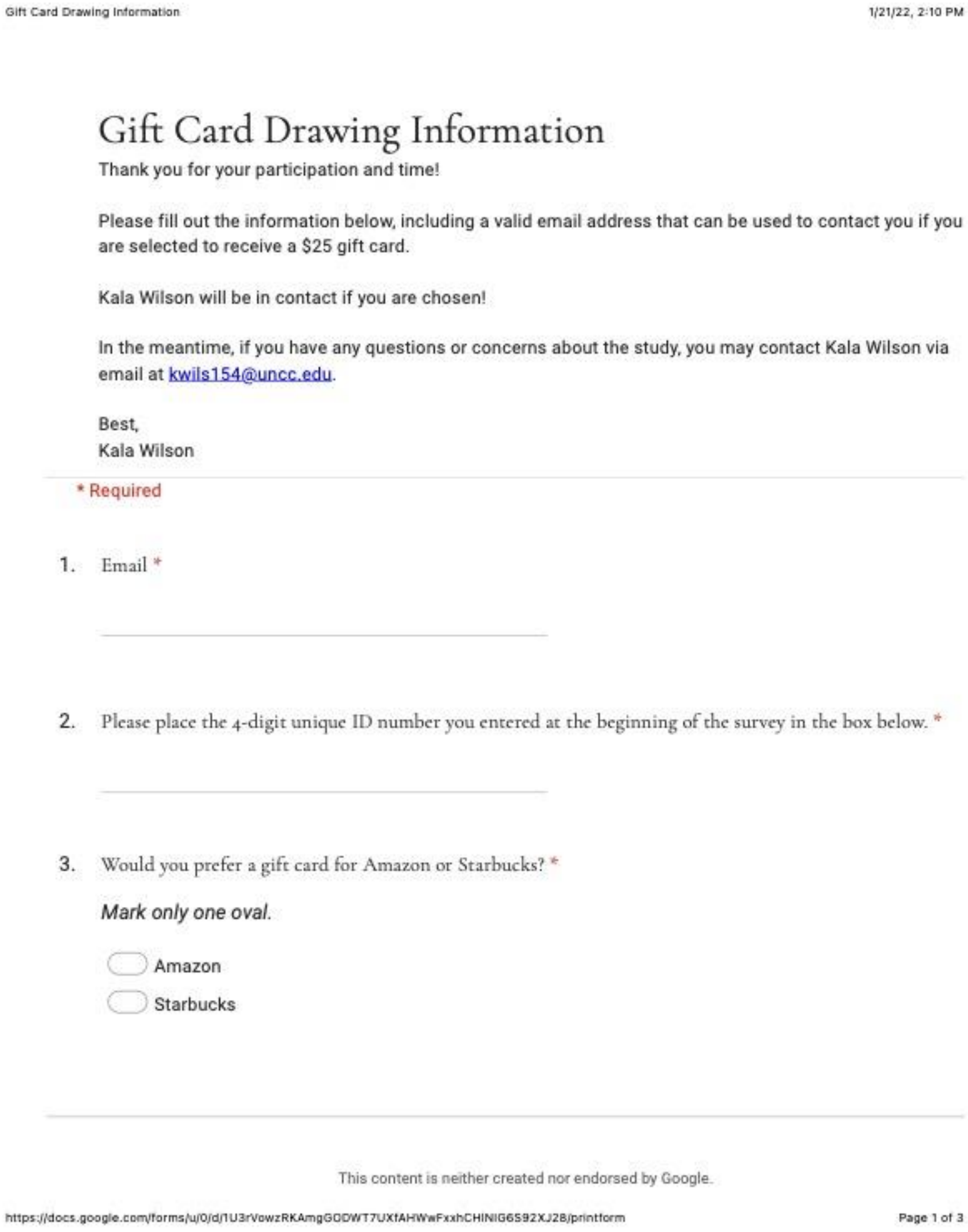
For additional information or access to the survey, please click the following link: __________________. You can also click the link or scan the QR code on the informational flyer attached below.

Thank you,

Kala S. Wilson, MPA
University of North Carolina at Charlotte
Doctoral Candidate | PhD in Public Health Sciences
Instructor | HSMT 4400 001 & 002
College of Health and Human Services
9201 University City Blvd. | Charlotte, NC 28223
kwils154@uncc.edu | 614.546.9951

Michael F. Dulin, MD, PhD
University of North Carolina at Charlotte
Professor | Department of Public Health Sciences
Director of the Academy for Population Health Innovation (APHI)
CHHS 341C
9201 University City Blvd. | Charlotte, NC 28223
Mdulin3@uncc.edu | 704.687.7899

Appendix A4. Gift Card Google Form



Gift Card Drawing Information 1/21/22, 2:10 PM

Gift Card Drawing Information

Thank you for your participation and time!

Please fill out the information below, including a valid email address that can be used to contact you if you are selected to receive a $25 gift card.

Kala Wilson will be in contact if you are chosen!

In the meantime, if you have any questions or concerns about the study, you may contact Kala Wilson via email at kwils154@uncc.edu.

Best,
Kala Wilson

* Required

1. Email *

2. Please place the 4-digit unique ID number you entered at the beginning of the survey in the box below. *

3. Would you prefer a gift card for Amazon or Starbucks? *

Mark only one oval.

○ Amazon
○ Starbucks

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https://docs.google.com/forms/u/0/d/1U3rVowzRKAmgGODWT7UXfAHWwFxxhCHINlG6592XJ28/printform Page 1 of 3

Appendix A5. Adapted Version of the National Electronic Health Record Survey (NEHRS)

Healthcare Provider:

1. During the COVID-19 pandemic (March 2020-Current), did you deliver care via telemedicine technology?
2. What type(s) of telemedicine tools do you use for your patient visits?
3. What, if any, issues affected your use of telemedicine during the pandemic?
4. To what extent are you able to provide similar quality of care during telemedicine visits as you do during in-person visits?

Appendix A6. Adapted Version of the Electronic Health Record End User Survey

1. Based on your experience during the pandemic, please indicate whether you believe the effect of the EHR on your clinical practice has been detrimental, beneficial, or neither, using the scale below:

	Highly detrimental	**Detrimental overall**	**Neither detrimental nor beneficial**	**Beneficial overall**	**Highly beneficial**
Quality of healthcare	☐	☐	☐	☐	☐
Avoiding errors (such as overlooking a drug interaction)	☐	☐	☐	☐	☐
Clinicians' access to up-to-date knowledge	☐	☐	☐	☐	☐
Interaction within the healthcare team	☐	☐	☐	☐	☐
Enjoyment of clinical practice	☐	☐	☐	☐	☐
Clinicians' stress-level	☐	☐	☐	☐	☐
Personal and professional privacy	☐	☐	☐	☐	☐
Diversity and inclusion efforts of clinical practice	☐	☐	☐	☐	☐
Patients' satisfaction with the quality of	☐	☐	☐	☐	☐

care they receive					
Efficiency of clinical practice	☐	☐	☐	☐	☐
Comprehensiveness of patient care	☐	☐	☐	☐	☐
The rapport between clinicians and patients	☐	☐	☐	☐	☐

CHAPTER FOUR. INVESTIGATING THE IMPORTANCE OF PERCEIVED BARRIERS IN CARE DELIVERY VIA TELEHEALTH DURING COVID-19

4.1 INTRODUCTION

Numerous healthcare professionals maintain that inaccurate and incomplete data in the electronic health record because of poor EHR-documentation can jeopardize patient safety and is a significant barrier to providing coordinated, patient-centric care.[1] Many legislative efforts have been made to improve care quality and patient safety. This was illustrated on July 29th, 2005, when President George W. Bush signed Public Law (PL) 109-41, the Patient Safety and Quality Improvement Act of 2005 (PSQIA), in response to the IOM's report, "To Err is Human."[2] Although it has been nearly twenty years since this act was implemented, there have been numerous technological advancements, including telehealth and telemedicine paired with a stark increase in patient safety and quality research since 1999; medical errors, otherwise known as preventable adverse events, are the third leading cause of death in the U.S., claiming up to 440,000 lives each year.[3] Moreover, patients are experiencing harm at ten times the rate as in the 1990s, with more Americans dying from preventable adverse events than car accidents or breast cancer.[4,5]

Prior research [6–9] indicates that the U.S. health system is inefficient, and history will continue to repeat without a data-driven systems approach to patient safety. Data on the impact of HIT, patient safety, and care quality are conflicting. Some results [10] maintain that HIT tools like artificial intelligence (AI) and machine learning can improve patient outcomes. Whereas other researchers [11,12] suggest that HIT tools are not associated with higher care quality and may even exacerbate poor health outcomes and disparities, offering a flaw in our understanding of HIT utilization, usability, and usefulness. To this end, Sivashanker & Gandhi [13] argue that numerous patient safety lessons and strategies have evolved over the past twenty years and can be applied to generate informed strategic efforts for increased promotion of health equity. For example, it is of great concern to ensure that health systems prioritize having an infrastructure to lead equity efforts within healthcare and that the step is not siloed but instead aligned with other quality and safety efforts.[13]

With growing concerns such as these and digital transformation within healthcare, there has been a concerted effort by healthcare professionals, policymakers, researchers, and other stakeholders to move the needle toward digital health equity as well.[14–16] As digital solutions have continued to increase, especially during the COVID-19 pandemic, it has been imperative to shift the focus from solely assessing social determinants of health as they relate to patient safety and quality, but *digital* determinants of health as well, such as digital access and literacy.[13,15,17–19] These arguments demonstrate a demand to further explore and understand how we can achieve zero inequity, the same way we aspire to achieve zero harm – because there is no such thing as improved health technology and safe, high-quality care that is inequitable.[13,20] Likewise, over 12 million outpatients in the U.S. experience a diagnostic error every year, as well as roughly 6 to 17% of all hospitalized patients.[21] Prior studies [22–25] suggest that including the patient’s perspective and encouraging patient activation can uncover the underlying causes of medical errors that may be difficult to ascertain and improve the effectiveness, efficiency, and quality of care. Furthermore, researchers have found that the patient's perceptions of care quality are associated with the utilization of Electronic Medical Records (EMRs),[26] Personal Health Records (PHRs),[27] and EHRs.[28]

This paper investigated the effects of patient demographic and healthcare-related characteristics on perceived telemedicine barriers. Based on the prior literature,[24–26,29–33] the hypothesis for this study was that patients who experience a medical error, have a high patient activation level (i.e., levels three or four), or use the EHR are more likely to face at least one perceived telemedicine barrier within the healthcare system. The findings from this study emphasize the need to give specific attention to demographic and healthcare-related characteristics' influence on perceptions of access to or the safety of health information technology services such as telehealth or telemedicine care delivery.

4.2 METHODS

Data Source

This study was based on a pilot cross-national, cross-sectional research design and included telemedicine (virtual care) patients in the U.S. This study used an anonymous web questionnaire to determine the multidimensional relationship between demographic and healthcare-related characteristics and perceived telemedicine barriers through an equitable and sociotechnical systems lens. The study consisted of adult (18+), English-speaking telemedicine patients who sought virtual care during the COVID-19 pandemic (March 2020-Current) across the U.S. from various hospitals, health systems, and institutions. Patients were excluded if they did not receive virtual care during the indicated timeframe. Eligible patients were informed of an 18-question anonymous online questionnaire through multiple social media platforms (i.e., Twitter, Facebook, Slack, and LinkedIn). Patients interested in the study could click the survey link or scan the QR code for the electronic informed consent form and the web-based questionnaire. Prospective respondents were invited to participate in the survey via Qualtrics (www.qualtrics.com). The survey developed consisted of 18 questions divided into five sections: telemedicine utilization (3 questions), patient activation (1 question), patient-reported medical errors (1 question), EHR impact on inequities (2 questions), and patient demographic and healthcare-related characteristics (11 questions). The telemedicine utilization section contained questions adapted from the National

Electronic Health Record Survey (NEHRS), a validated survey tool developed and conducted by the National Center for Health Statistics (NCHS) in partnership with RTI International and sponsored by the Office of the National Coordinator for Health Information Technology (ONC).[34] The survey items in the telemedicine utilization section used checklist and a 5-point Likert scale, including *fully, to a great extent, to some extent, to a small extent, or not at all*.

Data collection occurred in a 6-week timeframe, from March 1st, 2022, to April 11th, 2022. Logistic regression models were used to predict the odds of patients reporting at least one perceived telemedicine barrier during the COVID-19 pandemic based on patient activation level, reported medical errors, and EHR utilization. Descriptive and summary statistics for our sample of patients are presented, along with statistical modeling results for hypothesis testing. The descriptive information for the variables was also assessed graphically via histograms. Researchers obtained approval for this study from the University of North Carolina at Charlotte's Institutional Review Board (IRB#: 22-0700). Our final sample consisted of N=103 telemedicine patients after 26 patients, who did not receive telemedicine care during the stated timeframe, and 18 patients for incomplete questionnaires were excluded (**Table 1d**).

Study Variables and Statistical Analysis

Telemedicine Measure

Outcome Variable. The dependent variable, *perceived telemedicine barriers*, was binary and measured by the question, "What if any factors affected your use of telemedicine? Please check all that apply." This question was initially asked in checklist format, including 14 response options. The response options were recoded into a dichotomous variable ('none' or 'at least one telemedicine barrier') to avoid multicollinearity and produce more meaningful results. The validated National Electronic Health Records Survey (NEHRS) was utilized to minimize measurement error and internal validity issues. The NEHRS is an annual survey conducted by the

National Center for Health Statistics (NCHS) in partnership with RTI International and sponsored by the Office of the National Coordinator for Health Information Technology (ONC).[26] The survey has been conducted since 2008 and provides information on EHR systems adoption and utilization practices within HCOs in the United States.[26] In addition, results from the NEHRS have been instrumental in providing data to progress toward meeting the policy goals of The Health Information Technology for Economic and Clinical Health (HITECH) Act.[26] The NEHRS was developed with guidance from experts on survey research, health information technology, and healthcare management and policy.[28] This study explored telemedicine utilization during the COVID-19 pandemic using an adapted version of the NEHRS, asking questions related to telemedicine deployment, the types of tools utilized, barriers faced with telemedicine, and telemedicine care quality **(Appendix B1)**.

Demographic and Healthcare-Related Measures

Predictor Variables. Based on a review of literature related to telehealth and telemedicine access and utility, the following independent variables were 1) selected as predictor variables, 2) had ordinal and nominal scaling, and 3) constituted two content-related groups: demographics and healthcare-related factors. The demographic variables were geographic location, age, sex, race, ethnicity, and education. The healthcare-related factors were patient activation level, patient-reported medical errors, EHR utilization, telemedicine quality, insurance coverage, chronic conditions, and healthcare facility. For the multivariable analysis, two variables (geographic location and insurance coverage) were reduced in the number of categories to produce more meaningful results and to avoid multicollinearity. For example, in the variable “state of residency,” various states (n=23) were not represented throughout the sample. Therefore, the states were aggregated into regions labeled ‘Geographic Location.’ To minimize internal validity and measurement error issues, the Patient-Reported Experiences of Safety – Primary Care (PREOS-

PC) 35 and the Patient Activation Measure (PAM) 36 were used to measure the primary and secondary exposure variables, *perceived medical errors*, and *patient activation level.*

Statistical Analysis. Summary statistics of telemedicine patients' demographic and healthcare-related characteristics and outcomes were calculated. Univariable logistic regression analyses were conducted to determine whether the variables were statistically independent or correlated with perceived telemedicine barriers, estimating the unadjusted odds ratios (ORs). Confounding could be detected by comparing these unadjusted ORs with the adjusted ORs determined in the multivariable analyses. Multivariable logistic regression analysis was utilized to examine the joint explanatory power of the independent variables on perceived telemedicine barriers. One final model was tested that included ten of the explanatory variables. The reference categories were picked to allow comparisons of polarized groups. The final model illustrates the statistical probabilities of patient activation, patient-reported medical errors, and EHR utilization on perceived telemedicine barriers when controlling for demographic and other healthcare-related factors such as geographic location, age, sex, race, ethnicity, insurance coverage, education, and the number of diagnosed chronic conditions.

Through a series of collinearity diagnostics, multicollinearity was present for various independent variables. Therefore, not all variables were included in the multivariable analyses. Factors not showing a statistically significant association with the outcome variable in the univariable analysis were still included in the multivariable analysis to detect any apparent non-associations and account for clinical or biological relevance. These factors were used as control variables. Statistical significance was set at p=0.02 [37] for the univariable and preliminary multivariable models to identify factors for inclusion in the multivariable model. Statistical significance was set at p=0.05 for the final multivariable model. All results are presented as odds ratios (ORs), with the 95% confidence interval (95% CI) listed in the table. All statistical analyses and data manipulation, such as scrubbing and reshaping, were done in StataCorp (version 2019.16.1, Stata Statistical Software, College Station, TX).

