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Assessing Clinical Software User Needs for Improved Clinical Decision Support Tools

Kimberly B. Denney
Walden University

Walden University

College of Management and Technology

This is to certify that the doctoral study by

Kimberly Denney

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the review committee have been made.

Review Committee
Dr. Craig Martin, Committee Chairperson, Doctor of Business Administration Faculty

Dr. Edward Paluch, Committee Member, Doctor of Business Administration Faculty

Dr. Lynn Szostek, University Reviewer, Doctor of Business Administration Faculty

Chief Academic Officer
Eric Riedel, Ph.D.

Walden University
2015

Abstract

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by

Kimberly B. Denney

MBA, University of Miami, 2003

BS, Indiana University, 1984

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Walden University

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Abstract

Consolidating patient and clinical data to support better-informed clinical decisions remains a primary function of electronic health records (EHRs). In the United States, nearly 6 million patients receive care from an accountable care organization (ACO). Knowledge of clinical decision support (CDS) tool design for use by physicians participating in ACOs remains limited. The purpose of this quantitative study was to examine whether a significant correlation exists between characteristics of alert content and alert timing (the independent variables) and physician perceptions of improved ACO quality measure adherence during electronic ordering (the dependent variable). Sociotechnical theory supported the theoretical framework for this research. Sixty-nine physician executives using either a Cerner Incorporated or Epic Systems EHR in a hospital or health system affiliated ACO participated in the online survey. The results of the regression analysis were statistically significant, $R^2 = .108$, $F(2,66) = 3.99$, $p = .023$, indicating that characteristics of alert content and timing affect physician perceptions for improving their adherence to ACO quality measures. However, analysis of each independent variable showed alert content highly correlated with the dependent variable ($p = .007$) with no significant correlation found between workflow timing and the dependent variable ($p = .724$). Understanding the factors that support physician acceptance of alerts is essential to third-party software developers and health care organizations designing CDS tools. Providing physicians with improved EHR-integrated CDS tools supports the population health goal of ACOs in delivering better patient care.

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Dedication

I dedicate this work to my husband, Lamar. You never complained when I chose to study for classes and write papers on the weekend instead of spending that time with you. Instead, you were a constant source of encouragement and strength. I became concerned with letting you down if I failed to finish this endeavor further igniting my determination to buckle down and get it done. You are the love of my life and my life's partner. I thank you, and I count my blessings to be able to continue enjoying our life's journey together.

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I am thankful to share this accomplishment with my children, Jake and Joey and my parents, Marty and Tom Brodsky. They provided needed encouragement while grounding me in my life's purpose. Lamar, as stated before, takes top honors for cheerleading and for always maintaining a perfect "command central." I must acknowledge our two pugs, Magnus and Ceasar. Magnus left me with great memories of his companionship and snoring through long periods of study. Ceasar continues to provide his unwavering support, always game to accompany me in my office whether for one hour or for eight.

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Table of Contents

List of Tables v

List of Figures vi

Section 1: Foundation of the Study 1

Background of the Problem 1

Problem Statement 2

Purpose Statement 2

Nature of the Study 3

Research Question 5

Hypotheses 5

Survey Questions 6

Theoretical Framework 6

Definition of Terms 8

Assumptions, Limitations, and Delimitations 10

Assumptions 10

Limitations 11

Delimitations 11

Significance of the Study 12

Contribution to Business Practice 12

Implications for Social Change 12

A Review of the Professional and Academic Literature 13

Legislation and EHR Use 14

The ACO Model 15

Achieving MU of EHRs 18
Application of Sociotechnical Theory 20
Rival Theories 24
Discussion of the Independent Variables 30
Independent Variable A: Type of CDS Tool 32
Independent Variable B: Workflow Timing 35
Methodologies Supporting the Dependent Variable 37
Overcoming Current EHR Limitations 44
Future CDS Research Opportunities 54
Summary 59
Transition and Summary 60
Section 2: The Project 62
Purpose Statement 62
Role of the Researcher 63
Participants 64
Research Method and Design 65
Population and Sampling 69
Sample Size 71
Ethical Research 74
Data Privacy 75
Data Collection 76
Instruments 78

Data Collection Technique 81
Data Organization Techniques 84
Data Analysis Technique 85
Reliability and Validity 87
Reliability 88
Validity 89
Transition and Summary 89
Section 3: Application to Professional Practice and Implications for Change 91
Overview of Study 91
Presentation of the Findings 93
Descriptive Statistics 93
Parametric Assumptions and Tests for Normality 97
Discussion 101
Applications to Professional Practice 104
Implications for Social Change 106
Recommendations for Action 107
Recommendations for Further Study 109
Reflections 110
Summary and Study Conclusions 111
References 113
Appendix A: Survey Questions Presented to Online Participants 135
Appendix B: CMS ACO Quality Measures 137

Appendix C: Letter of Cooperation 138

Appendix D: Communication with Community Partner 140

Appendix E Informed Consent Background and Information 141

Appendix F: Personalized Participant Email Invitation.....143

Appendix G: Residual Statistics 144

List of Tables

Table 1. Sample Size Calculation for Proposed Study Using G*Power 3.1 Software……73

Table 2. Survey Scales by Question and Supporting Literature…….....80

Table 3. Analysis of Cronbach's Alpha Coefficients in a Pilot Study.....83

Table 4. Descriptive Statistics on Composite Scores.....94

Table 5. Correlations.....97

Table 6. Tests for Tolerance and Collinearity (VIF Values).....98

Table 7. Characteristics of Alert Content and Timing Supporting Improved ACO Quality Measure Adherence.....102

List of Figures

Figure 1. Meeks et al. (2014) combined Sittig and Singh's (2010) socio technical framework with a three-stage safety model supporting application to evolving HIT use by advanced health systems.....8

Figure 2. EHR type by respondent (N = 69).....95

Figure 3. Normal P-P plot of regression standardized residual of dependent variable, quality.....99

Figure 4. Normal P-P plot of regression standardized residual of independent variable, content.....100

Figure 5. Normal P-P plot of regression standardized residual of independent variable, timing.....101

Section 1: Foundation of the Study

The optimal use of health information technology (HIT) brings the right information to the right people at the right time (Krist et al., 2014). Improving the access to patient and clinical data supports the delivery of better patient care (Path, 2013). As accountable care organizations (ACOs) coordinate care of chronically ill patients, poor interoperability of electronic health record (EHR) systems remains a known contributor to patient harm (Rudin & Bates, 2013). Therefore, designing clinical decision support (CDS) software tools based on an improved understanding of physician needs for patient-specific information presents an opportunity to improve the quality of care physicians deliver (Beeler, Bates, & Hug, 2014).

Background of the Problem

Clinical software users and vendors hold differing opinions regarding software user needs for electronically accessing patient data (Eastaugh, 2013). In addition, the adoption of EHRs by U.S. health systems occurred with minimal design input from clinical software users (Ancker, Kern, Abramson, & Kaushal, 2012; Hollin, Griffin, & Kachnowski, 2012; Kawamoto et al., 2012). The risk for patient harm surfaces when clinical software users lack workflow appropriate tools (Beeler et al., 2014; Meeks, Takian, Sittig, Singh, & Barber, 2014). Capturing software user needs for improved and workflow-compatible EHR-integrated tools provides the foundation for the research study. Including the sociotechnical needs of clinical software users among the variables assessed in this study potentially addresses the data access and workflow limitations of

EHRs and may offer insight into clinical software user needs for EHR-integrated CDS tools.

Problem Statement

Access by U.S. health systems to $19 billion in incentive payments requires demonstrating meaningful use (MU) of EHR systems through use of CDS software tools supporting improved patient outcomes (Chalasani, Jain, Dhumal, Moghimi, & Wickramasignho, 2014; Xiao et al., 2012). New health care reform models such as ACOs depend on the accurate electronic exchange of patient data (Berwick, 2011). A lack of EHR-integrated decision support tools jeopardizes a measurable return on the billions of dollars invested in HIT (Dubois et al., 2014; Koppel, 2013).

The general business problem is the lack of EHR-integrated CDS tools supporting physicians managing complex patients (McMurray et al., 2013). The specific business problem is a lack of understanding by third-party software developers about physicians' preferences for integrated alerts supporting adherence to ACO quality measures while placing their electronic orders.

Purpose Statement

The purpose of this quantitative, correlation study was to examine the nature of any association between physician preferences for CDS alerts and perceptions of improved adherence to ACO quality measures during electronic ordering. The independent variables consisted of sociotechnical attributes related to the type of decision support provided and the workflow timing for presenting an alert to physicians. The

dependent variable was physicians' perceptions of improved adherence to ACO quality measures.

The study population consisted of physician executives from U.S. integrated delivery health system ACOs using CDS tools in either a Cerner Corporation or Epic Systems EHR. Integrated health systems with ACOs typically use advanced HIT tools with participation from academic medical centers (Muhlestein, Gardner, Merrill, Petersen, & Tu, 2014; Shortell, Wu, Lewis, Colla, & Fisher, 2014). Cerner Incorporated and Epic Systems hold the largest market share among integrated health systems with ACOs (Chalasani et al., 2014). Data from the Healthcare Information and Management Systems Society (HIMSS) includes details on the population of 90 integrated health system ACOs using market leading EHRs (HIMSS, 2014). Improving commercial CDS software supports the primary social change goal of ACOs in safely managing high-risk patient populations through improved use of HIT (Kuperman & McGowan, 2013).

Nature of the Study

A quantitative, correlation design best fits the nature of the research problem. Development and use of a Likert-scaled survey and analysis of the data have the potential to yield fresh insights into the sociotechnical needs of physician software users. Results may direct product development efforts toward design of improved CDS alerts needed by clinicians coordinating care for patients in integrated health system ACOs.

Use of quantitative, correlation research methods are commonly applied in health care and information technology related investigations. Xiao et al. (2012) examined relationships of ambulatory physician use of EHRs and the extent to which MU of an

EHR positively affected patient care. Utilizing a 5-point Likert-scaled survey, the authors captured two dependent variables of efficiency and quality of health care. Quantitative methods applied by Wan, Masri, Ortiz, and Lin, (2014) employed correlation analysis examining executive perceptions of the opportunities and challenges inherent in forming an ACO. Similarly, Peikari, Zakaria, Yasin, Shah, and Elhissi (2013) applied a quantitative correlation approach in their study assessing the usability of CDS alerts within a computerized physician order entry (CPOE) application.

A classic taxonomy of stakeholders defined by Hamilton and Chervany (1981) was expanded by Turunen and Talmon (2000), who defined the users of HIT systems as physicians, nurses, and others. Turunen and Talmon (2000) further expanded the stakeholder definition of developers including users with a health care background and others. Use of expanded stakeholder definitions supports selection of physician users from a population of U.S. ACOs using market-leading EHRs. An understanding of the relative importance of software attributes from a sociotechnical standpoint provides software developers with new insights and potentially predictive value regarding unmet user needs (Path, 2013; Sittig & Singh, 2010).

Qualitative approaches are not aligned with the stated research problem. Qualitative researchers seek to understand unstructured phenomena by uncovering themes through semistructured or open-ended interviews and observations (Bryman, 2012). Although qualitative case studies expand the lens for examining a given phenomenon, the approach generates insufficient data enabling quantitative assessment of a stated research hypothesis (Constantinides, 2013; Meeks et al., 2014). Further,

qualitative research lacks the rigor of scientific inquiry expected by leading health care professionals and technology industry stakeholders for whom the research bears interest. Although a mixed-methods approach potentially generates additional data for analysis than a survey alone, the approach requires substantially more time and resources than are feasible. Information sciences researchers suggested the judicious selection of a mixed-method approach especially in cases where a single method well applied suffices to answer the research question (Venkatesh, Brown, & Bala, 2013). This quantitative, correlation study supported an analysis of survey responses sufficient to accept or reject the stated research hypothesis.

Research Question

The central research question underpinning the research considered whether sociotechnical factors addressed in the design of CDS software tools affect physician ordering behavior. The independent variables were the alert content attributes and the timing of triggering alerts in the physician's electronic ordering workflow. The dependent variable was the physician's perception of improved adherence to ACO quality measures.

Hypotheses

H_{O1}: A significant relationship does not exist between the content of an alert deployed and a physician's adherence to ACO quality measures.

H_{a1}: A significant relationship does exist between the content of a deployed alert and a physician's adherence to ACO quality measures.

*H*o$_2$ A significant relationship does not exist between the timing of when an alert is deployed in a physician's electronic ordering workflow and a physician's adherence to ACO quality measures.

*H*a$_2$ A significant relationship does exist between the timing of when an alert is deployed in a physician's electronic ordering workflow and a physician's adherence to ACO quality measures.

Survey Questions

A Likert-based survey based on a 5-point scale where 5 = "always" and 1 = "never" incorporates sociotechnical factors associated with the content design of alerts, the timing for placement of alerts in a physician's computerized ordering workflow, and the physician's perception of an alert supporting adherence to ACO quality measures. Previous physician surveys and research associated with physician preferences for CDS tools informed the questions for the survey (Anderson et al., 2013; Bell et al., 2014; Bowman, 2013; Dubois et al., 2014; Jung et al., 2013; Koopman et al., 2011; McCoy et al., 2012; Pham et al., 2012; Sittig, Krall, Dykstra, Russell & Chin, 2006; Smith et al., 2013; Xiao et al., 2012). However, no previously validated instrument supports the combination of variables intended for examination. The entire survey instrument (Appendix A) contains the questions necessary for examining the central research question through the specific variables selected.

Theoretical Framework

Pasmore (1988) attributed to Trist (1951) the creation of sociotechnical theory. Pasmore's contribution to sociotechnical theory extended to considering an

organization's interaction with highly complex and turbulent environments. Pasmore suggested sociotechnical designers consider how technology affects the work experience while safeguarding human interests with deploying new technology in the workplace. The purpose of applying sociotechnical design to complex organizations such as health care systems arises from understanding that productivity misses occur as a result of both human and technical factors (Sittig & Singh, 2010). A sociotechnical framework assists software developers in addressing complex systems through an improved understanding of the communication patterns, workflows, and tools required by users across the system (Path, 2013; Sittig & Singh, 2010).

Without access to software tools that incorporate users' sociotechnical needs, ACO providers may miss important patient data resulting in decisions that harm patients (Krist et al., 2014). Gaining a better understanding of the sociotechnical preferences of ACO software users might inform improvements in developing new decision support tools for safely improving patient care at lower costs. Meeks, Takian, Sittig, and Barber (2014) published findings specific to applying a sociotechnical framework in deploying and using EHRs. Figure 1illustrates where the ACO model aligns with the Phase 3 objective of enhanced patient safety through EHR enabled health care systems.

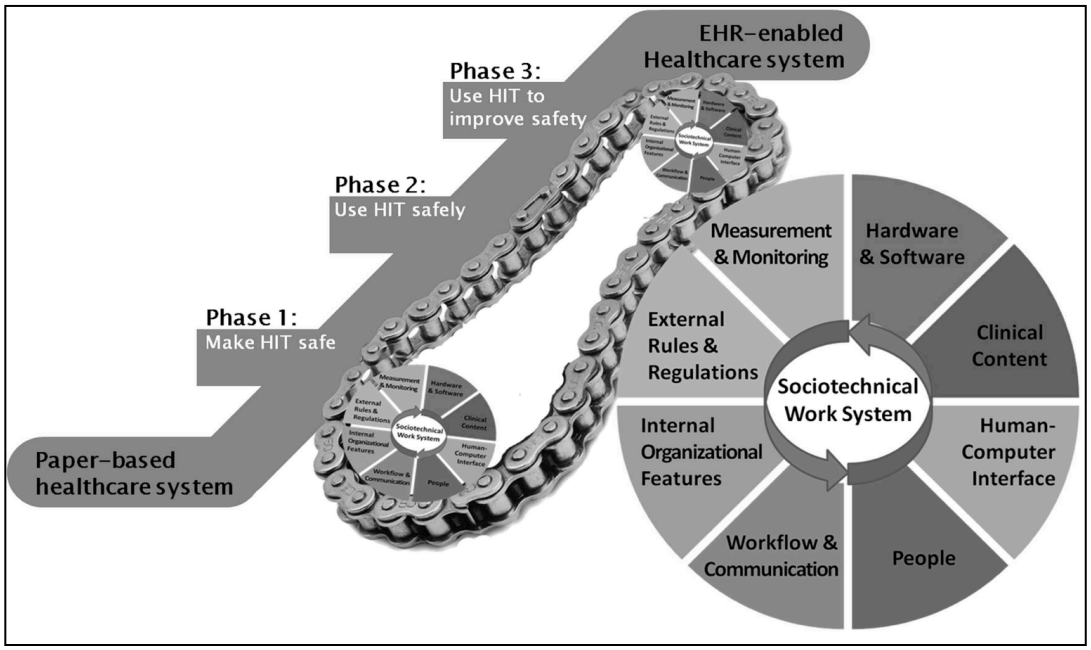

Figure 1. Meeks et al. (2014) combined Sittig and Singh's (2010) sociotechnical framework with a three-stage safety model supporting application to evolving HIT use by advanced health systems.

Definition of Terms

Accountable care organization (ACO): Coordinated care of a designated patient population by health care providers and organizations that may share any savings realized after fulfilling specific performance measures (CMS, 2014).

Accountable care organization quality measures: A set of 33 national measures defined by the Centers for Medicare and Medicaid Savings (CMS) inclusive of one measure aligned with the demonstration of MU (CMS, 2014).

Clinical decision support software (*CDS*): The use of automated recommendations or alerts based on peer-reviewed evidence that support clinicians in making better decisions for their patients (HIMSS, 2010).

Clinical workflow: A specific sequence of tasks performed by physicians and other health care providers as they coordinate and deliver patient care (HIMSS, 2014).

Electronic health record (*EHR*). An electronically managed system containing specific patient and clinical data used by clinicians in the routine management of patient care (HIMSS, 2014).

Integrated delivery system ACO: A type of accountable care organization characterized by the participation of hospitals and physician practice groups jointly managing complex patient populations with a more sophisticated use of HIT and analytics (Shortell et al., 2014).