4.3 RESULTS

Among patients who sought virtual care during the COVID-19 pandemic, perception disparities were present, with significant disparities according to patient activation level, patient-reported medical errors, EHR utilization, telemedicine quality, geographic location, age, sex, race, and the total number of diagnosed chronic conditions.

Patient Demographic and Healthcare-Related Factors

Descriptive Findings

The study sample included 103 adult telemedicine patients **(Table 1d)**. Majority of the telemedicine patients identified as White (51%) women (68%) between 18 to 40 years of age (85%). Nearly 56% of patients obtained a patient activation level of 3, which indicates a patient who *takes action* regarding their health and healthcare needs and has the perspective: “I am part of my healthcare team.” Similarly, close to 38% of the patients obtained a patient activation level of 4, which indicates a patient who *maintains their behaviors and pushes further* regarding their health and healthcare needs and has the perspective: “I am my own advocate.” Compared to patients who obtained an activation level of 3 or 4, about 7% of patients obtained a level 2, indicating a patient who is *becoming aware, but still struggling* and has the perspective: “I could be doing more,” and there were no patients who obtained a level 1, indicating a patient who is *disengaged and overwhelmed* and takes on the perspective of: “My doctor is in charge of my health.” The majority of patients reported experiencing a medical error via telemedicine (66%), utilizing the EHR (89%), residing in the southern region of the country (53%), were not of

Hispanic, Latinx, or Spanish origin (81%), had private insurance (63%), at least an undergraduate degree (49%), had been diagnosed with anxiety (21%), depression (17%), or COVID-19 (13%), currently living with 1 or 2 chronic conditions (54%), and received care during the pandemic at a private or group practice (27%), or hospital (21%). Also, roughly 76% of patients reported experiencing a telemedicine barrier and feeling as though they could receive the same quality of care virtually to ‘a great extent’ (41%) compared to traditional care.

Perceived Telemedicine Barriers (Unadjusted and Adjusted)

Unadjusted Findings

Table 2d (Model 1) shows the simple logistic regression analysis findings. Telemedicine quality, patient activation, medical errors, geographic location, and chronic conditions all were associated with statistically significant increased odds of perceiving a telemedicine barrier. Patients who felt like they could receive the same care quality via telemedicine to ‘a small extent’ (OR=9.75; $p<0.01$), ‘some extent’ (OR= 5.00; $p<0.05$), or ‘a great extent’ (OR=4.22; $p<0.05$) were more likely to perceive a telemedicine barrier than their counterparts. Patients living in the Western, Northeastern, or Southern regions of the country (OR=10.39, $p<0.01$; OR=4.40, $p<0.05$; 3.36, $p<0.01$) or had been diagnosed with one or two chronic conditions (OR=4.55; $p<0.01$) had increased odds of perceiving a telemedicine barrier. Similar associations were found for patients who reported experiencing a medical error (OR=3.45; $p<0.001$) or with an activation level of 3 (OR=1.95; $p<0.05$).

In contrast, chronic conditions, race, age, and insurance coverage were associated with statistically significant decreased odds of perceiving a telemedicine barrier. Patients were less likely to perceive at least one telemedicine barrier compared to their counterparts if they reported three to four diagnosed chronic conditions (OR=0.85; $p<0.05$) or identified as Black (OR=0.36;

$p<0.01$), Asian (OR=0.24; $p<0.05$), or Native Hawaiian (OR=0.32; $p<0.05$). Similarly, patients were also less likely to perceive a telemedicine barrier if they were between the ages of 41 to 56 years old (OR=0.20; $p<0.01$) or if they were uninsured or had VA insurance (OR=0.16; $p<0.05$).

Adjusted Findings

Table 2d (Model 2) shows the findings of the multiple logistic regression. Ethnicity and education were excluded from the model, and all other factors were retained as independent variables associated with perceived telemedicine barriers. Patients who felt they could receive the same care quality to ‘a small extent’ (OR=82.42; $p<0.05$) or ‘some extent’ (OR= 33.43; $p<0.05$) had increased odds of perceiving a telemedicine barrier compared to their counterparts and holding all other variables constant. Similarly, patients living in the Northeastern (OR=97.23; $p<0.05$) or Southern (OR=72.89; $p<0.05$) regions of the country between the ages of 41 to 56 (OR=67.83; $p<0.05$) and 25 to 40 (OR=41.89; $p<0.05$) were more likely to report at least one telemedicine barrier. Telemedicine patients utilizing the patient-facing EHR (OR=27.72; $p<0.05$), with an activation level of 3 (OR=17.37; $p<0.05$), living with one or two chronic conditions (OR=10.06; $p<0.05$), and experiencing a medical error (OR=1.22; $p<0.05$) also had increased odds of perceiving a telemedicine barrier compared to their counterparts and holding all other variables constant.

On the contrary, female patients (OR=0.06; $p<0.05$) who identified as Black (OR=0.10; $p<0.001$) and were living with three or four chronic conditions (OR=0.10; $p<0.01$) were less likely to perceive a telemedicine barrier compared to their counterparts while holding all other variables constant.

4.4 DISCUSSION

We employed quantitative research methods to identify which factors impact perceived telemedicine utilization barriers during the COVID-19 pandemic. Our findings align with existing literature and extend it in two ways. First, we found that patient's perceptions of care quality are not only associated with EHRs,[30] but also with their activation level and experiencing a medical error. And second, we found that although the COVID-19 pandemic created an urgent need for remote access to healthcare services,[38] disparities persist across various demographic characteristics. Therefore, our findings underscore the impact of using data to promote equitable telemedicine access and quality through rigorous and persistent data analysis addressing two significant questions: First, how do utilization and access differ by key demographic measures, and second, what barriers are intensifying these disparities, whether related to digital literacy, patient-facing telemedicine utility, or access to high-speed broadband internet.

Current telemedicine and HIT practices reveal the blatant disparities and inequities in healthcare access and health outcomes.[13,14,18,39–41] Our findings are a necessary first step toward ensuring that telemedicine access and quality are equitably distributed. To further enable learning health systems, we propose for further investigation to be conducted on the patient’s perspective and experience with pandemic-induced telemedicine and the corresponding patient health outcomes.

Limitations

Several limitations are noted. First, given that this study had a pilot cross-national design, our sample size was relatively small, likely due to the limited timeframe for data collection. Future studies will expand and conduct this work on a larger scale to increase the generalizability of the findings. Second, our data were limited to patients who only sought virtual care during the pandemic. Some patients sought care via traditional in-person and virtually, potentially limiting the results' generalizability. Third, the study focused on patients who sought care between March of 2020 and the present; perceptions of the EHR's impact on care delivery for patients who sought telemedicine services before then may differ. Fourth, the data was limited to a six-week timeframe. Changes in telemedicine volume, as well as recent policy updates (for example, The 21st Century Cures Act and Cures 2.0), which focused on policies to advance the delivery of treatments and innovations to patients via telehealth across the U.S. and provides federal guidance to CMS to extend telehealth access and coverage to beneficiaries of Medicare, Medicaid, and Children's Health Insurance Program (CHIP),[42] may cause the findings to change over time, signifying a need for continued assessment of the evolution of healthcare perceptions. Future work will focus on addressing these limitations and verifying our findings through the development of further equity and health information technology-based qualitative research.

CONCLUSION

Telemedicine utilization has exponentially increased during the COVID-19 pandemic. Still, it has done so without sufficient consideration and awareness of disparities by age, race, geography, and various health system-related factors. Our findings suggest that aside from a patient's race, age, and geographic location, a patient's activation level, experience with medical errors, and use of the EHR all influence their perception of facing barriers with telemedicine as a care modality. In particular, our findings indicated that Black women living with 3 or 4 chronic conditions were less likely to report perceiving a telemedicine barrier. Interestingly, these findings align with current literature suggesting that Black women, women of color, and individuals living with chronic conditions are less likely to engage with their healthcare systems and lack trust in the providers and health systems delivering their care.[43–47] Thus, future research should focus on designing and promoting equitable digital tools that properly engage various populations and communities based on their unique needs and preferences.[48–52] These findings may help inform efforts to ensure equitable access to and adoption of high-quality telemedicine services and promote a more-improved health equity design and infrastructure within healthcare systems that is safer and patient-centered.

Table 1d: Patient Demographic and Healthcare–Related Characteristics (N=103)

Variables	Frequency (n)	Percentage (%)
Telemedicine Utilization		
Telemedicine barriers		
No	25	24.27
Yes	78	75.73
Telemedicine Quality		
Fully	5	4.85
To a great extent	42	40.78
To some extent	39	37.86
To a small extent	15	14.56
Not at all	2	1.94
Demographic and Healthcare-Related Characteristics		
Patient Activation Level		
Level 1	-	-
Level 2	7	6.86
Level 3	57	55.88
Level 4	38	37.25
Medical Errors		
No	35	33.98
Yes	68	66.02
EHR Use		
No	11	10.68
Yes	92	89.32
Geographic Location		

Northeast	13	13.40
Midwest	18	18.56
West	14	14.43
South	52	53.61
Age		
18-24	41	41.41
25-40	44	44.44
41-56	13	14.14
Sex		
Male	27	26.21
Female	70	67.96
Other or prefer not to answer	6	5.83
Race		
White or Caucasian	52	50.49
Black or African American	24	23.30
American Indian or Alaska Native	2	1.94
Asian Indian	3	2.91
Asian	7	6.80
Native Hawaiian	1	0.97
Other or prefer not to answer	14	13.59
Ethnicity		
No	81	81.00
Hispanic, Latinx, or Spanish Origin	16	16.00

Prefer not to answer	3	3.00
Insurance coverage		
Private	65	63.11
Public	28	27.18
Uninsured	4	3.88
VA	6	5.83
Education		
High school graduate or less	8	8.60
Some college or trade school	39	41.94
College graduate or more	46	49.46
Chronic condition		
None	32	20.25
Angina/heart problem	6	3.80
Arthritis	12	7.59
Chronic pain	11	6.96
Depression	26	16.46
Anxiety	34	21.52
Diabetes	3	1.90
Hypertension	9	5.70
Cancer	1	0.63
High cholesterol	4	2.53
COVID-19	20	12.66
Total number of chronic conditions		
One to two	53	54.64
Three to four	14	14.43
5 or more	2	2.06

None	28	28.87
Healthcare facility		
Hospital	41	21.35
Emergency Department	21	10.94
Urgent Care center	29	15.10
Nursing home	5	2.60
Rehabilitation center	5	2.60
Hospice	4	2.08
Mental health center	19	9.90
Birth center	3	1.56
Community health center	14	7.29
Private or group practice clinic	51	26.56

Abbreviations: EHR, Electronic Health Record

Table 2d: Unadjusted and Adjusted Odds Ratios and 95% Confidence Intervals for the Association between Demographic and Healthcare–Related Characteristics and Telemedicine Barriers

	Telemedicine Barriers[a] Unadjusted[a]		Telemedicine Barriers[b] Adjusted[b]	
	Odds Ratio (OR)	**95% Confidence Interval (CI)**	**Odds Ratio (OR)**	**95% Confidence Interval (CI)**
Telemedicine Utilization				
Telemedicine Quality				
Fully	1.00	Referent	1.00	1.00
To a great extent	**4.22***	1.62 – 28.74	2.45	
To some extent	**5.00***	1.71 – 34.72	**33.43***	1.22 – 57.23
To a small extent	**9.75****	1.95 – 99.96	**82.42***	1.73 – 181.04
Not at all	–[c]	–[c]	–[c]	–[c]
Patient Demographic and Healthcare-Related Characteristics				
Patient Activation Level				
Level 1	–[c]	–[c]	–[c]	–[c]
Level 2	1.00	Referent	1.00	Referent
Level 3	**1.95***	1.77 – 4.91	**17.37***	1.97 – 62.37
Level 4	–[c]	–[c]	–[c]	–[c]
Medical Errors				
No	1.00	Referent	1.00	Referent
Yes	**3.45*****	1.35 – 8.79	**1.22***	1.08 – 14.77
EHR Use				
No	1.00	Referent	1.00	Referent
Yes	0.66	0.13 – 3.31	**27.72***	1.10 – 79.69
Geographic Location				
Northeast	**4.40***	1.75 – 25.84	**97.23***	1.43 – 178.76
Midwest	1.00	Referent	1.00	Referent
West	**10.39****	1.11 – 97.33	–[c]	–[c]
South	**3.36****	1.05 – 10.69	**72.89***	1.96 – 153.84

Age				
18-24	1.00	Referent	1.00	Referent
25-40	0.93	0.30 – 2.83	**41.89***	1.80 – 94.14
41-56	**0.20****	0.05 – 0.77	**67.83***	1.14 – 128.03
Sex				
Male	1.00	Referent	1.00	Referent
Female	0.36	0.09 – 1.34	**0.06***	0.00 – 1.24
Race				
White or Caucasian	1.00	Referent	1.00	Referent
Black or African American	**0.36****	0.11 – 1.13	**0.10*****	0.00 – 0.33
American Indian or Alaska Native	0.18	0.01 – 3.21	–[c]	–[c]
Asian Indian	–[c]	–[c]	–[c]	–[c]
Asian	**0.24***	0.04 – 0.89	0.73	0.01 – 35.81
Native Hawaiian	**0.32***	0.08 – 0.94	0.05	0.00 – 5.72
Ethnicity				
No	1.00	Referent	–[c]	–[c]
Hispanic, Latinx, or Spanish Origin	0.85	0.24 – 2.98	–[c]	–[c]
Insurance coverage				
Private	1.00	Referent	1.00	Referent
Public	1.96	0.59 – 6.50	0.75	0.04 – 13.67
Uninsured/VA	**0.16***	0.02 – 0.98	1.75	0.00 – 437.92
Education				
High school graduate or less	1.00	Referent	1.00	Referent
Some college or trade school	0.48	0.05 – 4.40	–[c]	–[c]
College graduate or more	0.45	0.05 – 4.11	–[c]	–[c]
Total number of chronic conditions				
One to two	**4.55****	1.34 – 15.33	**10.06***	1.79 – 87.37
Three to four	**0.85***	0.22 – 3.29	**0.10****	0.00 – 0.67
5 or more	–[c]	–[c]	–[c]	–[c]

None	1.00	Referent	1.00	Referent

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[a] Model measured the primary outcome: perceived telemedicine barriers; unadjusted, no confounders identified

[b] Model measured the primary outcome: perceived telemedicine barriers; adjusted for telemedicine quality, patient activation level, perceived medical errors, patient-facing EHR use, geographic location, age, sex, race, and total number of chronic conditions

[c] Not applicable or omitted due to multicollinearity

Abbreviations: CI, Confidence Interval; EHR, Electronic Health Record; OR, Odds Ratio; VA, Veteran Affairs

P-Values: *$p<0.05$ **$p<0.01$ ***$p<0.001$

4.5 REFERENCES

1. Kent J. Poor Data Quality, Weak Algorithms Lead to Patient Matching Issues. HealthITAnalytics. Published 2020. Accessed January 8, 2022. https://healthitanalytics.com/news/poor-data-quality-weak-algorithms-lead-to-patient-matching-issues

2. Fassett WE. Patient Safety and Quality Improvement Act of 2005. *Ann Pharmacother*. 2006;40(5):917-924. doi:10.1345/aph.1G485

3. James JT. A new, evidence-based estimate of patient harms associated with hospital care. *J Patient Saf*. 2013;9(3):122-128. doi:10.1097/PTS.0b013e3182948a69

4. Pestonik S, Lemon V. Improving Patient Safety—Why Data Matters. Health Catalyst. Published April 30, 2019. Accessed May 24, 2021. https://www.healthcatalyst.com/insights/use-data-improve-patient-safety/

5. Bates DW, Singh H. Two Decades Since *To Err Is Human* : An Assessment Of Progress And Emerging Priorities In Patient Safety. *Health Aff (Millwood)*. 2018;37(11):1736-1743. doi:10.1377/hlthaff.2018.0738

6. Lind DP, Andresen DR, Williams A. Medical Errors in Iowa: Prevalence and Patients' Perspectives. *J Patient Saf*. 2020;16(3):e199-e204. doi:10.1097/PTS.0000000000000523

7. Carayon P. Human factors of complex sociotechnical systems. *Appl Ergon*. 2006;37(4):525-535. doi:10.1016/j.apergo.2006.04.011

8. Carayon P, Bass EJ, Bellandi T, Gurses AP, Hallbeck MS, Mollo V. Sociotechnical systems analysis in health care: a research agenda. *IIE Trans Healthc Syst Eng*. 2011;1(3):145-160. doi:10.1080/19488300.2011.619158

9. Carayon P. Sociotechnical systems approach to healthcare quality and patient safety. *Work*. 2012;41:3850-3854. doi:10.3233/WOR-2012-0091-3850

10. Bates DW, Levine D, Syrowatka A, et al. The potential of artificial intelligence to improve patient safety: a scoping review. *Npj Digit Med*. 2021;4(1):54. doi:10.1038/s41746-021-00423-6

11. Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the health of populations. Published online 2019:8.