Health information technology (*HIT*): A specific application of technology supporting clinicians and other health care organizations and providers in delivering more efficient and better patient care through computers (HIMSS, 2014).

Interoperability: The ability for patient and clinical data to be electronically accessible and usable across disparate systems by clinicians and other health care providers irrespective of where the data originated (HIMSS, 2014).

Meaningful use (MU): A set of guidelines defined by the Department of Health and Human Services (HHS) that supports the allocation of financial incentives and penalties to hospitals and eligible health care providers demonstrating their use of HIT to improve the quality, efficiency, and safety of patient care (CMS, 2014).

Software as a service (SaaS): A method of delivering the same software solution to many users or subscribers through a cloud-based platform rather than through the installation of individual and locally maintained systems (HIMSS, 2014).

Assumptions, Limitations, and Delimitations

Assumptions

Five key assumptions underscored the research. The first assumption was the willingness of physician executive software users to complete the survey. The second assumption involved accurately selecting ACOs for inclusion in the research. Muhlestein et al. (2014) and Shortell et al. (2014) identified a type of ACO characterized by the inclusion of hospitals and provider groups using advanced HIT systems. I assumed that the inclusion of hospital-led ACOs using leading EHR systems aligned with the integrated delivery system (IDS) ACO type and best supported the goals of the research. The third and fourth assumptions pertained to the research participants' knowledge and experience. I assumed executive clinical software users with extensive HIT experience understand their obligations to meet CMS ACO quality measures. I assumed that these software users may perceive how decision support software affects physician ordering behavior and the quality of care the ACO provides. The final assumption pertained to survey participant honesty. Leroux, Rizzo, and Sickles (2012) suggested that survey responses are biased as responders interpret survey questions in relation to their current experience. Supplying the participants with reference material on the ACO quality measures might reduce the risk that a research participant lacks sufficient knowledge of national ACO quality measures. Testing the questions and responses with a small, pilot group might provide insights for reducing the risk for bias associated with self-reporting (Bryman, 2012).

Limitations

Limitations arise from the type of instrument selected and the research methodology. The selection of a Likert-scaled survey imposes several limitations. Specifically, quantitative research conducted with such defined scales limits research participants to a set of predetermined questions and responses unlike qualitative approaches enabling capture of unrestrained responses. In addition, respondents frequently select a neutral response on the scale limiting the usefulness in analyzing actual attitudes (Yusoff & Janor, 2014). Another limitation stems from the nonresponse bias potentially limiting data analysis (Hohwu et al., 2013; Schaeffer & Dykema, 2011). The choice of a correlational study limits the analysis to depicting a potential relationship between the variables studied without the means for determining any causation (Prematunga, 2012).

Delimitations

To test the research hypothesis, I limited participation in the survey to qualified physician executive software users such as the directors of medical informatics and chief medical officers. These are individuals who influence third-party software procurement decisions and frequently self-develop and manage decision support tools requested by hospital and ambulatory physician users. In addition, the exclusion of ACOs using non Epic or Cerner EHR systems without the participation of a hospital is an important delimitation to this research. The results applicable to the ACO type included in the survey may not be generalizable to other types of ACOs such as those comprised solely of private practice physicians using less sophisticated EHRs. Hospitals sponsored nearly

half of all ACOs in 2013 with the majority of hospital-led ACOs using a Cerner Corporation or Epic Systems EHR (Barnes, Unruh, Chukmaitov, & van Ginnekan, 2014; CMS, 2014). According to leading experts, organizations demonstrating HIT competency with an infrastructure enabling population health management stand a better chance at providing better care (Chukmaitov, Harless, Bazzoli, Carretta, & Siangphoe, 2014). Other software users such as nurses, allied health care professionals, and patients remain excluded from the study population since the type of CDS software tool envisioned aligns most closely with the ordering activities performed by physicians.

Significance of the Study

Contribution to Business Practice

This research seeks to examine how software users perceive the ability of integrated CDS tools to meet their sociotechnical needs while enhancing their ability to comply with ACO quality measures. The insights from this research may inform improvements in the design of decision support software enabling third-party SaaS vendors to improve the usability of EHR integrated CDS tools tailored for physician users (Krist et al., 2014; Middleton et al., 2013; Riskin, Koppel, & Riskin, 2014).

Implications for Social Change

Latest estimates from CMS suggested that nearly 6 million patients receive care from an ACO (CMS, 2014). Providing physicians with improved automated decision support tools in their clinical workflow supports the population health goal of ACOs in delivering better outcomes and safer patient care more efficiently.

A Review of the Professional and Academic Literature

The literature review includes a brief overview of recent legislative and regulatory actions supporting adoption of EHRs and new models for population health management in the U.S. Extending from the legal and regulatory framework, key findings from the published literature highlight the current state and the expected future use of software technology for improving the cost and quality of care provided to patients. Use of supporting literature provides examples of the limitations of current software tools as experienced by clinical software users. The literature review provides further justification in the selection of sociotechnical theory over rival theories. Specifically, incorporating the research findings published from the leading medical informatics and health research journals underscores the value of considering sociotechnical requirements of clinical software users in the development of new CDS software tools. Descriptions of the two independent variables and the dependent variable selected for study provide context for examining the selected study methodology.

The approach taken for the review of the academic literature included the use of both Walden library databases as well as routinized searches in Google Scholar. Keywords utilized for searching the literature included *clinical decision support, electronic health records, patient records, accountable care organizations, interoperability*, *medical error*, *and health care information technology*. Other search parameters included selection of peer-reviewed articles published within the last five years. The highly topical nature of this research remains apparent as 93% of the articles cited are within 5 years of the expected publication of this study. Non-peer-reviewed

articles and books represented fewer than 6% of the total citations included in the literature review.

Legislation and EHR Use

The U.S. government's passage of the American Reinvestment and Recovery Act (ARRA) in 2009 included $19 billion dollars in incentives in the accompanying Health Information Technology for Economic and Clinical Health Act (HITECH) for procurement of EHRs by eligible health care providers and hospitals (CMS, 2014; Riskin et al., 2014). The ability to receive incentive payments aligns with eligible providers (EPs) and health care organizations attesting to the MU of their EHRs in distinct stages over specific time periods as defined by the Centers for Medicare and Medicaid Services (CMS) (CMS, 2014). Progression through each MU Stage requires adoption and demonstration of increasingly advanced software functionality such as the use of integrated CDS tools for improving patient outcomes (Xiao et al., 2012).

Porter (2009) published an editorial before the enactment of the HITECH Act. He proposed that health care delivery be restructured placing the patient at the center of care to derive maximum value. Arguing that care should be organized and delivered centrally, Porter's (2009) recommendations aligned well with more recent health care reform legislation establishing the creation of ACOs with expectations for use of advanced HIT systems. Porter suggested that improvements in health care arise only as the practice of medicine shifts from a focus on volume to that of value. Porter envisioned a roadmap and specific entities governing change with the mandate to establish, review, and manage HIT standards.

With the passage of the Patient Protection and Affordable Care Act (PPACA) in 2010, CMS gained authorization establishing shared savings programs including recognition of ACOs as a new legal entity or health care provider (CMS, 2014). Health care providers and hospitals with a minimum of 5000 Medicare patients became eligible to register for CMS shared savings. ACOs effective in 2012 participated in shared savings for a minimum of three years (CMS, 2014). Berwick (2011) anticipated ACOs delivering improvements in how patient data is shared, supporting reductions in care variation, elimination of unnecessary costs, and more robust and timely clinical decision making. He outlined three primary goals for the establishment of ACOs referred to as the "triple aim": (a) better care for each patient participating in an ACO, (b) better care for groups of patients being managed for the same chronic conditions, such as diabetes or heart failure, and (c) reduction in costs associated with care. Envisioned as a major reform in U.S health care, providers and organizations establishing an ACO share in any savings realized once all required quality measures are met by specified dates. Berwick highlighted access to patient information and HIT as vital ingredients for success in the ACO model. Recognizing that providers relied on fragmented HIT systems, he postulated one outcome of moving to ACOs would be an increased focus on how patient data is shared using HIT for more robust and timely clinical decision making.

The ACO Model

Payne et al. (2013) reviewed the current state of HIT implementation across several large health care systems with the objective of identifying best practices contributing to lowered health care costs and improved care quality. More than $30

billion in investments directed toward HIT procurements occurred since 2009 specific to the adoption of EHRs. MU criteria established by CMS mandates adopting hospitals and providers demonstrate active use of the EHR in clinical decision-making through reporting of quality measures and validation of evidenced based clinical orders and rules (CMS, 2014).

Establishing the ACO model provided CMS with additional means for directing the focus of providers toward the achievement of better population health at lower costs (Barnes et al., 2014). Specifically, CMS established ACO quality measures with requirements for ACOs to transition from reporting on adherence to these measures to assuming increasing financial risk associated with improved patient outcomes. The use of HIT provides a key mechanism for providers and organizations to successfully manage and share such risk (Barnes et al., 2014). Given the unprecedented national investments in HIT, Payne et al. (2013) sought to answer the question of whether recent investments in HIT actually improved financial and quality health care outcomes. Such concerns stimulated the development of recommendations from professional practice societies for actions needed by software vendors and physicians focused on improving EHR use through improvements in software testing, design, and implementation (Middleton et al., 2013).

The ACO model with its focus on population health necessitates collaboration across primary care physician practices (Schultz et al., 2013; Barnes et al., 2014). The traditional Medicare ACO requires the inclusion of 5,000 Medicare patients over a three-year period (CMS, 2014). ACOs formed outside of Medicare by private payers share

similar features specific to the assumption of risk and shared reward with the management of defined patient populations (Barnes et al., 2014). The attribution of patients to most ACOs begins with primary care practices (Barnes et al., 2014). Krist et al. (2014) identified the evolving needs of primary care physicians for improved decision support tools supporting population health goals. Barnes, Unruh, Chukmaitov, and van Ginnekan, (2014) suggested providers faced with lower fee for services reimbursement aligned with or formed new ACOs as a defensive posture during a period of substantive change.

In the setting of any ACO, Krist et al. (2014) identified new needs for high quality, patient contextualized information accessible to physicians across integrated health systems. Barnes et al. (2014) noted the value of integrated HIT systems supporting access to better information with greater reliance on decision support tools. Schultz et al. (2013) described similar implications of the ACO model on current and future family practitioners. With a focus on reducing the cost of care, these authors anticipated ACO's directing providers toward shared risk models requiring proactive patient engagement.

Greater use of community-based health resources shifts the burden from caring for patients in hospitals to managing care across a number of other venues including the patient's home (Schultz et al., 2013). Supporting the transition to accountable care requires development of population health management tools with the right practitioners in roles capable of utilizing new tools and resources (Krist et al., 2014; Schultz et al., 2013). Concerning the need to prepare physicians for accountable care, these authors

highlighted the growing need for clinicians to have timely access to patient, clinical, and cost effectiveness data as patient care is conceived and delivered.

Leavitt Partners, a leading HIT consultancy firm began assessing the expansion of ACOs in 2010 (Muhlestein et al., 2014). They estimated more than 600 ACOs operated in the U.S. having expanded beyond the original CMS scope through inclusion of non Medicare patient populations. The authors supplemented their ACO database with a survey and qualitative research conducted with more than 100 ACO executives. Muhlestein et al. (2014) identified the classification of "Full Spectrum Integrated" (FSI) as the type of ACO most aligned with early thinking in regard to an ACO model achieving health care's "Triple Aim." Characterized by their proven adoption of HIT, robust financing, interaction with insurers on risked based agreements, and higher participation of academic medical centers, the authors anticipated FSI ACOs actively engaging with software vendors. Muhlestein et al. identified opportunities and challenges specific to the FSI ACO type suggesting a greater need for software tools spanning all care venues with advanced measurement tools tracking provider behavior specific to their use of costly interventions.

Achieving MU of EHRs

Because the procurement of EHRs in isolation does not equate to better patient outcomes, CMS established goals at each stage of the MU program aimed at aligning EHR use with activities associated with better patient care (CMS, 2014). The government's MU program specifically addresses physician use of CDS in the EHR and reportable quality measures as key ingredients supporting a shift from fee-based care to

value (CMS, 2014). Each successive stage of the MU program expands the requirements that patient centric care aligns with the best medical evidence (Krist et al., 2014).

Harle, Huerta, Ford, Diana, and Menachemi (2013) examined the differences among U.S. hospitals attesting to Stage 1 MU while managing ongoing EHR implementation challenges. Cross-referencing survey data from the American Hospital Association's (AHA) 2010 annual EHR survey with a 2011 CMS database, they identified 313 of 2475 hospitals sampled received MU payments. 2,162 surveyed hospitals intending to obtain MU payments in 2011 failed to accomplish that objective. Harle et al. (2013) identified implementation of CPOE as vital in determining a hospital's success in receiving MU payments. The authors' recommended EHR vendors work in tandem with the government addressing factors impeding CPOE adoption. With MU Stage 2 criteria requiring physician demonstration of quality improvements, the authors concluded that incentives alone fall short in achieving the program's goals.

Riskin, Koppel, and Riskin (2014) argued the focus on EHR and software design must shift to usability as physicians and health systems align efforts toward achievement of improved population health outcomes. Harle et al. (2013) further noted the importance for consideration of cultural and technological factors related to EHR use. The authors expressed concern for a widening gap between for-profit and academic medical centers that successfully implemented EHR systems and the nonprofit and smaller hospitals that failed to implement successfully. Leaving smaller or rural hospitals behind undermines the overarching goal for improving the quality and safety of care for all patients.

Application of Sociotechnical Theory

Considering the seminal work of Trist and Barnforth (1951) particular to sociotechnical theory, Westbrook et al. (2007) recognized the applicability of sociotechnical theory to the successful design and implementation of HIT systems. Specifically, improvements in care quality and safety anticipated with the implementation of new software tools concurrently disrupted software end-users' complex clinical workflows. Carayon et al. (2014) expanded work system definitions to include aspects of safety and quality including outcomes. Software tools lacking appropriate sociotechnical considerations impedes adoption thus falling short of solving health care's "wicked" problems of improving the safety and efficiency of care (Westbrook et al., 2007). Horsky et al. (2012) described the risks of poorly designed software tools contributing to inappropriate care stemming from undocumented patient problems, incomplete medication reconciliation, adverse events associated with incorrect medication dosages, and poor response by providers to alerts.

Cresswell and Sheikh (2013) extended the HIT implementation framework research of Rippen, Pan, Russell, Byrne, and Swift, (2013) targeting analysis of organizational challenges with the adoption of new HIT solutions. The authors identified several factors supporting or diminishing success during the uptake of new HIT solutions. Cresswell and Sheikh characterized success factors along three dimensions including (a) technical characteristics, (b) social aspects, and (c) organizational factors. Their application of sociotechnical theory included references to several previous studies in Canada and the U.S. specific to EHR adoption and the incorporation of CDS software

tools. Specifically, the authors substantiated use of a sociotechnical framework based on previously published studies by Ludwick and Doucette (2009), Ash et al. (2007), Berg (1999), and Harrison, Koppel, and Bar-Lev (2009). The authors further discussed a concept that adopting HIT innovations remained complex by virtue of needing to connect human needs with technology in a state of constant evolution.

Meeks et al. (2014) analyzed longitudinal case study data obtained from interviews of stakeholders participating in the United Kingdom's disbanded National Health Service (NHS) Program for IT (NPfIT). The authors identified important sociotechnical aspects of EHR deployment increasing risks for patient safety. Concluding that risks change as organizations moved through the process of EHR implementation, the earliest risks equated to getting systems up and running. Later risks equated to the sustained use, and reliance of the data entered and maintained within an EHR. The authors applied two different models in assessing risk and patient safety. Among the models applied, the authors leveraged Sittig and Singh's (2010) framework also referenced by Overby et al. (2013). The incorporation of Sittig and Singh's framework highlighted the value of capturing clinical software user needs for improved, shared, CDS tools (Meeks et al., 2014; Murphy, Singh, & Berlin, 2014).

Similar to challenges identified by Constantinides (2013), rigid adherence to hierarchically derived solutions contributed to England's failed national HIT program. Overby et al. (2013) participated in a collaborative effort, the eMERGE network, facilitating an understanding of how to best incorporate CDS solutions across different EHRs in applications of genomic medicine. The recommendation of Overby et al.

included the requirement for organizations to have access to tools to adapt solutions locally. In addition, the eMERGE consortium suggested deployment of toolkits supporting customization by local users of new CDS tools. Overby et al. (2013) recommended new CDS solutions include tools for rapid summarization of patient data, automated settings to facilitate data queries by user and patient circumstances, and incorporation of more than one diagnosis or condition.

Research conducted by Smith et al. (2013) focused on software user satisfaction and new CDS tools for tracking undocumented test results arising from abnormal values. With an effort toward aligning software development with the sociotechnical needs of HIT users, Smith et al. developed CDS concepts for assessment within the VA's EHR test environment. Two new tools addressed the test reporting needs of physicians and stakeholders managing four types of cancer patients. Recognizing busy physicians might miss an initial alert, the new CDS tool generated contextual and specific reminders for physicians to review abnormal test results. The new software concept met users' needs for additional reminders without negatively affecting clinical workflow practices. The authors noted initial reports of abnormal test results frequently remained unrecognized within the context of a busy health care practice. Missed test results increase the risk for patient harm when clinical care proceeds as directed by providers unaware of significant, new clinical findings (Smith et al., 2013).

The alerts provided to physicians using the VA's EHR remained in an inbox location until such time as a physician opted to click open and review each alert (Smith et al., 2013). Once reviewed, the alert dropped from the physician's view requiring

physicians to remember all alerts previously read. Overcoming issues of alert fatigue and dependencies on the physician's memory, the CDS prototype designers considered three sociotechnical requirements including (a) "software usability," (b) "technical compatibility," and (c) "fit with the clinical workflow and organization." A novel aspect of the new CDS tool included development of a dashboard supporting quick analysis of patients for whom abnormal test findings remained undocumented (Smith et al., 2013).