12. Panch T, Mattie H, Atun R. Artificial intelligence and algorithmic bias: implications for health systems. *J Glob Health*. 2019;9(2):010318. doi:10.7189/jogh.09.020318

13. Sivashanker K, Gandhi TK. Advancing Safety and Equity Together. *N Engl J Med*. 2020;382(4):301-303. doi:10.1056/NEJMp1911700

14. Wood BR, Young JD, Abdel-Massih RC, et al. Advancing Digital Health Equity: A Policy Paper of the Infectious Diseases Society of America and the HIV Medicine Association. *Clin Infect Dis*. 2021;72(6):913-919. doi:10.1093/cid/ciaa1525

15. Brewer LC, Fortuna KL, Jones C, et al. Back to the Future: Achieving Health Equity Through Health Informatics and Digital Health. *JMIR MHealth UHealth*. 2020;8(1):e14512. doi:10.2196/14512

16. Crawford A, Serhal E. Digital Health Equity and COVID-19: The Innovation Curve Cannot Reinforce the Social Gradient of Health. *J Med Internet Res*. 2020;22(6):e19361. doi:10.2196/19361

17. Shaw J, Brewer LC, Veinot T. Recommendations for Health Equity and Virtual Care Arising From the COVID-19 Pandemic: Narrative Review. *JMIR Form Res*. 2021;5(4):e23233. doi:10.2196/23233

18. Saeed SA, Masters RM. Disparities in Health Care and the Digital Divide. *Curr Psychiatry Rep*. 2021;23(9):61. doi:10.1007/s11920-021-01274-4

19. Eberly LA, Khatana SAM, Nathan AS, et al. Telemedicine Outpatient Cardiovascular Care During the COVID-19 Pandemic: Bridging or Opening the Digital Divide? *Circulation*. 2020;142(5):510-512. doi:10.1161/CIRCULATIONAHA.120.048185

20. O'Kane M, Agrawal S, Anthem, Inc., et al. An Equity Agenda for the Field of Health Care Quality Improvement. *NAM Perspect*. 2021;11(9). doi:10.31478/202109b

21. Singh H, Graber ML, Hofer TP. Measures to Improve Diagnostic Safety in Clinical Practice. *J Patient Saf*. 2019;15(4):311-316. doi:10.1097/PTS.0000000000000338

22. Giardina TD, Haskell H, Menon S, et al. Learning From Patients' Experiences Related To Diagnostic Errors Is Essential For Progress In Patient Safety. *Health Aff (Millwood)*. 2018;37(11):1821-1827. doi:10.1377/hlthaff.2018.0698

23. Pandolfe F, Crotty BH, Safran C. Medication Harmony: A Framework to Save Time, Improve Accuracy and Increase Patient Activation. *AMIA Annu Symp Proc AMIA Symp*. 2016;2016:1959-1966.

24. Hibbard JH, Greene J. What The Evidence Shows About Patient Activation: Better Health Outcomes And Care Experiences; Fewer Data On Costs. *Health Aff (Millwood)*. 2013;32(2):207-214. doi:10.1377/hlthaff.2012.1061

25. Greene J, Hibbard JH. Why does patient activation matter? An examination of the relationships between patient activation and health-related outcomes. *J Gen Intern Med*. 2012;27(5):520-526. doi:10.1007/s11606-011-1931-2

26. Finney Rutten LJ, Vieux SN, St Sauver JL, et al. Patient perceptions of electronic medical records use and ratings of care quality. *Patient Relat Outcome Meas*. 2014;5:17-23. doi:10.2147/PROM.S58967

27. Lester M, Boateng S, Studeny J, Coustasse A. Personal Health Records: Beneficial or Burdensome for Patients and Healthcare Providers? *Perspect Health Inf Manag*. 2016;13:1h.

28. Heath S. Patients Say EHR Use Improves Care Quality, Provider Communication. PatientEngagementHIT. Published March 19, 2019. Accessed January 21, 2022. https://patientengagementhit.com/news/patients-say-ehr-use-improves-care-quality-provider-communication

29. Lind DP, Andresen DR, Williams A. Medical Errors in Iowa: Prevalence and Patients' Perspectives. *J Patient Saf*. 2020;16(3):e199-e204. doi:10.1097/PTS.0000000000000523

30. Powell KR. Patient-Perceived Facilitators of and Barriers to Electronic Portal Use: A Systematic Review. *CIN Comput Inform Nurs*. 2017;35(11):565-573. doi:10.1097/CIN.0000000000000377

31. Nguyen M, Waller M, Pandya A, Portnoy J. A Review of Patient and Provider Satisfaction with Telemedicine. *Curr Allergy Asthma Rep*. 2020;20(11):72. doi:10.1007/s11882-020-00969-7

32. Van den Bulck SA, Hermens R, Slegers K, Vandenberghe B, Goderis G, Vankrunkelsven P. Designing a Patient Portal for Patient-Centered Care: Cross-Sectional Survey. *J Med Internet Res*. 2018;20(10):e269-e269. doi:10.2196/jmir.9497

33. Raths D. Emory Healthcare Takes Data-Driven Approach to Improving Patient Portal. *Healthc Innov Website*. Published online 2020. https://www.hcinnovationgroup.com/clinical-it/patient-portals/article/21122984/emory-healthcare-takes-datadriven-approach-to-improving-patient-portal

34. Centers for Disease Control and Prevention. NEHRS - National Electronic Health Records Survey Homepage. Published 2021. Accessed January 9, 2022. https://www.cdc.gov/nchs/nehrs/about.htm

35. Ricci-Cabello I, Avery AJ, Reeves D, Kadam UT, Valderas JM. Measuring Patient Safety in Primary Care: The Development and Validation of the "Patient Reported Experiences and Outcomes of Safety in Primary Care" (PREOS-PC). *Ann Fam Med*. 2016;14(3):253-261. doi:10.1370/afm.1935

36. Hibbard JH, Stockard J, Mahoney ER, Tusler M. Development of the Patient Activation Measure (PAM): Conceptualizing and Measuring Activation in Patients and Consumers: Development of the Patient Activation Measure (PAM). *Health Serv Res*. 2004;39(4p1):1005-1026. doi:10.1111/j.1475-6773.2004.00269.x

37. Zhang Z. Model building strategy for logistic regression: purposeful selection. *Ann Transl Med*. 2016;4(6):111-111. doi:10.21037/atm.2016.02.15

38. Suran M. Increased Use of Medicare Telehealth During the Pandemic. *JAMA*. 2022;327(4):313. doi:10.1001/jama.2021.23332

39. Sutton MY, Anachebe NF, Lee R, Skanes H. Racial and Ethnic Disparities in Reproductive Health Services and Outcomes, 2020. *Obstet Gynecol*. 2021;137(2):225-233. doi:10.1097/AOG.0000000000004224

40. Lau J, Knudsen J. Reducing Disparities In Telemedicine: An Equity-Focused, Public Health Approach: Perspective examines ways to reduce disparities in telemedicine. *Health Aff (Millwood)*. 2022;41(5):647-650. doi:10.1377/hlthaff.2022.00314

41. Azzopardi-Muscat N, Sørensen K. Towards an equitable digital public health era: promoting equity through a health literacy perspective. *Eur J Public Health*. 2019;29(Supplement_3):13-17. doi:10.1093/eurpub/ckz166

42. Office of the Commissioner. 21st Century Cures Act. FDA. Published January 31, 2020. Accessed August 17, 2022. https://www.fda.gov/regulatory-information/selected-amendments-fdc-act/21st-century-cures-act

43. Institute of Medicine (IOM). *Unequal Treatment: Confronting Racial and Ethnic Disparities in Health Care (with CD)*. National Academies Press; 2003:12875. doi:10.17226/12875

44. Chinn JJ, Martin IK, Redmond N. Health Equity Among Black Women in the United States. *J Womens Health*. 2021;30(2):212-219. doi:10.1089/jwh.2020.8868

45. Nouri S, Khoong EC, Lyles CR, Karliner L. Addressing Equity in Telemedicine for Chronic Disease Management During the Covid-19 Pandemic. Published online 2020:13.

46. Krishnan V, Workflows GM of ID. Digital Patient Engagement: Actionable Communications to Help Patients Navigate Healthcare White Paper | HIMSS. Published November 15, 2021. Accessed June 15, 2022. https://www.himss.org/resources/digital-patient-engagement-actionable-communications-help-patients-navigate-healthcare

47. Gimbel RW, Rennert LM, Crawford P, et al. Enhancing Patient Activation and Self-Management Activities in Patients With Type 2 Diabetes Using the US Department of Defense Mobile Health Care Environment: Feasibility Study. *J Med Internet Res*. 2020;22(5):e17968-e17968. doi:10.2196/17968

48. Eaton S, Biggerstaff D, Petrou S, et al. Young people's preferences for the use of emerging technologies for asymptomatic regular chlamydia testing and management: a discrete choice experiment in England. *BMJ Open*. 2019;9(1):e023663-e023663. doi:10.1136/bmjopen-2018-023663

49. Gordon NP, Crouch E. Digital Information Technology Use and Patient Preferences for Internet-Based Health Education Modalities: Cross-Sectional Survey Study of Middle-Aged and Older Adults With Chronic Health Conditions. *JMIR Aging*. 2019;2(1):e12243-e12243. doi:10.2196/12243

50. den Ouden H, Vos RC, Reidsma C, Rutten GEHM. Shared decision making in type 2 diabetes with a support decision tool that takes into account clinical factors, the intensity of

treatment and patient preferences: design of a cluster randomised (OPTIMAL) trial. *BMC Fam Pract*. 2015;16:27-27. doi:10.1186/s12875-015-0230-0

51. Brennan PF, Strombom I. Improving health care by understanding patient preferences: the role of computer technology. *J Am Med Inform Assoc JAMIA*. 1998;5(3):257-262. doi:10.1136/jamia.1998.0050257

52. Kim C, Berta WB, Gagliardi AR. Exploring approaches to identify, incorporate and report patient preferences in clinical guidelines: Qualitative interviews with guideline developers. *Patient Educ Couns*. 2021;104(4):703-708. doi:10.1016/j.pec.2020.10.001

53. Basch P, Smith J. CMS Payment Policy, E&M Guideline Reform, and the Prospect of Electronic Health Record Optimization. *Appl Clin Inform*. 2018;09(04):914-918. doi:10.1055/s-0038-1676337

54. Anderson L. Realizing the Future We Want: Leveraging Technology to Achieve a Better Health Care Experience for All. *N C Med J*. 2019;80(4):224-228. doi:10.18043/ncm.80.4.224

55. Gold R, Cottrell E, Bunce A, et al. Developing Electronic Health Record (EHR) Strategies Related to Health Center Patients' Social Determinants of Health. *J Am Board Fam Med*. 2017;30(4):428-447. doi:10.3122/jabfm.2017.04.170046

56. Cottrell EK, Dambrun K, Cowburn S, et al. Variation in Electronic Health Record Documentation of Social Determinants of Health Across a National Network of Community Health Centers. *Am J Prev Med*. 2019;57(6):S65-S73. doi:10.1016/j.amepre.2019.07.014

57. Butler TJ, Firestone KS, Grow JL, Kantak AD. Standardizing Documentation and the Clinical Approach to Apnea of Prematurity Reduces Length of Stay, Improves Staff Satisfaction, and Decreases Hospital Cost. *Jt Comm J Qual Patient Saf*. 2014;40(6):263-AP1. doi:10.1016/S1553-7250(14)40035-7

58. Rowlands S, Coverdale S, Callen J. Documentation of clinical care in hospital patients' medical records: A qualitative study of medical students' perspectives on clinical documentation education. *Health Inf Manag J*. 2016;45(3):99-106. doi:10.1177/1833358316639448

59. Soto CM, Kleinman KP, Simon SR. Quality and correlates of medical record documentation in the ambulatory care setting. *BMC Health Serv Res*. 2002;2(1):22. doi:10.1186/1472-6963-2-22

60. Lette M, Ambugo EA, Hagen TP, Nijpels G, Baan CA, de Bruin SR. Addressing safety risks in integrated care programs for older people living at home: a scoping review. *BMC Geriatr*. 2020;20(1):81. doi:10.1186/s12877-020-1482-7

61. Fried TR, Niehoff KM, Street RL, et al. Effect of the Tool to Reduce Inappropriate Medications on Medication Communication and Deprescribing. *J Am Geriatr Soc*. 2017;65(10):2265-2271. doi:10.1111/jgs.15042

62. Becich MJ, Gilbertson JR, Gupta D, Patel A, Grzybicki DM, Raab SS. Pathology and patient safety: the critical role of pathology informatics in error reduction and quality initiatives. *Clin Lab Med*. 2004;24(4):913-943. doi:10.1016/j.cll.2004.05.019

63. Amaniyan S, Faldaas BO, Logan PA, Vaismoradi M. Learning from Patient Safety Incidents in the Emergency Department: A Systematic Review. *J Emerg Med*. 2020;58(2):234-244. doi:10.1016/j.jemermed.2019.11.015

64. Kuriakose R, Aggarwal A, Sohi R, Goel R, Rashmi N, Gambhir R. Patient safety in primary and outpatient health care. *J Fam Med Prim Care*. 2020;9(1):7. doi:10.4103/jfmpc.jfmpc_837_19

65. Patel J, Otto E, Taylor JS, et al. Patient safety in dermatology: a ten-year update. *Dermatol Online J*. 2021;27(3). doi:10.5070/D3273052763

66. Watson AJ, Redbord K, Taylor JS, Shippy A, Kostecki J, Swerlick R. Medical error in dermatology practice: Development of a classification system to drive priority setting in patient safety efforts. *J Am Acad Dermatol*. 2013;68(5):729-737. doi:10.1016/j.jaad.2012.10.058

67. Bates DW, Singh H. Two decades since to err is human: An assessment of progress and emerging priorities in patient safety. *Health Aff (Millwood)*. 2018;37(11):1736-1743. doi:10.1377/hlthaff.2018.0738

68. Gross CP, Essien UR, Pasha S, Gross JR, Wang S yi, Nunez-Smith M. Racial and Ethnic Disparities in Population-Level Covid-19 Mortality. *J Gen Intern Med*. 2020;35(10):3097-3099. doi:10.1007/s11606-020-06081-w

69. Röösli E, Rice B, Hernandez-Boussard T. Bias at warp speed: how AI may contribute to the disparities gap in the time of COVID-19. *J Am Med Inform Assoc*. 2021;28(1):190-192. doi:10.1093/jamia/ocaa210

70. Ye J. The Role of Health Technology and Informatics in a Global Public Health Emergency: Practices and Implications From the COVID-19 Pandemic. *JMIR Med Inform*. 2020;8(7):e19866. doi:10.2196/19866

71. Dagliati A, Malovini A, Tibollo V, Bellazzi R. Health informatics and EHR to support clinical research in the COVID-19 pandemic: an overview. *Brief Bioinform*. 2021;22(2):812-822. doi:10.1093/bib/bbaa418

72. Davies AR, Honeyman M, Gann B. Addressing the Digital Inverse Care Law in the Time of COVID-19: Potential for Digital Technology to Exacerbate or Mitigate Health Inequalities. *J Med Internet Res*. 2021;23(4):e21726. doi:10.2196/21726

73. Furukawa MF, Poon E. Meaningful use of health information technology: evidence suggests benefits and challenges lie ahead. *Am J Manag Care*. 2011;17(12 Spec No.):SP76a-SP.

74. Lomotan E. *Advancing Evidence into Practice Through Shareable Clinical Decision Support*.; 2019.

75. Kosseim P, Brady M. POLICY BY PROCRASTINATION: SECONDARY USE OF ELECTRONIC HEALTH RECORDS FOR HEALTH RESEARCH PURPOSES. 2008;2:41.