The application of a sociotechnical framework to software development and assessment continues to surface in HIT-related research efforts. Rippen, Pan, Russell, Byrne, and Swift (2013) assessed the field of HIT for associated theories underpinning aspects of software tool deployment and use. Rippen et al. (2013) characterized HIT implementation through the aid of a new framework incorporating components of leading theories specific to software user activities and needs. Recognizing that HIT implementations remain a complex organizational undertaking, the authors suggested their framework provided organizations with an improved roadmap for successful HIT implementations. Rippen et al. applied sociotechnical theory as well as other technology use related theories such as multi-method, task-technology fit, and technology acceptance. In consideration of the suitability of sociotechnical theory to their new framework, the authors cited the seminal work by Passmore (1995) and the related research conducted by Westbrook et al. (2007).

Specifically, Westbrook et al. (2007) surveyed medical staff utilizing the Safety Attitudes Questionnaire (SAQ), a validated instrument measuring an organization's safety culture. The authors identified prior use of the SAQ by Colla, Bracken, Kenney,

and Weeks (2005) associating measures of safety climate with both patient outcome measures and the capture of medical errors. The authors' findings further support the application of a sociotechnical framework in the development of CDS tools for the reduction of medical error.

It was Pasmore (1988) who noted "huge investments in new technologies may not result in the cost savings expected, particularly if the new technology proves too complex, unreliable, inflexible, or costly to operate" (p. 92). Pasmore's (1988) application of sociotechnical theory resonates with health researchers and software developers facing the challenges associated with the design and use of HIT by clinical software end-users. Pasmore (1988) concluded "to the extent that technology influences the design of work, we need to influence the design of technology in order to affect the performance of organizations" (p. 152).

Rival Theories

Sociotechnical theory guides the research effort. The extant literature supports the application of sociotechnical theory in physician assessment of CDS tools presented in the medication ordering workflow (Jung et al., 2013; Rippen et al., 2013; Smith et al., 2013). Other theories such as Complex Adaptive Systems (CAS) theory, Systems theory, or software usability related constructs such as the Technology Acceptance and Task Technology Fit models remain applicable to this type of research.

Complex adaptive systems. Leykum, Kumar, and Parchmann (2012) examined the relationships among physicians engaged in patient care in an acute hospital setting to identify how their interactions affected care. Following a period of observation, a

simulation model was derived to assess patterns of decision-making affecting patient outcomes. The authors drew from models of complex adaptive systems (CAS) to consider the interplay of communication on the behavior of physicians and their subsequent patient facing activities. The authors contended that the use of a CAS model enabled better recognition of how physicians interpreted information and reacted to evolving and frequently incomplete data. Two key findings included the importance of incorporating other team members in discussions related to patient care decisions and expanding the care team's access to a larger number of data sources. Their findings pointed toward team based CDS tools supporting a system-based approach toward improving patient care.

System of systems. Vockley (2013), a leading HIT consultant, explained the lack of interoperability of HIT systems in the context of a Systems of Systems (SoS) theory. Describing the current state of EHRs, Vockley identified that recent adopters failed to recognize the lack of bi-directional integration with devices limiting the usefulness of the EHR in optimizing patient care. Hospitals deployed numerous systems necessitating constant vigilance and inspection across each unique device or piece of equipment. Until vendors considered systems based design methodology, HIT users must contend with workflow interruptions and data gaps resulting in the risk for patient harm.

In addition, complexity arises from emerging requirements to link patient data across many venues of care. As HIT evolves to address SoS needs, Vockley suggested system developers address needs for connecting people to systems holistically or in a sociotechnical consistent fashion. Vockley based his observations from survey results of

American medical informaticists' greatest concerns with EHRs including the lack of interoperability and connectivity of devices and data.

Work-arounds and systems thinking. Novak, Holden, Anders, Hong, and Karsh (2013) conducted a qualitative study assessing nursing interaction with adoption of EHRs. The authors identified implications specific to conflicts in automated workflow compared to preferred clinical workflow and the workarounds such conflicts necessitated. Additional researchers such as Smith and Koppel (2014) similarly focused their research on clinical users identifying workarounds as potential flaws in EHR design. Smith and Koppel questioned the feasibility of adding back into the EHR some characteristics of paper-based communications. For instance, they suggested giving EHR users the ability to mark up a captured screen to express confusion, identify errors, or suggest design improvements. Novak et al. (2013) also sought to gain an understanding of workarounds as a means for informing improved system design. Use of a newly deployed medication bar code software system served as the basis for capturing workflow conflicts. In addition, Novak et al. captured the adaptations created by the nursing staff users of the new system. The authors identified that system developers designed step-wise processes based on the expectation of a linear clinical workflow that failed to replicate the way nurses performed medication administration tasks.

Novak et al. (2013) found systems designed solely on specific role requirements, without an appreciation of systems or a team-based approach to holistic and patient-centered care, generated substantial task tension. Intentional workarounds by a single group of users, such as nurses, introduced risk to patients even though users deviated

from designed protocols over concern for doing the right things. These findings by Novak et al. remain compelling in light of the increasing needs for cross-functional care teams coordinating patient care in the ACO model.

User and role specified design. Calman, Hauser, Lurio, Wu, and Pichardo (2012) identified the growing importance of EHRs for supporting improvements in the care of chronically ill patients. The authors described the experiences of a New York health information exchange system shared by the city of New York's Department of Public Health and Mental Hygiene (NYC DOHMH) and the Institute for Family Health. Calman et al. (2012) stressed the importance of well-designed alerts prompting both better clinical decision- making and improved sharing of patient data across a variety of care venues.

Lanham et al. (2014) conducted a novel, qualitative study exploring ambulatory physician perceptions for management of clinical uncertainty while interacting with an EHR. The authors categorized physicians by level of EHR engagement suggested to reflect each physician's comfort level with managing patient risk and uncertainty. Recognizing that physicians managed their uncertainty differently generated implications for how physicians might engage with an EHR. Previous research conducted by Lanham et al. focused on EHR engagement by provider groups rather than focusing on individual physician behavior. The authors developed two categories of uncertainty reflective of physicians "absorbing" uncertainty or "reducing" uncertainty. Reductionists sought more data such as querying test results to make better-informed decisions with the goal of reducing clinical uncertainty and risk. Absorbers dealt with clinical issues for which no

immediate data exists requiring greater risk acceptance. Absorbers relied on greater and extended communication with patients and other stakeholders to manage clinical uncertainty and risk (Lanham et al., 2014).

The authors observed three contrasting profiles where some physicians relied extensively on EHR data for managing uncertainty, some physicians relied more on team and patient communication, and some physicians exhibited a combination of both absorption and reduction behaviors. The heaviest EHR users exhibited the reductionist profile while the least engaged physicians exhibited characteristics of uncertainty absorption. The findings from Lanham et al. add implications for software developers designing CDS tools for physicians engaged in complex patient care such as ACOs. Whether physicians supporting ACO's responsible for improvements in care safety, costs, and outcomes for defined patient populations view uncertainty as nonreducible remains unknown. Their findings suggested EHR use remained low among physicians with a style and outlook aligned with nonreducible uncertainty and absorption. For CDS software developers, the authors indicated use of improved team communication tools as essential for engaging this type of physician.

Technology acceptance models. In regard to technology acceptance models focused on software usability, Horsky et al. (2012) identified a lack of usability as a primary barrier to the adoption of automated decision support in the EHR. Of all formats of CDS, alerts and reminders represented the most commonly used approach for triggering behavioral change in routine clinical practice. The authors emphasized that building trust with clinicians represented an emerging area of importance in CDS design

consideration. Providing clinical software users assurances that CDS tools arise from the best evidence and standard practice supported improved clinician trust and adoption. The authors further identified user access to software development tools as a key need. Thus, Horsky et al. proposed software developers support toolkits and apps ensuring better localization of CDS tools. These authors discovered that over-alerting physicians with nonessential data contributed to greater patient harm whereas alerts generated from patient-specific data reduced the potential for harm.

Designed for usability. Similarly, Yen and Bakken (2012) emphasized the importance of usability testing occurring throughout a solution's lifecycle. Repeated testing as a solution evolves over time captures the extent to which the system remains fit for former as well as anticipated uses. In their assessment of usability testing performed against CDS systems, the authors identified a gap in the previously published studies. The majority of researchers developing CDS solutions failed to incorporate a framework or theory incorporating the use of acceptance testing.

Other researchers proposed development of additional decision support tools such as dashboards for reducing the complexity and improving the efficiency of clinical decision-making processes. Koopman et al. (2011) conducted a small usability study examining the experience of ambulatory providers interacting with their EHRs while searching for specific data on fictitious diabetic patients. Physicians were observed using customary methods for querying records. Subsequently, the physicians were provided with a unique dashboard as an interface for compiling patient specific data and observed throughout their use of the new tool. Use of the dashboard tool enabled the physicians to

identify all relevant patient data whereas customary search approaches reduced the accuracy in the identification of relevant data by 6%. The dashboard saved physicians several minutes representing efficiency gains and possibly safety improvements. Physicians admitted that when faced with long searches they defaulted to ordering items previously ordered. Duplicative ordering increased costs and subjected patients to potential harm. The research by Koopman et al. suggested improving CDS tools supports reductions in cost and medical errors. These researchers elicited a recommendation from physician software users for the use of rules in the dashboard requiring real-time responses by physicians during clinical practice. Likewise, Wanderer, Mishra, and Ehrenfeld (2014) anticipated addressing the current limitations of EHRs and creating opportunities for reducing costly medical errors arises through the proliferation of new and improved software solutions.