76. Bell K. Public Policy and Health Informatics. *Semin Oncol Nurs*. 2018;34(2):184-187. doi:10.1016/j.soncn.2018.03.010

77. Basch P, Smith JRL. CMS Payment Policy, E&M Guideline Reform, and the Prospect of Electronic Health Record Optimization. *Appl Clin Inform*. 2018;9(4):914-918. doi:10.1055/s-0038-1676337

78. Agency for Healthcare Research and Quality (AHRQ). Use of Electronic Health Records | Agency for Healthcare Research and Quality. Chartbook on Care Coordination. Published 2018. Accessed August 3, 2022. https://www.ahrq.gov/research/findings/nhqrdr/chartbooks/carecoordination/measure5.html

79. Biden Administration Submits Budget Request to Congress | HIMSS. Published May 2, 2022. Accessed June 15, 2022. https://www.himss.org/resources/biden-administration-submits-budget-request-congress

80. Ferreira S. Sociological Observations of the Third Sector Through Systems Theory: An Analytical Proposal. *Volunt Int J Volunt Nonprofit Organ*. 2014;25(6):1671-1693. doi:10.1007/s11266-014-9469-7

81. Render J. What is Complexity Theory and How Can it Improve the Workplace? – Agile-Mercurial. Published 2019. Accessed May 4, 2021. https://agile-mercurial.com/2019/05/13/what-is-complexity-theory-and-how-can-it-improve-the-workplace/

82. Kruse CS, Stein A, Thomas H, Kaur H. The use of Electronic Health Records to Support Population Health: A Systematic Review of the Literature. *J Med Syst*. 2018;42(11):214. doi:10.1007/s10916-018-1075-6

83. Association of American Medical Colleges, Ommaya AK, Cipriano PF, et al. Care-Centered Clinical Documentation in the Digital Environment: Solutions to Alleviate Burnout. *NAM Perspect*. 2018;8(1). doi:10.31478/201801c

84. Kasiri N, Sharda R, Asamoah DA. Evaluating electronic health record systems: a system dynamics simulation. *SIMULATION*. 2012;88(6):639-648. doi:10.1177/0037549711416244

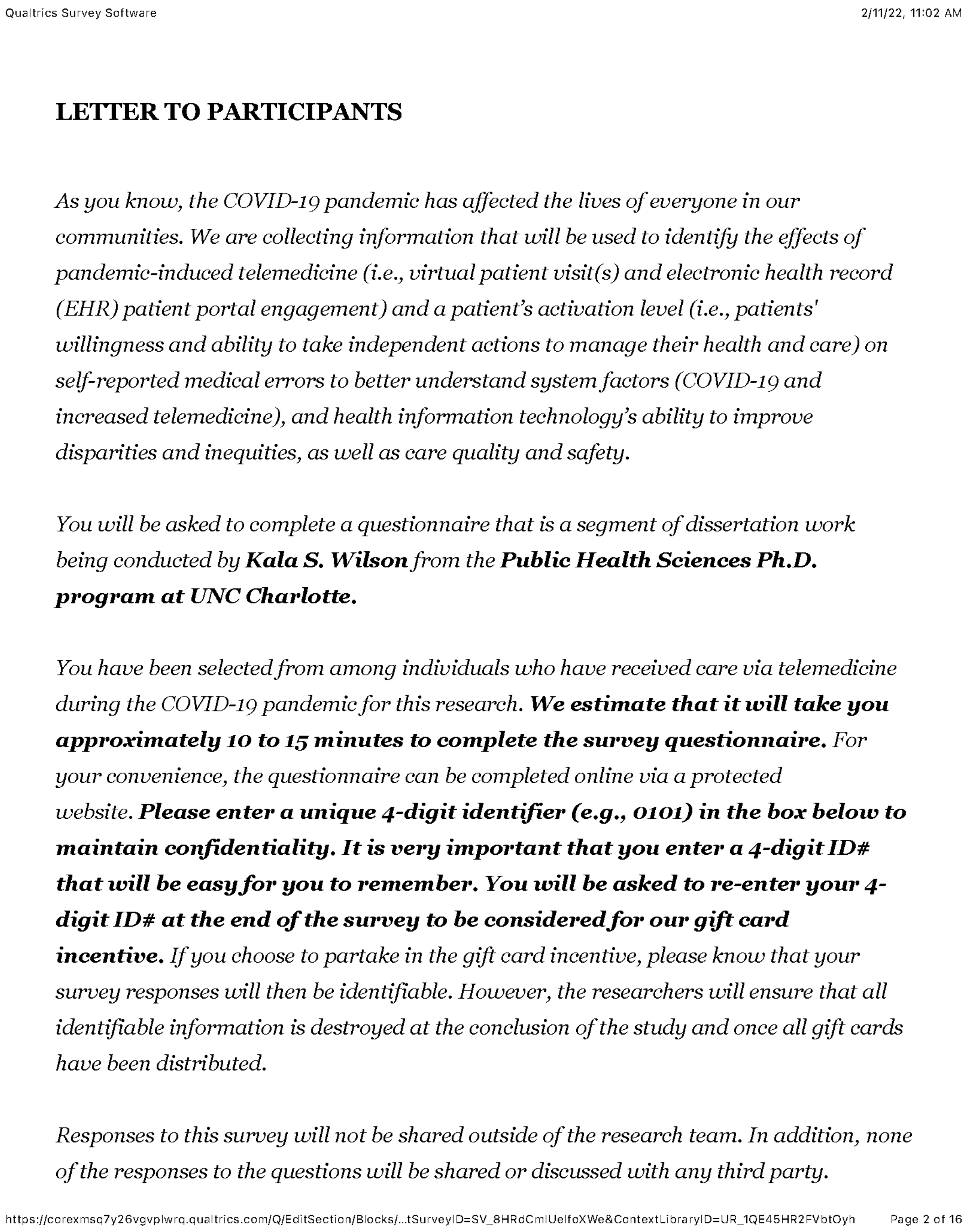
85. Carney TJ, Kong AY. Leveraging health informatics to foster a smart systems response to health disparities and health equity challenges. *J Biomed Inform*. 2017;68:184-189. doi:10.1016/j.jbi.2017.02.011

86. Wachter RM, Howell MD. Resolving the Productivity Paradox of Health Information Technology: A Time for Optimism. *JAMA*. 2018;320(1):25. doi:10.1001/jama.2018.5605

87. Benjamin R. *Race after Technology: Abolitionist Tools for the New Jim Code*. Polity; 2019.

4.6 APPENDIX B: SUPPLEMENTARY MATERIALS FOR CHAPTER FOUR

Appendix B1. Patient Perceptions of EHR and Telemedicine Survey



LETTER TO PARTICIPANTS

As you know, the COVID-19 pandemic has affected the lives of everyone in our communities. We are collecting information that will be used to identify the effects of pandemic-induced telemedicine (i.e., virtual patient visit(s) and electronic health record (EHR) patient portal engagement) and a patient's activation level (i.e., patients' willingness and ability to take independent actions to manage their health and care) on self-reported medical errors to better understand system factors (COVID-19 and increased telemedicine), and health information technology's ability to improve disparities and inequities, as well as care quality and safety.

You will be asked to complete a questionnaire that is a segment of dissertation work being conducted by ***Kala S. Wilson*** *from the* ***Public Health Sciences Ph.D. program at UNC Charlotte.***

You have been selected from among individuals who have received care via telemedicine during the COVID-19 pandemic for this research. ***We estimate that it will take you approximately 10 to 15 minutes to complete the survey questionnaire.*** *For your convenience, the questionnaire can be completed online via a protected website.* ***Please enter a unique 4-digit identifier (e.g., 0101) in the box below to maintain confidentiality. It is very important that you enter a 4-digit ID# that will be easy for you to remember. You will be asked to re-enter your 4-digit ID# at the end of the survey to be considered for our gift card incentive.*** *If you choose to partake in the gift card incentive, please know that your survey responses will then be identifiable. However, the researchers will ensure that all identifiable information is destroyed at the conclusion of the study and once all gift cards have been distributed.*

Responses to this survey will not be shared outside of the research team. In addition, none of the responses to the questions will be shared or discussed with any third party.

While taking the survey, if you encounter a question that you would rather not answer, you may skip that question and continue to move further along in the survey. You may decide to exit the survey at any time. This study is voluntary and is not tied to any health service(s) you may receive from any provider(s). We thank you in advance for your time and consideration. Thanks to the generosity of individuals like you, our research can make an important contribution to what is known about the multifaceted impact of system factors such as COVID-19 and increased telemedicine on our health and receiving equitable care throughout all patient communities.

For your voluntary participation and time, you will be asked to provide ***an email address, your 4-digit ID#, and gift card preference*** *to be included in a drawing to receive one of five* ***$25 gift cards*** *to your choice of either Amazon or Starbucks.*

If you have questions about the survey, please feel free to contact ***Kala Wilson*** *at* ***kwils154@uncc.edu*** *or* ***Michael Dulin*** *at* ***mdulin3@uncc.edu****, we would be happy to discuss questions or concerns with you.*

If you have questions about your rights as a research participant, or wish to obtain information, ask questions, or discuss any concerns about this study with someone other than the researcher(s), please contact the ***Office of Research Protections and Integrity*** *at* ***uncc-irb@uncc.edu****.*

Sincerely,

Kala S. Wilson, MPA

CONSENT

Thank you for taking the time to answer this survey. This survey's purpose is to investigate the impact of pandemic-induced Telehealth on care quality and safety outcomes and perceived EHR impact on disparities and inequities in health and healthcare.

The results of this survey will be used for dissertation work being completed at the University of North Carolina at Charlotte. All answers are confidential. After this study is complete, identifiers will be removed from the data and the data could be used for future research studies or distributed to another investigator for future research studies without additional informed consent.

To move forward with the survey process, please select either statement below that applies to you. To advance to the survey, you must consent to participate and be at least 18 years of age.

○ **I agree** to take part in the study
○ **I do not agree** to take part in the study

INSTRUCTIONS

INSTRUCTIONS: For each of the following questions, please select or enter the response that best describes you:

TELEMEDICINE UTILIZATION

TELEMEDICINE UTILIZATION: *Understandably, due to the COVID-19 pandemic many healthcare systems have needed to make the transition to provide virtual care to their patients. Questions 1-3 will ask about your telemedicine utilization experience.*

What type(s) of telemedicine tools did you use for your patient visit(s)? **PLEASE CHECK ALL THAT APPLY.**

☐ Synchronous videoconference software with audio (e.g., Zoom, WebEx, Facetime, or other interactive video connection

☐ Asynchronous videoconference software (e.g., sending images or medical data to your healthcare provider via secure web server, encrypted e-mail, or electronic health record (EHR)

☐ Telephone audio

☐ Secure private messaging (e.g., via web portal such as electronic health record (EHR), encrypted e-mail)

☐ Remote patient monitoring (e.g., wearables such as continuous glucose monitoring device (glucometer), activity trackers, or heart rate device)

What, if any, factors affected your use of telemedicine? **PLEASE CHECK ALL THAT APPLY.**

☐ Limited internet access or speed issues

☐ Limitations in my access to technology (e.g., smartphone, computer, tablet, internet)

☐ Limitations in my access to my data or health information in the electronic health record (EHR) patient-portal

☐ Telemedicine platform not easy to use or did not meet my needs overall

☐ Difficulty in my ability or knowledge to use technology or telemedicine platforms

☐ Lack of awareness and understanding of telehealth offerings from my health system or provider

☐ Lack of awareness and understanding of insurance coverage for telehealth for my health system or provider

☐ Lack of health insurance coverage

☐ Privacy and confidentiality (e.g., privacy in the home or security of the internet connection)

☐ Poor patient-provider communication

☐ Preference for in-person visits
☐ Poor patient-provider engagement
☐ All the above
☐ None

To what extent are you able to receive similar quality of care during telemedicine visits as you do during in-person visits?

○ Fully
○ To a great extent
○ To some extent
○ To a small extent
○ Not at all

PATIENT ACTIVATION

PATIENT ACTIVATION: *Question 4 will ask about your willingness and ability to take independent actions to manage your health and care.*

Please indicate whether you Disagree, Agree, or Neither for the following *statements*.

	Strongly Disagree	Disagree	Neither Disagree nor Agree	Agree	Strongly Agree
When all is said and done, I am the person responsible for taking care of my health	○	○	○	○	○

Taking an active role in my own health care is the most important thing that affects my health	○	○	○	○	○
I know what each of my prescribed medications do	○	○	○	○	○
I am confident that I can tell whether I need to go to the doctor or whether I can take care of a health problem myself	○	○	○	○	○
I am confident that I can tell a doctor concerns I have even when he or she does not ask	○	○	○	○	○
	Strongly Disagree	Disagree	Neither Disagree nor Agree	Agree	Strongly Agree
I am able to maintain (keep up with) lifestyle changes, like eating right or exercising	○	○	○	○	○
I know how to prevent problems with my health	○	○	○	○	○
I am confident I can figure out solutions when new problems arise with my health	○	○	○	○	○

I am confident that I can maintain lifestyle changes, like eating right and exercising, even during times of stress (e.g., COVID-19)	○	○	○	○	○

EXPERIENCE OF A SAFETY PROBLEM

EXPERIENCE OF A SAFETY PROBLEM: *Question 5 will ask about your experiences of any safety problems you may have experienced during any of your telemedicine visits with a healthcare provider during the pandemic.*

Thinking about the healthcare you have received via telemedicine since the beginning of the COVID-19 pandemic (March 2020-Current), do you believe you experienced a problem related to any of the following: **PLEASE MARK NO, YES, or I DO NOT KNOW**

	No	Yes	I do not know
Diagnosis of your problem (e.g., wrong diagnosis)	○	○	○
The **medication prescribed** or given to you via telemedicine? (e.g., receiving a medication that was meant for a different patient or diagnosis)	○	○	○

Vaccines prescribed via telemedicine or administered at your chosen health facility (e.g., receiving a vaccine that you already knew you were allergic to)	○	○	○
Blood tests or other lab tests ordered via telemedicine or performed at your chosen health facility (e.g., the test results being misplaced)	○	○	○
Diagnostic and monitoring procedures other than blood and lab tests **(e.g., biopsy)** ordered via telemedicine or performed at your chosen health facility (e.g., not receiving a procedure when needed)	○	○	○
	No	Yes	I do not know

Patient-provider communication via telemedicine (e.g., not receiving important information about your health issues or healthcare in general)	○	○	○
Provider-Provider Communication and Coordination within your health facility (e.g., important health information was not passed along between providers)	○	○	○
Provider-Provider Communication and Coordination outside of your health facility (e.g., miscommunication between primary provider and specialist)	○	○	○
Appointments (e.g., not getting an appointment when needed)	○	○	○

Health records (e.g., your health records are not available or accessible when needed)	○	○	○

EHR IMPACT ON INEQUITIES

EHR IMPACT ON INEQUITIES: *Questions 6 & 7 ask about your perceptions of the Electronic Health Record's (EHR's) impact on patient activation and overcoming disparities and inequities in healthcare.*

How can the Electronic Health Record (EHR) help patients (especially during times such as COVID-19 and telemedicine) become more active participants in their healthcare journey to decrease bias and disparities in care?

Please provide your response in the space provided below.

How do you believe a patient's access to the EHR, their visit notes, and health information data can impact overcoming biases, disparities, and inequities within healthcare systems?

Please provide your response in the space provided below.

PATIENT DEMOGRAPHIC, HOSPITAL, AND HEALTH SYSTEM CHARACTERISTICS

PATIENT DEMOGRAPHICS AND HEALTH SYSTEM CHARACTERISTICS: The following questions (8-18) ask about your background and characteristics of your health facility or facilities you received care from during the COVID-19 pandemic.

What state do you currently live in? **CHOOSE FROM THE DROPDOWN BOX BELOW.** (Responses are listed by region within the United States)

Did you receive care via telemedicine from any of the following health systems within North Carolina? **PLEASE CHECK ALL THAT APPLY.**

☐ Wake Forest Baptist Medical Center
☐ Novant Health
☐ Atrium Health
☐ Duke Health
☐ UNC Health
☐ WakeMed Health

What is your age?

○ 18-24
○ 25-40
○ 41-56
○ 57-64
○ 65 or older

What is your sex?

○ Male
○ Female
○ Non-binary
○ Other or prefer not to answer

What is your race and ethnicity?

○ White or Caucasian
○ Black or African American
○ American Indian or Alaska Native
○ Asian Indian
○ Asian
○ Native Hawaiian
○ Other or prefer not to answer

Are you of Hispanic, Latinx, or Spanish origin?

○ No
○ Yes
○ Prefer not to answer

What type of health insurance do you have?

○ Private
○ Public
○ Uninsured
○ VA

What is your highest level of education?

○ High school graduate or less
○ Some college or trade school
○ College graduate or more

How would you rate your **overall** health currently?

○ Poor
○ Fair
○ Good
○ Very Good
○ Excellent

How would you rate your **mental or emotional** health currently?

○ Poor
○ Fair
○ Good
○ Very Good
○ Excellent

Please mark if you have currently or in the past been diagnosed with any of the following chronic conditions: **PLEASE CHECK ALL THAT APPLY.**

☐ None

☐ Angina or heart problem
☐ Arthritis
☐ Chronic pain
☐ Depression
☐ Anxiety
☐ Diabetes
☐ Hypertension
☐ Lung disease
☐ Kidney disease
☐ Cancer
☐ High cholesterol
☐ COVID-19

What type of healthcare facility or facilities did you engage with during the COVID-19 pandemic? **PLEASE CHECK ALL THAT APPLY.**

☐ Hospital
☐ Emergency Department
☐ Urgent Care center
☐ Nursing home
☐ Rehabilitation
☐ Hospice
☐ Mental health center
☐ Addiction treatment center
☐ Birth center
☐ Community health center
☐ Private or group practice clinic

END OF SURVEY

WE THANK YOU FOR TAKING THIS SURVEY.

You have reached the end of the survey. If you have questions or concerns about the study, you may contact **Kala Wilson**, via email at kwils154@uncc.edu.
Thank you again for your feedback and for taking the time to complete this survey.
We really appreciate your time, and we will be in contact if you are selected to receive one of the $25 gift cards!

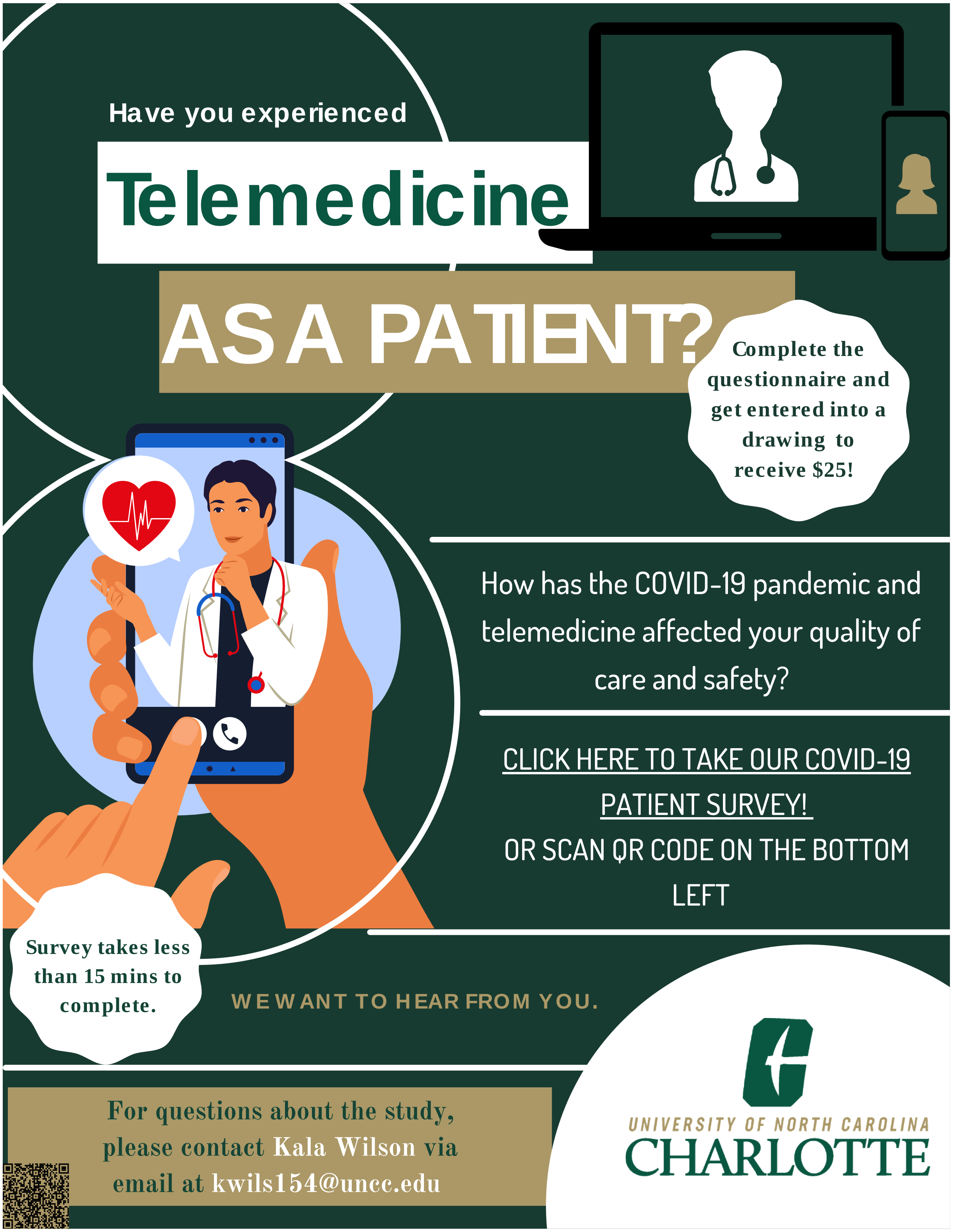
If you are interested in receiving a $25 gift card, please choose Yes or No to enter your email address, 4-digit ID #, and gift card preference.

○ Yes
○ No

Click here to fill out our Gift Card Form!

Powered by Qualtrics

Appendix B2. Patient Recruitment Flyer



Have you experienced

Telemedicine

AS A PATIENT?

Complete the questionnaire and get entered into a drawing to receive $25!

How has the COVID-19 pandemic and telemedicine affected your quality of care and safety?

CLICK HERE TO TAKE OUR COVID-19 PATIENT SURVEY!

OR SCAN QR CODE ON THE BOTTOM LEFT

Survey takes less than 15 mins to complete.

WE WANT TO HEAR FROM YOU.

For questions about the study, please contact Kala Wilson via email at kwils154@uncc.edu

UNIVERSITY OF NORTH CAROLINA
CHARLOTTE

Appendix B3. Patient Draft Recruitment Email

Dear XX,

As you know, the COVID-19 pandemic has affected the lives of everyone in our communities. This survey is being conducted by UNC Charlotte researchers to collect information that will be used to identify the effects of pandemic-induced telemedicine and a patient's activation level on care quality and patient safety to better understand system factors (COVID-19 and increased telemedicine) and health information technology's ability to improve disparities and inequities. For your voluntary participation and time, you will be asked to provide an email address to be included into a drawing to receive one of five $25 gift cards to your choice of either Amazon or Starbucks. If you have questions about the survey, please feel free to contact Kala Wilson at kwils154@uncc.edu, or Michael Dulin at mdulin3@uncc.edu, we would be happy to discuss questions or concerns with you.

For additional information or access to the survey, please click the following link: __________________. You can also click the link or scan the QR code on the informational flyer attached below.

Thank you,

Kala S. Wilson, MPA
University of North Carolina at Charlotte
Doctoral Candidate | PhD in Public Health Sciences
Instructor | HSMT 4400 001 & 002
College of Health and Human Services
9201 University City Blvd. | Charlotte, NC 28223
kwils154@uncc.edu | 614.546.9951

Michael F. Dulin, MD, PhD
University of North Carolina at Charlotte
Professor | Department of Public Health Sciences
Director of the Academy for Population Health Innovation (APHI)
CHHS 341C
9201 University City Blvd. | Charlotte, NC 28223
mdulin3@uncc.edu | 704.687.7899

Appendix B4. Adapted Version of the Patient Activation Measure – 10 (PAM-10)

1. When all is said and done, I am the person who is responsible for taking care of my health.
2. Taking an active role in my own healthcare is the most important thing that affects my health.
3. I know what each of my prescribed medications do.
4. I am confident that I can tell whether I need to go to the doctor or whether I can take care of a health problem myself.
5. I am confident that I can tell a doctor concerns I have even when he or she does not ask.
6. I am confident that I can follow through on medical treatments I may need to do at home.
7. I have been able to maintain (keep up with) lifestyle changes, like eating right or exercising.
8. I know how to prevent problems with my health.
9. I am confident I can figure out solutions when new problems arise with my health.
10. I am confident that I can maintain lifestyle changes, like eating right and exercising, even during times of stress (e.g., COVID-19).

Appendix B5. Adapted Version of the Patient Reported Experiences of Safety – Primary Care (PREOS-PC)

1. Thinking about the healthcare you have received via telemedicine since the beginning of the COVID-19 pandemic (March 2020-Current), do you believe you experienced a problem related to any of the following: Answer Yes, No, or I do not know.

Diagnosis of your problems (e.g., wrong DX)
The medication prescribed or given to you via telemedicine (e.g., receiving a medication that was meant for a different patient)
Vaccines prescribed via telemedicine or administered at your chosen health facility (e.g., receiving a vaccine that you already knew you were allergic to)
Blood tests and other laboratory tests ordered via telemedicine or performed at your chosen health facility (e.g., the test results being misplaced)
Diagnostic and monitoring procedures other than blood and laboratory tests (such as an ear examination, or biopsy, etc.) ordered via telemedicine or performed at your chosen health facility (e.g., not receiving a procedure when needed)
Communication between you and the healthcare professionals via telemedicine in your health facility (e.g., not receiving the information needed about your health problems or healthcare in general)
Communication and co-ordination between the healthcare professionals in your health facility (e.g., important information about your healthcare not being passed between the healthcare professionals)
Communication and co-ordination between professionals in your health facility and other professionals outside of the health facility (e.g., communication missing from primary provider to a specialist)
Your appointments (e.g., not getting an appointment when you needed one)
Your health records (e.g., your health records not being available or accessible when needed)

CHAPTER FIVE. DISCUSSION

MAIN CONCLUSIONS

We examined the impact of the pandemic and subsequent transition to telehealth on 1) clinical EHR data quality and data entry patterns, 2) provider perceptions of the EHR's influence on care delivery, and 3) patient perceptions of barriers related to pandemic-induced telemedicine. We found that an external change to healthcare operations – which modifies clinical practice – is correlated with clinical data entry patterns. Congruent with that, we found marked differences in the macro-processes (e.g., clinical data entry patterns or ordering diagnostic tests), which spanned multiple micro-systems (e.g., having disparate providers and clinical departments) within the healthcare organization. These marked differences aligned with the findings in Chapter 3, indicating that some variability in data recording can be explained by providers from different units – having distinct goals, thus, contributing to patient care and outcomes.

Furthermore, our data showed that clinical data entry is fragmented and exacerbated by complex systematic factors,[58,183–185] and for health systems to leverage the potential of data and technology in healthcare, one must acknowledge the importance and foundational aspect of high-quality clinical documentation and the antecedents influencing those health information patterns and behaviors, such as demographics and other related characteristics at multiple levels.[186–188] To that end, this research demonstrates that although there is an established need to achieve more equitable and standard-based data practices and decision-making in terms of safe, high-quality care delivery; perception disparities were present by providers based on diversity, equity, and inclusion (DEI) efforts, sex, age, race, ethnicity, board certification, and the number of years of experience with the EHR.

Unfortunately, it does not appear that providers' perceptions of the EHR's impact held the same value for care quality as it did patient safety. We uncovered that providers using the EHR and telemedicine were roughly 59 times more likely to report the EHR as beneficial for patient safety (OR=58.78; $p<0.05$), compared to approximately only 18 times more likely for care quality (OR=17.88; $p<0.05$). However, consistent with our findings in the first manuscript and prior literature, we found significant differences in perceptions of the EHR by the type of board certification a provider held. Providers board certified in Endocrinology, Dermatology, Geriatrics, Emergency Medicine, Family Medicine, and Pathology was significantly associated with perceiving the EHR as more beneficial for patient safety than care quality.[189–195] These findings have considerable implications for practice and policy, given that personal, contextual, and technological factors all interrelate and affect perceptions and subsequent adoption and use of digital technologies.[27,88,89,164,196–201]

Despite some of the findings from this comprehensive study indicating that pandemic-induced telemedicine impacts clinical data entry patterns and that most telemedicine providers found the EHR's impact on patient safety as beneficial overall, we found conflicting evidence when assessing patient perceptions of telemedicine barriers and their reported health outcomes. Our findings emphasized prior research indicating that patients continue to experience harm, and processes within the U.S. health system – whether in-person or virtual care – are inefficient and fragmented.[54–56,64–66,202] Policy and systems interventions must address the social and digital determinants of health related to patient safety and quality. As well as understand the patient perspective and other related characteristics to maximize the benefits of data and technology for attaining highly efficient, safe, and equitable care. Our findings highlighted this need, considering that roughly 76% of patients faced at least one telemedicine barrier, and 66% experienced a medical error via telemedicine during the pandemic.

Similarly, we uncovered patients were more likely to experience at least one telemedicine barrier if they utilized the patient-facing EHR (OR=27.72), had an activation level of three (OR=17.37), had been diagnosed with one or two chronic conditions (OR=10.06) and experienced a medical error. These findings suggest that more activated patients are further engaged in their healthcare compared to their counterparts and therefore have increased odds of identifying a barrier.[203–206] Interestingly, patients were less likely to report experiencing a telemedicine barrier if they identified as Black or Female or reported three to four diagnosed chronic conditions (OR=0.10; p<0.001, OR=0.06; p<0.05). These findings align with prior literature indicating the historically pervasive inequities and disparities amongst these subpopulations in healthcare. Black women, women of color, individuals living with multiple chronic conditions, and patients who identify their role and status as subordinate or passive to clinicians are more likely to be less engaged in their healthcare and have a lack of trust in the systems that serve them. [3,16,18,21–23,32,43,75,172,207]

These results, combined, have significant implications for health information technology's design, implementation, and utilization at the systems, provider, and patient levels. Prior research [94,129,208] and policies [41,42,146,209,210] have focused on investing in digital technology and tools to improve the quality, efficiency, safety, and equity of care. However, we find that solely investing in digital transformation without understanding the multidimensional and multilevel interrelationships between people, technology, and their environments, actually creates additional and often unintended inefficiencies in the system. The contributions of this dissertation demonstrate that many distinct elements or agents of a system (e.g., *clinical data entry processes*

(manuscript 1), *provider perceptions* **(manuscript 2),** *patient characteristics* **(manuscript 3),** and *pandemic-induced telemedicine* **(all manuscripts)**) have a hidden order and work with each other to shape the system and its outcomes, as well as how each component within a system changes over time.[100,101] These results suggest that behavioral responses and perceptions of elements related to health systems – in this case, health technology, and data affected by external influences such as COVID-19 – must be ingrained in the fabric of healthcare evaluations and interventions when attempting to improve the efficiency, quality, safety, and equity of care delivery.

FUTURE DIRECTIONS

Our findings underscore the need for further analysis to understand the interactions between the environment, processes, workflows, technological designs, patients, and the core operative nature of the system itself.[211–213] Health administrators, policymakers, and researchers must acknowledge that technology and data can act as a roadblock to achieving health equity throughout this nation’s healthcare systems if human and information technology systems continue to co-exist but not co-evolve concurrently.[25,214] In policy and practice, we must pull back the curtain and recognize the many forms of coded inequity [215] throughout our healthcare systems by becoming more aware of the social dimensions of technology that generate dominant and discriminatory structures encoded in apps, algorithms, and payment data used in health and healthcare, as well as the general architecture of the United States.