Summary. Across multiple theoretical approaches, researchers identified similar concerns specific to EHR clinical workflow and the need for improved decision support tools. Designing better software tools requires collaboration on the part of system users and developers. The findings from the proposed research may inform software tool improvements supporting physicians' use of EHRs in the setting of an ACO.

Discussion of the Independent Variables

The two independent variables selected for inclusion in the research consist of (a) the type of CDS tool deployed in the EHR; namely, pop-up alerts, and the timing for displaying an alert in a physician's ordering workflow. Rudin, a researcher with Rand Corporation, focused his research in areas of both HIT use and ACOs. Bates, a Professor

of Medicine at Harvard and Chief Quality Officer at Brigham and Women's Hospital in Boston is a leading authority on patient safety and use of evidence-based CDS tools for prevention of medical errors. A model proposed by Rudin and Bates (2013) proposed four elements technology vendors address through the development of new software tools: (a) identification of all providers and care givers responsible for a specific patient's care, (b) supporting seamless communication across the entire care team, (c) enabling all team members to share and create notes, adding to a patient's record, messaging others, and (d) enabling the constant tracking of a patient's status using proactive alerts. The development of such tools may overcome the hurdles care teams face due to the lack of interoperability of the current EHRs deployed. Yet, there is little research on desired CDS tools or how to develop them.

Aggeliddis and Chatzoglou (2012) demonstrated a construct for information quality or "content" presented to HIT end-users comprised of three components including the precision or "accuracy" of the information provided, the structure or "format", and the "timeliness" of information. These components supported improved HIT end-user acceptance. As ACO's coordinate care of chronically ill patients, the lack of interoperability and the siloed nature of EHRs remains a known contributor to patient harm. Rudin and Bates (2013) identified a need for software vendors to address the limitations of current EHRs through the design of improved CDS tools. The selection of the variables as characterized in this proposal may lend new insights into the design of enhanced CDS tools upon analysis of the final data.

Independent Variable A: Type of CDS Tool

Utilizing a definition previously articulated by the U.S. government's department for HIT, Karnik (2014) shared, "CDS software is loosely defined as any application that analyzes data to help health care providers make clinical decisions. CDS software is meant to enhance health outcomes by providing clinicians and patients with individualized application of medical knowledge, provided by an intelligently organized and filtering data processor." Types of CDS software applications include a variety of clinical workflow compatible tools such as the use of pop-up reminders triggered as physicians enter new patient orders and recommendations for specific care based on a potential diagnosis or problem (Karnik, 2014). The proposed CDS tool type consists of an alert that pops up in the physician's ordering screen during computerized order entry (CPOE).

Previous research assessing the affect of CDS use within EHRs on physician ordering demonstrated mixed results (McCullough, Zimmerman, Rodriguez, Bell, & Torrens, 2014). Some researchers found favorable physician responses when CDS tools triggered based on contextualized or specific patient data. For instance, the testing of new alerts and the use of an integrated dashboard uncovered areas for improving the specification for user action within the EHR (Smith et al., 2013). Pop-up prompting enabling physicians to address a patient order related to abnormal test results achieved high favorability by the evaluators. Smith et al. found that software testers reinforced their sociotechnical needs for automated, workflow compatible, and highly patient-contextualized CDS.

Other researchers such as Peikari et al. (2013) assessed the relationship of the quality of information provided to physicians during CPOE and physician medical related errors. The authors summarized that the intensity of information required by physicians for effective decision-making necessitates further consideration in how to deliver high-quality information that meets the needs of physicians working in an electronic ordering environment. Additional researchers such as Spaulding and Raghu (2013) examined medication management within CPOE and noted a limited effect on the cost and quality of care. The authors suggested a limitation of their study pertained to the short experience of CPOE at the time of their research. The authors anticipated improvements arising with the optimization of software addressing physician workflow requirements. These findings lend additional support as highlighted by other researchers concerned with the sociotechnical considerations for the evaluation of CDS tools (Koopman et al., 2011; McCullough et al., 2014; Smith et al., 2013).

A common type of CDS includes the application of clinical logic displayed as an alert or decision-making rule. Bell et al. (2014) developed and tested clinical algorithms or rules as a form of CDS meant to provide active guidance to physicians prescribing medications within EHRs. In the absence of active or automated CDS, providers missed critical patient data. Bell et al. reinforced current views that new data evolves faster than clinicians can assimilate such information in daily practice. Thus, the risk for missing critical information within a patient's record increases. The authors tested active CDS at St. Jude's Children's Research Hospital in a single vendor's EHR system deployed for

use across multiple care venues. The authors found the use of active CDS changed prescribing behavior of physicians in all but 5% of assessed cases.

Software applications of a specific CDS type such as a medication pop-up alert includes consideration for how physicians perceive the tool. McCoy et al. (2012) evaluated CDS alerts in EHRs from the provider's perspective. Better incorporation of user feedback supported improvements in alert design. The authors developed a framework for assessing the quality of alerts triggered in an EHR at Vanderbilt University Hospital. In their validation study, the authors hoped to address a shortcoming from a prior assessment of a CDS tool for managing patients with kidney disease. Prior evaluation of another CDS tool identified physicians ignored nearly 80% of the alerts fired. However, the prior assessment lacked the context for the patient's treatment preventing an understanding of whether the physician's actions were appropriate.

Provider or physician use of CDS such as automated allergy checks and other types of medication alerts potentially reduces medical error (McCullough et al., 2014; Peikari et al., 2013; Shaikh, Berrong, Nettiksimmons, & Byrd, 2014). Although previous studies documented reduction in medical errors through use of CPOE in the EHR, mistakes occurred as organizations transitioned from paper to electronic systems (Pham et al., 2012). Engagement of nurses and patients in the medicine reconciliation process generated fewer errors than when physicians managed the process alone. According to Pham et al. (2012) physicians believed HIT use contributed to improved care through automated CDS tools; however, improved communication tools are necessary to support patients transitioning between care venues. The authors identified uses of CDS

supporting end-to-end care processes. Examples included incorporating surgical checklists beginning with (a) the patient encounter, (b) through the pre-operative preparation with the care team, (c) continuing through the surgical procedure, (d) and extending to the patient's immediate post-operative care period. Other types of CDS such as checklists, order sets, and patient care plans remain excluded allowing greater focus on assessing a single type of CDS.

Independent Variable B: Workflow Timing

The timing of when physicians receive decision support in their workflow merits consideration. In a systematic review on the effectiveness of CDS, Kawamoto, Houlihan, Balas, and Lobach (2005) found physicians 112 times more likely to change their behavior when CDS was delivered automatically in their workflow. With a highly statistically significant correlation between a physician's outcomes and the automatic provision of CDS ($P < 0.00001$), the authors recommended providing physicians with computerized workflow-integrated CDS. Thus, the clinical workflow period of ordering items for patients within a CPOE application of the EHR supports the selection of workflow timing as a variable for inclusion in the study of electronic pop-up alerts.

Path (2013) identified current interoperability challenges of EHRs that prompted stakeholders to focus attention on hardware design. However, the barriers to interoperability include matters of care team communication and understanding of software users' clinical routines. Challenges with interoperability occur when success is measured narrowly; for instance, by EHR vendors providing only point-to-point data transfers. Addressing the challenges of interoperability requires greater focus on

simplifying processes and ensuring users are knowledgeable and confident contributors to the system (Path, 2013).

Utilizing expert reviewers, the framework proposed by McCoy et al. (2012) focused on two aspects of alerting including (a) consensus that each alert fired for the right reasons, and (b) agreement that a physician's response to a specific alert aligned with best-medical practice. Evaluating the response by physicians required greater appreciation for each patient care episode especially in urgent care situations. Use of a comprehensive framework for assessing alert management highlighted how physician intention differs; for example, when physicians dismissed or signaled agreement with an alert without changing practice behavior. The authors indicated a need for robust treatment algorithms and more post-alert analytics.

Bowman (2013) categorized several EHR error types including those related to the use of CDS. Summarizing known issues with "Alert Fatigue," the author observed clinicians dismissed a majority of alerts for two reasons: (a) disturbances to workflow and (b) lack of applicable alerts for the most complex clinical encounters. Specific to reducing errors related to the use of CDS software, Bowman (2013) advised disclosing known issues, events, and complaints. The author supported recommendations by the Institutes of Medicine that developers include automated reporting and feedback functionality for users from within the EHR.

Anderson et al. (2013) described assessment of a CDS tool designed for physicians interacting with patients at risk for a second stroke. The authors noted the importance of CDS tools derived from evidence and integrated with EHR use

incorporating algorithms for automating decision support upon specific patient identifiers. The first version of the tool assessed usability testing and an associated failure due to poor workflow attributes and poor accessibility by stroke patients. Their findings highlighted the ongoing need for workflow consistent, automated, and adaptive CDS tools.