GENERAL REFERENCES

1. Bodenheimer T. The Movement for Improved Quality in Health Care. *N Engl J Med*. 1999;340(6):488-492. doi:10.1056/NEJM199902113400621

2. Okoroh JS, Uribe EF, Weingart S. Racial and Ethnic Disparities in Patient Safety. *J Patient Saf*. 2017;13(3):153-161. doi:10.1097/PTS.0000000000000133

3. Gross CP, Essien UR, Pasha S, Gross JR, Wang S yi, Nunez-Smith M. Racial and Ethnic Disparities in Population-Level Covid-19 Mortality. *J Gen Intern Med*. 2020;35(10):3097-3099. doi:10.1007/s11606-020-06081-w

4. Centers for Disease Control and Prevention. Strategies for Reducing Health Disparities 2016 - Minority Health - CDC. Published 2016. Accessed January 8, 2022. https://www.cdc.gov/minorityhealth/strategies2016/index.html

5. Williams DR, Sternthal M. Understanding Racial-ethnic Disparities in Health: Sociological Contributions. *J Health Soc Behav*. 2010;51(1_suppl):S15-S27. doi:10.1177/0022146510383838

6. Manrai AK, Funke BH, Rehm HL, et al. Genetic Misdiagnoses and the Potential for Health Disparities. *N Engl J Med*. 2016;375(7):655-665. doi:10.1056/NEJMsa1507092

7. Piccardi C, Detollenaere J, Vanden Bussche P, Willems S. Social disparities in patient safety in primary care: a systematic review. *Int J Equity Health*. 2018;17(1):114. doi:10.1186/s12939-018-0828-7

8. Mayberry RM, Nicewander DA, Qin H, Ballard DJ. Improving Quality and Reducing Inequities: A Challenge in Achieving Best Care. *Bayl Univ Med Cent Proc*. 2006;19(2):103-118. doi:10.1080/08998280.2006.11928138

9. Mike EV, Laroche D. Preserving Vision in the COVID-19 Pandemic: Focus on Health Equity. *Clin Ophthalmol*. 2020;Volume 14:2073-2077. doi:10.2147/OPTH.S262586

10. O'Kane M, Agrawal S, Anthem, Inc., et al. An Equity Agenda for the Field of Health Care Quality Improvement. *NAM Perspect*. 2021;11(9). doi:10.31478/202109b

11. Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the health of populations. Published online 2019:8.

12. Panch T, Mattie H, Atun R. Artificial intelligence and algorithmic bias: implications for health systems. *J Glob Health*. 2019;9(2):010318. doi:10.7189/jogh.09.020318

13. Wood BR, Young JD, Abdel-Massih RC, et al. Advancing Digital Health Equity: A Policy Paper of the Infectious Diseases Society of America and the HIV Medicine Association. *Clin Infect Dis*. 2021;72(6):913-919. doi:10.1093/cid/ciaa1525

14. Kassamali B, Haddadi NS, Rashighi M, Cavanaugh-Hussey M, LaChance A. Telemedicine and the battle for health equity: Translating temporary regulatory orders into sustained policy change. *J Am Acad Dermatol*. 2020;83(6):e467-e468. doi:10.1016/j.jaad.2020.08.016

15. Veinot TC, Ancker JS, Bakken S. Health informatics and health equity: improving our reach and impact. *J Am Med Inform Assoc*. 2019;26(8-9):689-695. doi:10.1093/jamia/ocz132

16. Shaw J, Brewer LC, Veinot T. Recommendations for Health Equity and Virtual Care Arising From the COVID-19 Pandemic: Narrative Review. *JMIR Form Res*. 2021;5(4):e23233. doi:10.2196/23233

17. Veinot TC, Mitchell H, Ancker JS. Good intentions are not enough: how informatics interventions can worsen inequality. *J Am Med Inform Assoc*. 2018;25(8):1080-1088. doi:10.1093/jamia/ocy052

18. Röösli E, Rice B, Hernandez-Boussard T. Bias at warp speed: how AI may contribute to the disparities gap in the time of COVID-19. *J Am Med Inform Assoc*. 2021;28(1):190-192. doi:10.1093/jamia/ocaa210

19. Gianfrancesco MA, Tamang S, Yazdany J, Schmajuk G. Potential Biases in Machine Learning Algorithms Using Electronic Health Record Data. *JAMA Intern Med*. 2018;178(11):1544. doi:10.1001/jamainternmed.2018.3763

20. Khairat S, Haithcoat T, Liu S, et al. Advancing health equity and access using telemedicine: a geospatial assessment. *J Am Med Inform Assoc JAMIA*. 2019;26(8-9):796-805. doi:10.1093/jamia/ocz108

21. Brewer LC, Fortuna KL, Jones C, et al. Back to the Future: Achieving Health Equity Through Health Informatics and Digital Health. *JMIR MHealth UHealth*. 2020;8(1):e14512. doi:10.2196/14512

22. Crawford A, Serhal E. Digital Health Equity and COVID-19: The Innovation Curve Cannot Reinforce the Social Gradient of Health. *J Med Internet Res*. 2020;22(6):e19361. doi:10.2196/19361

23. Nouri S, Khoong EC, Lyles CR, Karliner L. Addressing Equity in Telemedicine for Chronic Disease Management During the Covid-19 Pandemic. Published online 2020:13.

24. Blagev DP, Barton N, Grissom CK, McKee KE, Harrison AM. On the Journey Toward Health Equity: Data, Culture Change, and the First Step. *NEJM Catal*. 2021;2(7):CAT.21.0118. doi:10.1056/CAT.21.0118

25. Carney TJ, Kong AY. Leveraging health informatics to foster a smart systems response to health disparities and health equity challenges. *J Biomed Inform*. 2017;68:184-189. doi:10.1016/j.jbi.2017.02.011

26. Cruz TM. Perils of data-driven equity: Safety-net care and big data's elusive grasp on health inequality. *Big Data Soc*. 2020;7(1):205395172092809. doi:10.1177/2053951720928097

27. Cruz TM, Smith SA. Health Equity Beyond Data: Health Care Worker Perceptions of Race, Ethnicity, and Language Data Collection in Electronic Health Records. *Med Care*. 2021;59(5):379-385. doi:10.1097/MLR.0000000000001507

28. Ortega G, Rodriguez JA, Maurer LR, et al. Telemedicine, COVID-19, and disparities: Policy implications. *Health Policy Technol*. 2020;9(3):368-371. doi:10.1016/j.hlpt.2020.08.001

29. Saeed SA, Masters RM. Disparities in Health Care and the Digital Divide. *Curr Psychiatry Rep*. 2021;23(9):61. doi:10.1007/s11920-021-01274-4

30. Zhang X, Hailu B, Tabor DC, et al. Role of Health Information Technology in Addressing Health Disparities: Patient, Clinician, and System Perspectives. *Med Care*. 2019;57(Suppl 2):S115-S120. doi:10.1097/MLR.0000000000001092

31. Institute of Medicine (IOM). *Crossing the Quality Chasm: A New Health System for the 21st Century*. National Academies Press; 2001:10027. doi:10.17226/10027

32. Institute of Medicine (IOM). *Unequal Treatment: Confronting Racial and Ethnic Disparities in Health Care (with CD)*. National Academies Press; 2003:12875. doi:10.17226/12875

33. Niland JC, Rouse L, Stahl DC. An Informatics Blueprint for Healthcare Quality Information Systems. *J Am Med Inform Assoc*. 2006;13(4):402-417. doi:10.1197/jamia.M2050

34. Otokiti A. Using informatics to improve healthcare quality. *Int J Health Care Qual Assur*. 2019;32(2):425-430. doi:10.1108/IJHCQA-03-2018-0062

35. Sarkar IN. Biomedical informatics and translational medicine. *J Transl Med*. 2010;8(1):22. doi:10.1186/1479-5876-8-22

36. Bernstam EV, Smith JW, Johnson TR. What is biomedical informatics? *J Biomed Inform*. 2010;43(1):104-110. doi:10.1016/j.jbi.2009.08.006

37. Kulikowski CA. Introducing Kuhn et al.'s Paper"Informatics and Medicine: From Molecules to Populations" and Invited Papers on this Special Topic. *Methods Inf Med*. 2008;47(04):279-282. doi:10.1055/s-0038-1627412

38. Sethi N. The Promotion of Data Sharing in Pharmacoepidemiology. *Eur J Health Law*. 2014;21(3):271-296. doi:10.1163/15718093-12341323

39. Bourke A, Dixon WG, Roddam A, et al. Incorporating patient generated health data into pharmacoepidemiological research. *Pharmacoepidemiol Drug Saf*. 2020;29(12):1540-1549. doi:10.1002/pds.5169

40. Biddle S, Milstead JA. The intersection of policy and informatics. *Nurs Manag (Harrow)*. 2016;47(2):12-13. doi:10.1097/01.NUMA.0000479453.73651.89

41. Kosseim P, Brady M. POLICY BY PROCRASTINATION: SECONDARY USE OF ELECTRONIC HEALTH RECORDS FOR HEALTH RESEARCH PURPOSES. 2008;2:41.

42. Bell K. Public Policy and Health Informatics. *Semin Oncol Nurs*. 2018;34(2):184-187. doi:10.1016/j.soncn.2018.03.010

43. Ye J. The Role of Health Technology and Informatics in a Global Public Health Emergency: Practices and Implications From the COVID-19 Pandemic. *JMIR Med Inform*. 2020;8(7):e19866. doi:10.2196/19866

44. Public Health Informatics Institute [PHII]. Defining Public Health Informatics. Published 2020. Accessed June 1, 2021. https://www.phii.org/defining-public-health-informatics

45. Burde H. THE HITECH ACT—An Overview. *AMA J Ethics*. 2011;13(3):172-175. doi:10.1001/virtualmentor.2011.13.3.hlaw1-1103

46. Chukwudi EC. Medical Errors / Patient Safety: Hospital Medication Errors Pre- & Post-Electronic Health Records (EHR) / Meaningful Use Act. Published online 2019.

47. Maryska M, Wagner J. REFERENCE MODEL OF BUSINESS INFORMATICS ECONOMICS MANAGEMENT. *J Bus Econ Manag*. 2013;16(3):621-637. doi:10.3846/16111699.2013.789449

48. Liu K, Li W. *Organisational Semiotics for Business Informatics*. 0 ed. Routledge; 2014. doi:10.4324/9780203550977

49. Beattie M, Murphy DJ, Atherton I, Lauder W. Instruments to measure patient experience of healthcare quality in hospitals: a systematic review. *Syst Rev*. 2015;4(1):97. doi:10.1186/s13643-015-0089-0

50. CMS. HCAHPS: Patients’ Perspectives of Care Survey | CMS. Published 2021. Accessed December 14, 2021. https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/HospitalQualityInits/HospitalHCAHPS

51. Alrubaiee L, Alkaa’ida F. The Mediating Effect of Patient Satisfaction in the Patients’ Perceptions of Healthcare Quality – Patient Trust Relationship. *Int J Mark Stud*. 2011;3(1):p103. doi:10.5539/ijms.v3n1p103

52. Landi H. CMS Transitioning to New Health IT Standard for Reporting eCQMs. Healthcare Innovation. Published November 1, 2017. Accessed September 2, 2022.

https://www.hcinnovationgroup.com/policy-value-based-care/news/13029385/cms-transitioning-to-new-health-it-standard-for-reporting-ecqms

53. Lind DP, Andresen DR, Williams A. Medical Errors in Iowa: Prevalence and Patients' Perspectives. *J Patient Saf*. 2020;16(3):e199-e204. doi:10.1097/PTS.0000000000000523

54. James JT. A new, evidence-based estimate of patient harms associated with hospital care. *J Patient Saf*. 2013;9(3):122-128. doi:10.1097/PTS.0b013e3182948a69

55. Bates DW, Singh H. Two decades since to err is human: An assessment of progress and emerging priorities in patient safety. *Health Aff (Millwood)*. 2018;37(11):1736-1743. doi:10.1377/hlthaff.2018.0738

56. Pestonik S, Lemon V. Improving Patient Safety—Why Data Matters. Health Catalyst. Published April 30, 2019. Accessed May 24, 2021. https://www.healthcatalyst.com/insights/use-data-improve-patient-safety/

57. Kreuzthaler M, Schulz S, Berghold A. Secondary use of electronic health records for building cohort studies through top-down information extraction. *J Biomed Inform*. 2015;53:188-195. doi:10.1016/j.jbi.2014.10.010

58. Gold R, Cottrell E, Bunce A, et al. Developing Electronic Health Record (EHR) Strategies Related to Health Center Patients' Social Determinants of Health. *J Am Board Fam Med*. 2017;30(4):428-447. doi:10.3122/jabfm.2017.04.170046

59. Ommaya AK, Cipriano PF, Hoyt DB, et al. Care-Centered Clinical Documentation in the Digital Environment: Solutions to Alleviate Burnout. *NAM Perspect*. Published online January 29, 2018. doi:10.31478/201801c

60. Combs T. The Importance of High-Quality Clinical Documentation Across the Healthcare Continuum | Journal Of AHIMA. Published April 1, 2020. Accessed May 4, 2021. https://journal.ahima.org/the-importance-of-high-quality-clinical-documentation-across-the-healthcare-continuum/

61. Shah SM, Khan RA. Secondary Use of Electronic Health Record: Opportunities and Challenges. *ArXiv200109479 Cs*. Published online January 26, 2020. doi:10.1109/ACCESS.2020.3011099

62. Botsis T, Hartvigsen G, Chen F, Weng C. Secondary Use of EHR: Data Quality Issues and Informatics Opportunities. *AMIA Summits Transl Sci Proc*. 2010;2010:1.

63. King D, Zaman S, Zaman SS, et al. Identifying Quality Indicators Used by Patients to Choose Secondary Health Care Providers: A Mixed Methods Approach. *JMIR MHealth UHealth*. 2015;3(2):e65-e65. doi:10.2196/mhealth.3808

64. Carayon P. Human factors of complex sociotechnical systems. *Appl Ergon*. 2006;37(4):525-535. doi:10.1016/j.apergo.2006.04.011

65. Carayon P, Bass EJ, Bellandi T, Gurses AP, Hallbeck MS, Mollo V. Sociotechnical systems analysis in health care: a research agenda. *IIE Trans Healthc Syst Eng*. 2011;1(3):145-160. doi:10.1080/19488300.2011.619158

66. Carayon P. Sociotechnical systems approach to healthcare quality and patient safety. *Work*. 2012;41:3850-3854. doi:10.3233/WOR-2012-0091-3850

67. Tinker A. The Top 7 Healthcare Outcomes Measures and Three Measurement Essentials. Published 2018. Accessed December 14, 2021. https://www.healthcatalyst.com/insights/top-7-healthcare-outcome-measures/

68. Köpcke F, Prokosch HU. Employing Computers for the Recruitment into Clinical Trials: A Comprehensive Systematic Review. *J Med Internet Res*. 2014;16(7). doi:10.2196/jmir.3446

69. Moskowitz A, Chen K. Defining the Patient Cohort. In: *Secondary Analysis of Electronic Health Records*. Springer International Publishing; 2016:93-100. doi:10.1007/978-3-319-43742-2_10

70. Shivade C, Raghavan P, Fosler-Lussier E, et al. A review of approaches to identifying patient phenotype cohorts using electronic health records. *J Am Med Inform Assoc*. 2014;21(2):221-230. doi:10.1136/amiajnl-2013-001935

71. Farzandipour M, Sheikhtaheri A, Sadoughi F. Effective factors on accuracy of principal diagnosis coding based on International Classification of Diseases, the 10th revision (ICD-10). *Int J Inf Manag*. 2010;30(1):78-84. doi:10.1016/j.ijinfomgt.2009.07.002

72. McDonald CJ, Huff SM, Suico JG, et al. LOINC, a Universal Standard for Identifying Laboratory Observations: A 5-Year Update. *Clin Chem*. 2003;49(4):624-633. doi:10.1373/49.4.624

73. O’Malley KJ, Cook KF, Price MD, Wildes KR, Hurdle JF, Ashton CM. Measuring Diagnoses: ICD Code Accuracy. *Health Serv Res*. 2005;40(5p2):1620-1639. doi:10.1111/j.1475-6773.2005.00444.x

74. Hsia DC, Krushat WM, Fagan AB, Tebbutt JA, Kusserow RP. Accuracy of Diagnostic Coding for Medicare Patients under the Prospective-Payment System. http://dx.doi.org/10.1056/NEJM198802113180604. doi:10.1056/NEJM198802113180604

75. Dagliati A, Malovini A, Tibollo V, Bellazzi R. Health informatics and EHR to support clinical research in the COVID-19 pandemic: an overview. *Brief Bioinform*. 2021;22(2):812-822. doi:10.1093/bib/bbaa418

76. Graber ML, Siegal D, Riah H, Johnston D, Kenyon K. Electronic Health Record–Related Events in Medical Malpractice Claims. 2019;15(2):9.

77. Singh H, Graber ML, Hofer TP. Measures to Improve Diagnostic Safety in Clinical Practice. *J Patient Saf*. 2019;15(4):311-316. doi:10.1097/PTS.0000000000000338

78. Giardina TD, Haskell H, Menon S, et al. Learning From Patients' Experiences Related To Diagnostic Errors Is Essential For Progress In Patient Safety. *Health Aff (Millwood)*. 2018;37(11):1821-1827. doi:10.1377/hlthaff.2018.0698

79. Nazi KM, Turvey CL, Klein DM, Hogan TP, Woods SS. VA OpenNotes: exploring the experiences of early patient adopters with access to clinical notes. *J Am Med Inform Assoc*. 2015;22(2):380-389. doi:10.1136/amiajnl-2014-003144

80. Bourgeois FC, Fossa A, Gerard M, et al. A patient and family reporting system for perceived ambulatory note mistakes: experience at 3 U.S. healthcare centers. *J Am Med Inform Assoc*. 2019;26(12):1566-1573. doi:10.1093/jamia/ocz142

81. Bell SK, Mejilla R, Anselmo M, et al. When doctors share visit notes with patients: a study of patient and doctor perceptions of documentation errors, safety opportunities and the patient–doctor relationship. *BMJ Qual Saf*. 2017;26(4):262-270. doi:10.1136/bmjqs-2015-004697

82. Bates DW, Singh H. Two Decades Since *To Err Is Human* : An Assessment Of Progress And Emerging Priorities In Patient Safety. *Health Aff (Millwood)*. 2018;37(11):1736-1743. doi:10.1377/hlthaff.2018.0738

83. Casey JA, Schwartz BS, Stewart WF, Adler NE. Using Electronic Health Records for Population Health Research: A Review of Methods and Applications. *Annu Rev Public Health*. 2016;37:61-81. doi:10.1146/annurev-publhealth-032315-021353

84. Lluch M. Healthcare professionals' organisational barriers to health information technologies—A literature review. *Int J Med Inf*. 2011;80(12):849-862. doi:10.1016/j.ijmedinf.2011.09.005

85. Menachemi N, Shin DY, Ford EW, Yu F. Environmental factors and health information technology management strategy. *Health Care Manage Rev*. 2011;36(3):275-285. doi:10.1097/HMR.0b013e3182048e7e

86. López L, Green AR, Tan-McGrory A, King RS, Betancourt JR. Bridging the Digital Divide in Health Care: The Role of Health Information Technology in Addressing Racial and Ethnic Disparities. *Jt Comm J Qual Patient Saf*. 2011;37(10):437-445. doi:10.1016/S1553-7250(11)37055-9

87. Joy M, Clement T, Sisti D. The Ethics of Behavioral Health Information Technology: Frequent Flyer Icons and Implicit Bias. *JAMA*. 2016;316(15):1539. doi:10.1001/jama.2016.12534

88. Connolly SL, Gifford AL, Miller CJ, Bauer MS, Lehmann LS, Charness ME. Provider Perceptions of Virtual Care During the Coronavirus Disease 2019 Pandemic: A Multispecialty Survey Study. *Med Care*. 2021;59(7):646-652. doi:10.1097/MLR.0000000000001562

89. Gumma J, Klimowich K, Pan J, Collins P, Cooley D. Physician perceptions of stress and telemedicine. *Osteopath Fam Physician*. Published online November 1, 2021:9-16. doi:10.33181/13053

90. Schinasi DA, Foster CC, Bohling MK, Barrera L, Macy ML. Attitudes and Perceptions of Telemedicine in Response to the COVID-19 Pandemic: A Survey of Naïve Healthcare Providers. *Front Pediatr*. 2021;9:647937. doi:10.3389/fped.2021.647937

91. Heeringa J, Mutti A, Furukawa MF, Lechner A, Maurer KA, Rich E. Horizontal and Vertical Integration of Health Care Providers: A Framework for Understanding Various Provider Organizational Structures. *Int J Integr Care*. 2020;20(1):2. doi:10.5334/ijic.4635

92. Forsyth R, Maddock CA, Iedema RAM, Lassere M. Patient perceptions of carrying their own health information: approaches towards responsibility and playing an active role in their own health - implications for a patient-held health file: Patient perceptions of carrying their own health information. *Health Expect*. 2010;13(4):416-426. doi:10.1111/j.1369-7625.2010.00593.x

93. Dontje K, Corser WD, Holzman G. Understanding Patient Perceptions of the Electronic Personal Health Record. *J Nurse Pract*. 2014;10(10):824-828. doi:10.1016/j.nurpra.2014.09.009

94. Nguyen M, Waller M, Pandya A, Portnoy J. A Review of Patient and Provider Satisfaction with Telemedicine. *Curr Allergy Asthma Rep*. 2020;20(11):72. doi:10.1007/s11882-020-00969-7

95. Freed CR, Hansberry ST, Arrieta MI. STRUCTURAL AND HIDDEN BARRIERS TO A LOCAL PRIMARY HEALTH CARE INFRASTRUCTURE: AUTONOMY, DECISIONS ABOUT PRIMARY HEALTH CARE, AND THE CENTRALITY AND SIGNIFICANCE OF POWER. *Res Sociol Health Care*. 2013;31:57-81. doi:10.1108/S0275-4959(2013)0000031006

96. Hausmann LRM, Hannon MJ, Kresevic DM, Hanusa BH, Kwoh CK, Ibrahim SA. Impact of perceived discrimination in healthcare on patient-provider communication. *Med Care*. 2011;49(7):626-633. doi:10.1097/MLR.0b013e318215d93c

97. Nong P, Raj M, Creary M, Kardia SLR, Platt JE. Patient-Reported Experiences of Discrimination in the US Health Care System. *JAMA Netw Open*. 2020;3(12):e2029650. doi:10.1001/jamanetworkopen.2020.29650

98. Chandrashekar P, Jain SH. Addressing Patient Bias and Discrimination Against Clinicians of Diverse Backgrounds. *Acad Med*. 2020;95(12S):S33-S43. doi:10.1097/ACM.0000000000003682

99. Rivenbark JG, Ichou M. Discrimination in healthcare as a barrier to care: experiences of socially disadvantaged populations in France from a nationally representative survey. *BMC Public Health*. 2020;20(1):31. doi:10.1186/s12889-019-8124-z

100. Ferreira S. Sociological Observations of the Third Sector Through Systems Theory: An Analytical Proposal. *Volunt Int J Volunt Nonprofit Organ*. 2014;25(6):1671-1693. doi:10.1007/s11266-014-9469-7

101. Render J. What is Complexity Theory and How Can it Improve the Workplace? – Agile-Mercurial. Published 2019. Accessed May 4, 2021. https://agile-mercurial.com/2019/05/13/what-is-complexity-theory-and-how-can-it-improve-the-workplace/

102. Semenov I, Osenev R, Gerasimov S, Kopanitsa G, Denisov D, Andreychuk Y. Experience in Developing an FHIR Medical Data Management Platform to Provide Clinical Decision Support. *Int J Environ Res Public Health*. 2019;17(1):E73. doi:10.3390/ijerph17010073

103. Hohnloser JH, Fischer MRG, König A, Emmerich B. Data quality in computerized patient records: Analysis of a haematology biopsy report database. *Int J Clin Monit Comput*. 1994;11(4):233-240. doi:10.1007/BF01139875

104. Weiner MG. Toward Reuse of Clinical Data for Research and Quality Improvement: The End of the Beginning? *Ann Intern Med*. 2009;151(5):359. doi:10.7326/0003-4819-151-5-200909010-00141

105. Food and Drug Administration (FDA). Use of Electronic Health Record Data in Clinical Investigations Guidance for Industry. Published online 2018:15.

106. Weiskopf NG, Weng C. Methods and dimensions of electronic health record data quality assessment: enabling reuse for clinical research. *J Am Med Inform Assoc*. 2013;20(1):144-151. doi:10.1136/amiajnl-2011-000681

107. Beres LK, Simbeza S, Holmes CB, et al. Human-Centered Design Lessons for Implementation Science: Improving the Implementation of a Patient-Centered Care Intervention. *J Acquir Immune Defic Syndr 1999*. 2019;82 Suppl 3:S230-S243. doi:10.1097/QAI.0000000000002216

108. Wulff A, Mast M, Hassler M, Montag S, Marschollek M, Jack T. Designing an openEHR-Based Pipeline for Extracting and Standardizing Unstructured Clinical Data Using Natural Language Processing. *Methods Inf Med*. 2020;59(S 02):e64-e78. doi:10.1055/s-0040-1716403

109. Braveman PA, Arkin E, Proctor D, Kauh T, Holm N. Systemic And Structural Racism: Definitions, Examples, Health Damages, And Approaches To Dismantling: Study examines definitions, examples, health damages, and dismantling systemic and structural racism. *Health Aff (Millwood)*. 2022;41(2):171-178. doi:10.1377/hlthaff.2021.01394

110. Krieger N, Van Wye G, Huynh M, et al. Structural Racism, Historical Redlining, and Risk of Preterm Birth in New York City, 2013–2017. *Am J Public Health*. 2020;110(7):1046-1053. doi:10.2105/AJPH.2020.305656

111. Zambrana RE, Williams DR. The Intellectual Roots Of Current Knowledge On Racism And Health: Relevance To Policy And The National Equity Discourse: Article examines the roots of current knowledge on racism and health and relevance to policy and the national equity discourse. *Health Aff (Millwood)*. 2022;41(2):163-170. doi:10.1377/hlthaff.2021.01439

112. Knight HE, Deeny SR, Dreyer K, et al. Challenging racism in the use of health data. *Lancet Digit Health*. 2021;3(3):e144-e146. doi:10.1016/S2589-7500(21)00019-4

113. Yearby R, Clark B, Figueroa JF. Structural Racism In Historical And Modern US Health Care Policy: Study examines structural racism in historical and modern US health care policy. *Health Aff (Millwood)*. 2022;41(2):187-194. doi:10.1377/hlthaff.2021.01466

114. Berwick D, Fox DM. "Evaluating the Quality of Medical Care": Donabedian's Classic Article 50 Years Later: "Evaluating the Quality of Medical Care." *Milbank Q*. 2016;94(2):237-241. doi:10.1111/1468-0009.12189

115. Best M. Avedis Donabedian: father of quality assurance and poet. *Qual Saf Health Care*. 2004;13(6):472-473. doi:10.1136/qshc.2004.012591

116. Donabedian A. Evaluating the Quality of Medical Care. 1965;44(3):166-206.

117. Donabedian A. The Seven Pillars of Quality. In: Vol 114. ; 1990.

118. Mullan F. A Founder of Quality Assessment Encounters A Troubled System Firsthand. *Health Aff (Millwood)*. 2001;20(1):137-141. doi:10.1377/hlthaff.20.1.137

119. Carlile S, Sefton AJ. Healthcare and the information age: implications for medical education. *Med J Aust*. 1998;168(7):340-343. doi:10.5694/j.1326-5377.1998.tb138963.x

120. Yasnoff WA, O'Carroll PW, Koo D, Linkins RW, Kilbourne EM. Public Health Informatics: Improving and Transforming Public Health in the Information Age: *J Public Health Manag Pract*. 2000;6(6):67-75. doi:10.1097/00124784-200006060-00010

121. Jacobs W, Amuta AO, Jeon KC. Health information seeking in the digital age: An analysis of health information seeking behavior among US adults. Alvares C, ed. *Cogent Soc Sci*. 2017;3(1):1302785. doi:10.1080/23311886.2017.1302785

122. Lambert SD, Loiselle CG. Health Information—Seeking Behavior. *Qual Health Res*. 2007;17(8):1006-1019. doi:10.1177/1049732307305199

123. Percheski C, Hargittai E. Health Information-Seeking in the Digital Age. *J Am Coll Health*. 2011;59(5):379-386. doi:10.1080/07448481.2010.513406

124. Martin CM. Complex adaptive systems approaches in health care—A slow but real emergence? *J Eval Clin Pract*. 2018;24(1):266-268. doi:10.1111/jep.12878

125. AHRQ A for HR and Q. Six Domains of Health Care Quality. Published 2018. Accessed December 14, 2021. https://www.ahrq.gov/talkingquality/measures/six-domains.html

126. Singh H, Sittig DF. Measuring and improving patient safety through health information technology: The Health IT Safety Framework. Published online 2002:7.

127. Baxter G, Sommerville I. Socio-technical systems: From design methods to systems engineering. *Interact Comput*. 2011;23(1):4-17. doi:10.1016/j.intcom.2010.07.003

128. Park YR, Lee Y, Kim JY, et al. Managing Patient-Generated Health Data Through Mobile Personal Health Records: Analysis of Usage Data. *JMIR MHealth UHealth*. 2018;6(4):e89-e89. doi:10.2196/mhealth.9620

129. Lomotan E. *Advancing Evidence into Practice Through Shareable Clinical Decision Support*.; 2019.

130. Barken TL, Thygesen E, Soderhamn U. Advancing beyond the system: telemedicine nurses' clinical reasoning using a computerised decision support system for patients with COPD - an ethnographic study. *BMC Med Inform Decis Mak*. 2017;17(1):181-181. doi:10.1186/s12911-017-0573-7

131. Bascom E. Survey: Clinicians' perceptions of telehealth vary based on specialty. Published 2022. Accessed August 3, 2022. https://www.healio.com/news/primary-care/20220610/survey-clinicians-perceptions-of-telehealth-vary-based-on-specialty

132. Raths D. Emory Healthcare Takes Data-Driven Approach to Improving Patient Portal. *Healthc Innov Website*. Published online 2020. https://www.hcinnovationgroup.com/clinical-it/patient-portals/article/21122984/emory-healthcare-takes-datadriven-approach-to-improving-patient-portal

133. Van den Bulck SA, Hermens R, Slegers K, Vandenberghe B, Goderis G, Vankrunkelsven P. Designing a Patient Portal for Patient-Centered Care: Cross-Sectional Survey. *J Med Internet Res*. 2018;20(10):e269-e269. doi:10.2196/jmir.9497

134. Kruse CS, Beane A. Health Information Technology Continues to Show Positive Effect on Medical Outcomes: Systematic Review. *J Med Internet Res*. 2018;20(2):e41. doi:10.2196/jmir.8793

135. Leslie D, Mazumder A, Peppin A, Wolters MK, Hagerty A. Does "AI" stand for augmenting inequality in the era of covid-19 healthcare? *BMJ*. Published online March 15, 2021:n304. doi:10.1136/bmj.n304

136. Wang CJ, Ng CY, Brook RH. Response to COVID-19 in Taiwan: Big Data Analytics, New Technology, and Proactive Testing. *JAMA*. 2020;323(14):1341. doi:10.1001/jama.2020.3151

137. Di Ciaula A. Towards 5G communication systems: Are there health implications? *Int J Hyg Environ Health*. 2018;221(3):367-375. doi:10.1016/j.ijheh.2018.01.011

138. Ekong I, Chukwu E, Chukwu M. COVID-19 Mobile Positioning Data Contact Tracing and Patient Privacy Regulations: Exploratory Search of Global Response Strategies and the Use of Digital Tools in Nigeria. *JMIR MHealth UHealth*. 2020;8(4):e19139. doi:10.2196/19139

139. Cho H, Ippolito D, Yu YW. Contact Tracing Mobile Apps for COVID-19: Privacy Considerations and Related Trade-offs. *ArXiv200311511 Cs*. Published online March 30, 2020. Accessed January 6, 2022. http://arxiv.org/abs/2003.11511

140. Dorsey ER, Topol EJ. State of Telehealth. Campion EW, ed. *N Engl J Med*. 2016;375(2):154-161. doi:10.1056/NEJMra1601705

141. Tuckson RV, Edmunds M, Hodgkins ML. Telehealth. *N Engl J Med*. 2017;377(16):1585-1592. doi:10.1056/NEJMsr1503323

142. Hong Z, Li N, Li D, et al. Telemedicine During the COVID-19 Pandemic: Experiences From Western China. *J Med Internet Res*. 2020;22(5):e19577. doi:10.2196/19577

143. Wootton R. Recent advances: Telemedicine. *BMJ*. 2001;323(7312):557-560. doi:10.1136/bmj.323.7312.557

144. Vest JR, Gamm LD. Health information exchange: persistent challenges and new strategies: Table 1. *J Am Med Inform Assoc*. 2010;17(3):288-294. doi:10.1136/jamia.2010.003673

145. Vest JR, Kern LM, Campion TR, Silver MD, Kaushal R. Association between use of a health information exchange system and hospital admissions. *Appl Clin Inform*. 2014;05(01):219-231. doi:10.4338/ACI-2013-10-RA-0083

146. Basch P, Smith JRL. CMS Payment Policy, E&M Guideline Reform, and the Prospect of Electronic Health Record Optimization. *Appl Clin Inform*. 2018;9(4):914-918. doi:10.1055/s-0038-1676337

147. Ash JS, Berg M, Coiera E. Some Unintended Consequences of Information Technology in Health Care: The Nature of Patient Care Information System-related Errors. 2004;11(2):9.