Dixon et al. (2013) conducted a pilot study assessing the utility of cloud-based CDS tools. Ambulatory clinicians gained access to the web portal enabling transmission of data queries. A SaaS model permitted access from multiple organizations and EHRs. Specialized software and coding enabled physician queries to return evidence based alerts derived from current patient data. The pilot study focused on the use of cloud-based CDS supporting the real-time care of cardiac and diabetic patients. Although limited to three ambulatory providers, their research finding provided insights for improving cloud based and community supported CDS tools. Dixon et al. identified how the initial placement of alerts in the clinical workflow hindered physician acceptance. The authors reinforced the importance of understanding clinical workflow when designing and integrating new CDS software functionality.

Methodologies Supporting the Dependent Variable

I selected perceived improvement in adherence to ACO reportable quality measures as the dependent variable. Specifically, CMS established a set of 33 quality measures as part of the ACO Shared Savings Program (Appendix B). Physicians and hospitals managing the care of Medicare patients realize a shared reward as they deliver health care at a lower cost while reporting on and demonstrating improved performance

with these measures (Barnes et al., 2014). Among the 33 quality measures, 12 measures pertain to the management of at-risk populations including patients with Diabetes, Hypertension, Ischemic Vascular Disease, Heart Failure, and Coronary Artery Disease (CMS, 2014). An additional measure defines the percentage of primary care physicians participating in an ACO achieving an MU incentive payment. CMS included this measure in anticipation that physicians meeting MU requirements deliver higher quality care (CMS, 2014).

Many researchers assessing the effectiveness of CDS and specifically the use of alerts suggested a focus on alert design holds the promise of supporting improved adherence to performance measures. In their survey of 225 primary care physicians, Sittig, Krall, Dykstra, Russel and Chin (2006) concluded that physicians responded more favorably to CDS for older and sicker patients such as those with comorbid conditions. A key limitation to their study as noted by the authors further informed the selection of the variables for the proposed study. Sittig et al. (2006) concluded, "Whether clinical decision support should be, or can be, used to help clinicians reach specific clinical targets that correlate with specific financial incentives is still an unanswered question. In addition, we did not specifically ask questions about clinical workflow, user interface characteristics, or information content; issues that our previous work indicated were important user acceptance factors."

McCullough et al. (2014) suggested alerts contextualized with patient data and incorporating sociotechnical considerations of physician users holds great promise in reducing costs through better quality measure adherence. In their quantitative analysis,

the authors anticipated appropriate CDS use supporting the avoidance of one million unnecessary antibiotic prescriptions. In their conclusion, the authors recommended aligning CDS tools with quality initiatives.

Agha (2014) conducted quantitative analysis utilizing three sources of publically available data including annual hospital survey data, the CMS claims database, and HIT industry data specific to U.S. hospital adoption of EHRs with CDS. Agha examined the extent to which adoption of EHRs over a time span of seven years affected the cost and quality of care. Use of regression analysis failed to demonstrate any significant relationship between the use of HIT and reductions in mortality at one year among hospitals adopting EHRs. Finding no meaningful relationships between cost and quality with adoption of EHRs, the author suggested physician incentives present at the time of the analysis possibly influenced the results. As health care reform encourages providers to shift their practices from fee-based models to value and outcomes-based models, the potential for EHRs to support cost and quality improvements increases (Agha, 2014). Notably, Agha identified the window of the research as a potential limitation. Based on data collected between 1998 and 2005, the EHRs deployed then possibly lacked the CDS tools needed for supporting better care delivery. In addition, the clinical users potentially lacked sufficient experience to extract optimal value from the EHRs. Agha suggested future research consider the affect of MU requirements and health care reform models on the use of HIT and effects on care quality. Recognizing that deployment of EHRs alone failed to improve patient outcomes, Agha suggested EHRs might evolve as organizations

and providers are held to new standards such as MU criteria necessitating the use of EHRs in demonstrating such improvements.

Chokshi, Schectman, and Agawal (2013) discussed the Department of Veteran Affairs' (VA's) evolving experience toward patient-centric care. In terms of health care reform the growing need for care delivered beyond the walls of hospitals stimulated leaders at the VA to consider innovative care delivery platforms. Adoption of new platforms required development of team-based training programs, selection of patient-centered metrics, and recognition of risk as a cultural value. The authors identified team communication as a likely challenge inherent in new care models such as ACO's. As care focuses on the needs of population health management across different venues of care, the authors anticipated a greater reliance on software tools supporting team based care coordination and communication. Similarly, Dubois et al. (2014) while assessing ACO readiness survey respondents found several limitations ACOs had not adequately managed. The authors identified unfulfilled expectations for improved safety, care quality, and cost reductions. Noting many ACO clinical software users mostly relied on electronic prescriptions for purposes of managing generic drug substitutions, Dubois et al. found little evidence of improved physician prescribing decisions for reducing costly medical errors. Specifically, prevention of duplicate orders and dispensing medications at the right cost represented key challenges. The authors suggested current HIT systems failed to fulfill expectations for improved safety, care quality, and lower cost. Most ACO's demonstrated high use of electronically managed prescriptions and an ability to drive generic substitutions. However, higher order software functionality in support of

better prescribing decisions and algorithms for reducing costly mistakes remain largely unrealized (Dubois et al., 2014).

Confirming international experience. Several international researchers examined reasons existing CDS tools lacked complete adoption by physicians. Price, Singer, and Kim (2013) assessed the capabilities of EHRs in Canadian primary care practices against a framework that considered the current technology infrastructure. In their mixed methods study, the investigators analyzed survey responses by categorizing the use of electronic medical records (EMRs) into ten distinct categories. Three categories of EMRs identified as (a) CDS, (b) patient support, and (c) practice support, consistently ranked the lowest across all clinicians surveyed. Physicians were unlikely to use decision support features provided within the EMR for two reasons. Either the physician was unaware how to establish alerts and rules or the physician entered data as free text making such data ineligible for capture by the software. A key insight gleaned from the study included the physician's perception of poor data quality as an obstacle to adopting advanced functionality of EMRs.

Baysari, Reckmann, Day, and Westbrook (2012) assessed the frequency of CDS alerts used within an Australian EHR. The authors anticipated alerts fired due to a combination of poor functional design and physician lack of familiarity with approaches to prescribing electronically within an EHR. Concerned that poor design and physician usability concerns limited EHR adoption; the authors identified areas of improvement for software designers and teams responsible for EHR implementation. The authors found that EHR user failure to learn software commands resulted in less efficient ordering

practices and triggered unnecessary alerts. The authors recommended CDS software designers consider failure modes based on an improved understanding of user behavior and suboptimal use of high-level software features. The recommendations lend guidance for potentially avoiding design errors in the development of new CDS software tools.

Other international researchers also examined the use of CDS alerts in EHRs. Jung et al. (2013) conducted a mixed method international survey of predominately European physician users and nonusers of CPOE. Physicians from 11 hospitals participated in the survey of which eight hospitals provided physicians with access to CPOE. More than 1,000 physicians participated in the survey. In general, the physicians were in agreement of the benefit of alerts specific to medication use requiring documentation in EHRs. Respondents identified fairly uniform interest in the ability to tailor alerts for improved specificity. Many physicians identified alert fatigue as a concern. The attitudes of the physicians from hospitals that provided more advanced mechanisms for setting alerts were more favorable. Physicians mostly agreed that alerts specific to endangering a patient due to a drug allergy or drug-drug interaction should take precedence with opportunities to filter out less relevant alerts. Specifically, physicians identified a need for an intelligent EHR system surfacing patient specific and clinically relevant alerts rather than generic medication warnings. Physicians also preferred alerts triggered within their clinical workflow rather than disrupting the pace of their routine clinical practice.

Focusing on patient needs. Asch, Muller, and Volpp (2012) suggested computerized approaches to health care for better monitoring of patient behaviors.

Recognizing that prior health care models generated little interaction between caregivers and patients, the incorporation of HIT focused on patient needs resulted in better prescription adherence and measurable improvements in care. Depending on the severity of illness, the authors anticipated computerized patient interactions and caregiver follow up potentially reduces health care costs through reductions in unnecessary emergency room visits and avoided re-hospitalizations. Asch et al. recommended developing software applications automating engagement for those patients requiring constant monitoring for conditions such as chronic heart failure, cardiovascular disease, and diabetes.

Hackl et al. (2013) reported on a novel development of an adverse drug event (ADE) scorecard facilitating retrospective review and discussion across health care providers within a department or hospital unit. Based on a historical analysis of actual ADE's in each test department, scorecards incorporated a customized algorithm for the identification of potential events. The authors noted that integrated decision support tools prompted only the ordering physician without elevating the risk of an event to other stakeholders. Using a field-based experiment conducted over one year, Hackl et al. identified positive use cases for the scorecards confirmed by post use interviews with no correlation found in the actual rates of adverse events post implementation. The authors considered that the retrospective use of the tool versus active decision support in the workflow of the team might have been a limiting factor. However, the majority of the users were favorable toward a team based alerting mechanism creating the possibility for further design improvements of active CDS tools. They recommended a collaborative or

team based approach in reducing the risk of medical errors similar to the potential CDS tool needs of ACO providers.