148. Kent J. Poor Data Quality, Weak Algorithms Lead to Patient Matching Issues. HealthITAnalytics. Published 2020. Accessed January 8, 2022. https://healthitanalytics.com/news/poor-data-quality-weak-algorithms-lead-to-patient-matching-issues

149. Rowlands S, Coverdale S, Callen J. Documentation of clinical care in hospital patients' medical records: A qualitative study of medical students' perspectives on clinical documentation education. *Health Inf Manag J*. 2016;45(3):99-106. doi:10.1177/1833358316639448

150. Jamal WA, Grant C, Myrick K. An essential guide to clinical documentation improvement. Published online 2018:12.

151. Myrick K. Using Clinical Documentation Improvement to Improve Patient Care. *Insights Essays*. Published online February 25, 2019. Accessed May 4, 2021. https://www.longwoods.com/content/25772/using-clinical-documentation-improvement-to-improve-patient-care

152. Soto CM, Kleinman KP, Simon SR. Quality and correlates of medical record documentation in the ambulatory care setting. *BMC Health Serv Res*. 2002;2(1):22. doi:10.1186/1472-6963-2-22

153. Butler TJ, Firestone KS, Grow JL, Kantak AD. Standardizing documentation and the clinical approach to apnea of prematurity reduces length of stay, improves staff satisfaction, and decreases hospital cost. *Jt Comm J Qual Patient Saf*. 2014;40(6):263-269. doi:10.1016/s1553-7250(14)40035-7

154. Bradford A, Kunik ME, Schulz P, Williams SP, Singh H. Missed and Delayed Diagnosis of Dementia in Primary Care: Prevalence and Contributing Factors. *Alzheimer Dis Assoc Disord*. 2009;23(4):306-314. doi:10.1097/WAD.0b013e3181a6bebc

155. Meigs SL, Solomon M. Electronic Health Record Use a Bitter Pill for Many Physicians. *Perspect Health Inf Manag*. 2016;13:1d.

156. Savel RH. Research: Enhancing the Quality of Documentation. Published 2018. Accessed May 4, 2021. https://www.physicianleaders.org/news/research-enhancing-quality-of-documentation

157. Hartel MJ, Staub LP, Röder C, Eggli S. High incidence of medication documentation errors in a Swiss university hospital due to the handwritten prescription process. *BMC Health Serv Res*. 2011;11(1):199. doi:10.1186/1472-6963-11-199

158. Fassett WE. Patient Safety and Quality Improvement Act of 2005. *Ann Pharmacother*. 2006;40(5):917-924. doi:10.1345/aph.1G485

159. Bates DW, Levine D, Syrowatka A, et al. The potential of artificial intelligence to improve patient safety: a scoping review. *Npj Digit Med*. 2021;4(1):54. doi:10.1038/s41746-021-00423-6

160. Sivashanker K, Gandhi TK. Advancing Safety and Equity Together. *N Engl J Med*. 2020;382(4):301-303. doi:10.1056/NEJMp1911700

161. Eberly LA, Khatana SAM, Nathan AS, et al. Telemedicine Outpatient Cardiovascular Care During the COVID-19 Pandemic: Bridging or Opening the Digital Divide? *Circulation*. 2020;142(5):510-512. doi:10.1161/CIRCULATIONAHA.120.048185

162. Centers for Disease Control and Prevention. National Center for Chronic Disease Prevention and Health Promotion (NCCDPHP). Health Equity. Published 2020. https://www.cdc.gov/chronicdisease/healthequity/index.htm

163. Bickler PE, Feiner JR, Severinghaus JW. Effects of Skin Pigmentation on Pulse Oximeter Accuracy at Low Saturation. *Anesthesiology*. 2005;102(4):715-719. doi:10.1097/00000542-200504000-00004

164. van Ryn M, Burke J. The effect of patient race and socio-economic status on physicians' perceptions of patients. *Soc Sci Med*. 2000;50(6):813-828. doi:10.1016/S0277-9536(99)00338-X

165. Afzal N, Mallipeddi VP, Sohn S, et al. Natural language processing of clinical notes for identification of critical limb ischemia. *Int J Med Inf*. 2018;111:83-89. doi:10.1016/j.ijmedinf.2017.12.024

166. Lopez-Jimenez F, Attia Z, Arruda-Olson AM, et al. Artificial Intelligence in Cardiology: Present and Future. *Mayo Clin Proc*. 2020;95(5):1015-1039. doi:10.1016/j.mayocp.2020.01.038

167. Pons E, Braun LMM, Hunink MGM, Kors JA. Natural Language Processing in Radiology: A Systematic Review. *Radiology*. 2016;279(2):329-343. doi:10.1148/radiol.16142770

168. Popejoy AB, Ritter DI, Crooks K, et al. The clinical imperative for inclusivity: Race, ethnicity, and ancestry (REA) in genomics. *Hum Mutat*. 2018;39(11):1713-1720. doi:10.1002/humu.23644

169. Zou J, Schiebinger L. Ensuring that biomedical AI benefits diverse populations. *EBioMedicine*. 2021;67:103358. doi:10.1016/j.ebiom.2021.103358

170. Benjamin R. *Race after Technology: Abolitionist Tools for the New Jim Code*. John Wiley & Sons; 2019.

171. Hinton E. *From the War on Poverty to the War on Crime: The Making of Mass Incarceration in America*. Harvard University Press; 2016. doi:10.4159/9780674969223

172. Davies AR, Honeyman M, Gann B. Addressing the Digital Inverse Care Law in the Time of COVID-19: Potential for Digital Technology to Exacerbate or Mitigate Health Inequalities. *J Med Internet Res*. 2021;23(4):e21726. doi:10.2196/21726

173. Ekezue BF, Bushelle-Edghill J, Dong S, Taylor YJ. The effect of broadband access on electronic patient engagement activities: Assessment of urban-rural differences. *J Rural Health*. 2022;38(3):472-481. doi:10.1111/jrh.12598

174. Graves JM, Abshire DA, Amiri S, Mackelprang JL. Disparities in Technology and Broadband Internet Access Across Rurality: Implications for Health and Education. *Fam Community Health*. 2021;Publish Ahead of Print. doi:10.1097/FCH.0000000000000306

175. Quinton JK, Ong MK, Vangala S, et al. The Association of Broadband Internet Access and Telemedicine Utilization in rural Western Tennessee: an observational study. *BMC Health Serv Res*. 2021;21(1):765. doi:10.1186/s12913-021-06746-0

176. Das LT, Gonzalez CJ. Preparing Telemedicine for the Frontlines of Healthcare Equity. *J Gen Intern Med*. 2020;35(8):2443-2444. doi:10.1007/s11606-020-05941-9

177. Gray DM, Joseph JJ, Olayiwola JN. Strategies for Digital Care of Vulnerable Patients in a COVID-19 World—Keeping in Touch. *JAMA Health Forum*. 2020;1(6):e200734. doi:10.1001/jamahealthforum.2020.0734

178. Kassamali B, Haddadi NS, Rashighi M, Cavanaugh-Hussey M, LaChance A. Telemedicine and the battle for health equity: Translating temporary regulatory orders into sustained policy change. *J Am Acad Dermatol*. 2020;83(6):e467-e468. doi:10.1016/j.jaad.2020.08.016

179. van Dijk JAGM. Digital divide research, achievements and shortcomings. *Poetics*. 2006;34(4-5):221-235. doi:10.1016/j.poetic.2006.05.004

180. Egan K. Digital Technology, Health and Well-Being and the Covid-19 Pandemic: It's Time to Call Forward Informal Carers from the Back of the Queue. *Semin Oncol Nurs*. 2020;36(6):151088. doi:10.1016/j.soncn.2020.151088

181. Scheerder A, van Deursen A, van Dijk J. Determinants of Internet skills, uses and outcomes. A systematic review of the second- and third-level digital divide. *Telemat Inform*. 2017;34(8):1607-1624. doi:10.1016/j.tele.2017.07.007

182. Latulippe K, Hamel C, Giroux D. Social Health Inequalities and eHealth: A Literature Review With Qualitative Synthesis of Theoretical and Empirical Studies. *J Med Internet Res*. 2017;19(4):e136. doi:10.2196/jmir.6731

183. Basch P, Smith J. CMS Payment Policy, E&M Guideline Reform, and the Prospect of Electronic Health Record Optimization. *Appl Clin Inform*. 2018;09(04):914-918. doi:10.1055/s-0038-1676337

184. Anderson L. Realizing the Future We Want: Leveraging Technology to Achieve a Better Health Care Experience for All. *N C Med J*. 2019;80(4):224-228. doi:10.18043/ncm.80.4.224

185. Cottrell EK, Dambrun K, Cowburn S, et al. Variation in Electronic Health Record Documentation of Social Determinants of Health Across a National Network of Community Health Centers. *Am J Prev Med*. 2019;57(6):S65-S73. doi:10.1016/j.amepre.2019.07.014

186. Butler TJ, Firestone KS, Grow JL, Kantak AD. Standardizing Documentation and the Clinical Approach to Apnea of Prematurity Reduces Length of Stay, Improves Staff Satisfaction, and Decreases Hospital Cost. *Jt Comm J Qual Patient Saf*. 2014;40(6):263-AP1. doi:10.1016/S1553-7250(14)40035-7

187. Rowlands S, Coverdale S, Callen J. Documentation of clinical care in hospital patients' medical records: A qualitative study of medical students' perspectives on clinical

documentation education. *Health Inf Manag J*. 2016;45(3):99-106. doi:10.1177/1833358316639448

188. Soto CM, Kleinman KP, Simon SR. Quality and correlates of medical record documentation in the ambulatory care setting. *BMC Health Serv Res*. 2002;2(1):22. doi:10.1186/1472-6963-2-22

189. Lette M, Ambugo EA, Hagen TP, Nijpels G, Baan CA, de Bruin SR. Addressing safety risks in integrated care programs for older people living at home: a scoping review. *BMC Geriatr*. 2020;20(1):81. doi:10.1186/s12877-020-1482-7

190. Fried TR, Niehoff KM, Street RL, et al. Effect of the Tool to Reduce Inappropriate Medications on Medication Communication and Deprescribing. *J Am Geriatr Soc*. 2017;65(10):2265-2271. doi:10.1111/jgs.15042

191. Becich MJ, Gilbertson JR, Gupta D, Patel A, Grzybicki DM, Raab SS. Pathology and patient safety: the critical role of pathology informatics in error reduction and quality initiatives. *Clin Lab Med*. 2004;24(4):913-943. doi:10.1016/j.cll.2004.05.019

192. Amaniyan S, Faldaas BO, Logan PA, Vaismoradi M. Learning from Patient Safety Incidents in the Emergency Department: A Systematic Review. *J Emerg Med*. 2020;58(2):234-244. doi:10.1016/j.jemermed.2019.11.015

193. Kuriakose R, Aggarwal A, Sohi R, Goel R, Rashmi N, Gambhir R. Patient safety in primary and outpatient health care. *J Fam Med Prim Care*. 2020;9(1):7. doi:10.4103/jfmpc.jfmpc_837_19

194. Patel J, Otto E, Taylor JS, et al. Patient safety in dermatology: a ten-year update. *Dermatol Online J*. 2021;27(3). doi:10.5070/D3273052763

195. Watson AJ, Redbord K, Taylor JS, Shippy A, Kostecki J, Swerlick R. Medical error in dermatology practice: Development of a classification system to drive priority setting in patient safety efforts. *J Am Acad Dermatol*. 2013;68(5):729-737. doi:10.1016/j.jaad.2012.10.058

196. Azzopardi-Muscat N, Sørensen K. Towards an equitable digital public health era: promoting equity through a health literacy perspective. *Eur J Public Health*. 2019;29(Supplement_3):13-17. doi:10.1093/eurpub/ckz166

197. Ngongo BP, Ochola P, Ndegwa J, Katuse P. The technological, organizational and environmental determinants of adoption of mobile health applications (m-health) by hospitals in Kenya. *PloS One*. 2019;14(12):e0225167-e0225167. doi:10.1371/journal.pone.0225167

198. Adler-Milstein J, Holmgren AJ, Kralovec P, Worzala C, Searcy T, Patel V. Electronic health record adoption in US hospitals: the emergence of a digital “advanced use” divide. *J Am Med Inform Assoc JAMIA*. 2017;24(6):1142-1148. doi:10.1093/jamia/ocx080

199. Van Velthoven MH, Cordon C. Sustainable Adoption of Digital Health Innovations: Perspectives From a Stakeholder Workshop. *J Med Internet Res*. 2019;21(3):e11922-e11922. doi:10.2196/11922

200. Politi MC, Adsul P, Kuzemchak MD, Zeuner R, Frosch DL. Clinicians' perceptions of digital vs. paper-based decision support interventions. *J Eval Clin Pract*. 2015;21(2):175-179. doi:10.1111/jep.12269

201. Saman DM, Walton KM, Harry ML, et al. Understanding primary care providers' perceptions of cancer prevention and screening in a predominantly rural healthcare system in the upper Midwest. *BMC Health Serv Res*. 2019;19(1):1019-1019. doi:10.1186/s12913-019-4872-9

202. Lind DP, Andresen DR, Williams A. Medical Errors in Iowa: Prevalence and Patients' Perspectives. *J Patient Saf*. 2020;16(3):e199-e204. doi:10.1097/PTS.0000000000000523

203. Birnbaum F, Lewis D, Rosen RK, Ranney ML. Patient Engagement and the Design of Digital Health. Miner J, ed. *Acad Emerg Med*. 2015;22(6):754-756. doi:10.1111/acem.12692

204. Gimbel RW, Rennert LM, Crawford P, et al. Enhancing Patient Activation and Self-Management Activities in Patients With Type 2 Diabetes Using the US Department of Defense Mobile Health Care Environment: Feasibility Study. *J Med Internet Res*. 2020;22(5):e17968-e17968. doi:10.2196/17968

205. Vitger T, Austin SF, Petersen L, Tonder ES, Nordentoft M, Korsbek L. The Momentum trial: the efficacy of using a smartphone application to promote patient activation and support shared decision making in people with a diagnosis of schizophrenia in outpatient treatment settings: a randomized controlled single-blind trial. *BMC Psychiatry*. 2019;19(1):185-185. doi:10.1186/s12888-019-2143-2

206. Edbrooke-Childs J, Edridge C, Averill P, et al. A Feasibility Trial of Power Up: Smartphone App to Support Patient Activation and Shared Decision Making for Mental Health in Young People. *JMIR MHealth UHealth*. 2019;7(6):e11677-e11677. doi:10.2196/11677

207. Sutton MY, Anachebe NF, Lee R, Skanes H. Racial and Ethnic Disparities in Reproductive Health Services and Outcomes, 2020. *Obstet Gynecol*. 2021;137(2):225-233. doi:10.1097/AOG.0000000000004224

208. Furukawa MF, Poon E. Meaningful use of health information technology: evidence suggests benefits and challenges lie ahead. *Am J Manag Care*. 2011;17(12 Spec No.):SP76a-SP.

209. Agency for Healthcare Research and Quality (AHRQ). Use of Electronic Health Records | Agency for Healthcare Research and Quality. Chartbook on Care Coordination. Published 2018. Accessed August 3, 2022. https://www.ahrq.gov/research/findings/nhqrdr/chartbooks/carecoordination/measure5.html

210. Biden Administration Submits Budget Request to Congress | HIMSS. Published May 2, 2022. Accessed June 15, 2022. https://www.himss.org/resources/biden-administration-submits-budget-request-congress

211. Kruse CS, Stein A, Thomas H, Kaur H. The use of Electronic Health Records to Support Population Health: A Systematic Review of the Literature. *J Med Syst*. 2018;42(11):214. doi:10.1007/s10916-018-1075-6

212. Association of American Medical Colleges, Ommaya AK, Cipriano PF, et al. Care-Centered Clinical Documentation in the Digital Environment: Solutions to Alleviate Burnout. *NAM Perspect*. 2018;8(1). doi:10.31478/201801c

213. Kasiri N, Sharda R, Asamoah DA. Evaluating electronic health record systems: a system dynamics simulation. *SIMULATION*. 2012;88(6):639-648. doi:10.1177/0037549711416244

214. Wachter RM, Howell MD. Resolving the Productivity Paradox of Health Information Technology: A Time for Optimism. *JAMA*. 2018;320(1):25. doi:10.1001/jama.2018.5605

215. Benjamin R. *Race after Technology: Abolitionist Tools for the New Jim Code*. Polity; 2019.