Grace et al. (2013) explored the use of CDS systems in the care of patients with multiple, chronic conditions. Using a qualitative approach, the authors focused on general practitioners in Ireland facing health reform efforts pertaining to population health management. The authors considered a key challenge of managing chronic care in primary care practice as the volume of patient visits increased the volume of patient data managed and shared. Grace et al. relied on the Sensibility Framework, previously validated in other CDS assessment research. Their findings identified that EHR systems used in a community captured better patient data from each visit but restricted a physician's ability to synthesize data and make informed clinical decisions when dealing with complex patients. One of the key limitations noted by the authors was a lack of accessible evidence-based practice guidelines in the EHR necessitating external web searches by the clinicians to resolve their clinical questions. The limitation of existing CDS within ambulatory EHRs raised the question of whether developing specialized CDS tools for chronic disease management should include real-time access to evidence-based guidelines.

Overcoming Current EHR Limitations

Timbie, Damberg, Schneider, and Bell (2012) identified the current challenges faced by hospital specialists interacting with existing CDS deployed in EHRs. The authors recognized limitations specific to the access of patient data in the EHR clinical workflow. Ideally, clinicians connect recorded patient data with clinical insight supported

by decision tools driven from current evidence. Developers of CDS tools frequently lacked clinical insights arising from their limited clinical domain experience. Recognizing the need for improved CDS tools, Timbie et al. (2012) developed a new process to capture CDS requirements. The authors identified early involvement with clinical specialists as an essential element in developing improved CDS tools. The authors suggested that CDS objectives identified by clinical specialty better-informed new solutions and encouraged greater participation of specialists in product development activities. Timbie et al. suggested software developers consistently embed clinicians in new software application design initiatives.

Cloud based and open source platforms. Slavov et al. (2013) shared their recent experience using the Health Level 7 (HL7) version 3 standard to perform data queries across disparate EHRs. Recognizing the issue of closed EHRs limiting longitudinal access to clinical and patient data, the researchers focused their efforts on querying data irrespective of location. The authors selected the field of cancer given the complexity involved in assimilating voluminous data in a constantly evolving field. A cloud-based environment became the common portal for linking several hundred physicians throughout various testing phases. Other researchers such as Atkins & Cullen (2013) considered the future affect of web or cloud-based solutions. Incorporating open source software, Slavov et al. successfully demonstrated the ability for physicians to run clinical queries and assemble data without extracting or sending patient files from a secure environment such as an EHR. Recognizing the challenges of obtaining longitudinal

patient and clinical data, Slavov et al. developed a novel software routine incorporating the use of the new standard and open source software.

Exploration of cloud-based options for CDS software delivery continued with research performed by Goldberg et al. (2014). The researchers developed evidence-based CDS tools for deployment at Partners HealthCare System. Partners, affiliated with Harvard, participated in research specific to the needs of integrated health systems and managed care models. Among the first organizations establishing an ACO in the CMS pioneer program, the authors contributed to a consortium of experts focused on developing CDS solutions for widespread use in health care systems. The output of their effort was the creation of ECRS; an enterprise-based approach to clinical rules dissemination built on concepts of service-oriented architecture (SOA). Designed as a web-based offering, Goldberg et al. considered the modular nature of their approach and the web-based design as key drivers for the scalability and the adoption of CDS tools across health care organizations.

Integration of primary care practices. Audet, Squires, and Doty (2014) conducted quantitative, regression analysis assessing HIT use in association with factors such as physician practice size, integration with hospital systems, and the use of government stimulus funding. The authors noted nearly 75% of physician practices adopted HIT. Comparing available primary care survey data prior to HIT stimulus funding in 2009 and since 2012, the authors anticipated identifying new insights related to the growing use of HIT by primary care physicians. Among the areas of interest assessed by the authors included HIT enabled ordering software for physicians and CDS.

By 2012, nearly two thirds of physicians utilized electronic order entry. The use of CDS also improved as 20% more primary care physicians reported using CDS tools such as evidence-based reminders concerning selection of patient tests or medications. A noted limitation across primary care physicians concerned the inability to create patient-specific reports. Only 1/3 of physicians surveyed relied on HIT systems for exchanging patient-specific data across care venues and among other care providers (Audet, Squires, & Doty, 2014).

Linder, Schnipper, and Middleton (2012) retrospectively quantified the quality of care patients received by auditing a subset of quality measures documented within primary care EHRs. The authors noted limited initial use of CDS with a trend demonstrating improvements in care quality through more active CDS use. The study upheld previous research findings that merely owning an EHR failed to improve care quality. Improving patient care remained dependent upon how the clinician interacted with the EHR and the extent to which CDS tools integrated with clinical workflow habits. The authors touched on the importance of a common EHR platform, physician training, and standardized documentation templates supporting improved HIT adoption.

Adoption of HIT tools remains highest for those physicians practicing within an integrated care delivery network or health system. According to Audet et al. (2014), the difference among physicians' HIT usage widened in comparison between small practices and large physician groups. Larger physician practices utilized advanced HIT functionality nearly four times as often as solo practices. They identified opportunities for

improving adoption of CDS tools suggesting the need for advanced software enabling patient-specific reporting and sharing of data.

VA researchers Maciejewski et al. (2013) examined the quality of care diabetic U.S. veterans received when managed by sole or multiple health care providers. The authors compared the adherence to evidence-based guidelines as veterans sought care either within the VA system or externally to the VA system. Their research focus added significant context specific to the continuity of care for patients with chronic conditions moving from single provider settings to ACO's. Both under-testing and over-testing occurred more frequently outside the VA health care system. The authors' surmised access to a common EHR in the VA health care system resulted in patients receiving care aligned with evidence-based guidelines. The use of a common software system potentially enhanced care quality through the provision of better visibility to the totality of the care patients received.

Denham et al. (2013) conducted a national survey polling HIT and clinical leaders in regard to their concerns for safety with the use of EHR applications such as CPOE. The misuse of HIT ranked among the highest concerns by those surveyed. Specifically, close to 90% of those surveyed expressed the greatest concern for improperly paired or "mismatched" data entered into the EHR system and shared by care team members. Use of a simulation tool identified significant medication-related errors, possibly life threatening and likely undetected during routine use of the system. In addition, use of the same system at different hospitals yielded different simulation results suggesting unacceptably high levels of variability.

The researchers recommended the routine use of simulation tools post EHR deployment and specifically identified a scalable, EHR modified "flight simulator" tool as applicable for these assessments. According to the authors, every adverse patient event costs a community hospital roughly $4,000. Recognizing that nearly half of all large community hospitals installed EHRs with CPOE capability, the authors highlighted the need for further focus on post-EHR implementation safety assessments. Denham et al. (2013) advised software developers to actively address the known limitations of CDS through improvements in CPOE applications and care team collaboration.

Patient centric care. Liebovitz (2013) outlined several clinical decision-making examples for leveraging the EHR system for improved patient care. Noting how EHRs simply substituted a patient's paper chart for an electronic chart, Liebovitz (2013) identified the lack of an integrated patient view in the EHR results in the same issues encountered when managing patients on paper. In addition, the need for patient medications to be reconciled on admission and discharge remained hampered by systems that failed to incorporate the patient's complete medication history. For example, the ICU patient that is at risk for an acquired hospital infection is rarely escalated for proactive prevention as a result of the EHR system lacking sufficient support for complex decision routines. Liebovitz (2013) and Atkins & Cullen (2013) anticipated EHRs evolving to support a more patient-centric model of care requiring new tools and dashboards for facilitating transparent and shared decision making.

Elshaug, McWilliams, and Landon (2013) expressed support for the evidence-based identification of tests, procedures, and medications expressed as "don't do" CDS

for use by health care providers committed to safely eliminating waste in health care. As the development of "don't do" lists supported by medical societies commences, the authors identified challenges in the scaling of such lists in routine clinical practice. Without patient contextual information readily available during patient encounters, a service initially deemed medically unnecessary becomes relevant and clinical necessary when unique patient characteristics become known.

The authors noted that current payment models rewarded physicians for extending services across different patient populations irrespective of the evidence for the use of those interventions. Incomplete or missing patient documentation resulted in missed opportunities for identifying the relevancy of a prescribed intervention. Eliminating payment for list-based items misses the mark given the need to contextualize circumstances for each patient. Elshaug et al. (2013) proposed the right solution requires the design and development of new, point of care CDS tools. The authors suggested the development of CDS tools supporting the reduction in unnecessary medical interventions in alignment with the goals of health care reform.

Similarly, Berwick and Hackbarth (2012) identified several categories of waste accounting for as much as 20% of current health care costs. Among the six segments of waste defined by the authors, improvements in HIT software potentially addresses waste stemming from inappropriately ordered care along with poorly coordinated and executed patient care. The segment of inappropriate care included items such as the over utilization of antibiotic medications. Overzealous treatment including unnecessary surgeries in patients with end-stage conditions accounted for more than $200 million in costs.

Berwick and Hackbarth recommended the continuation of medical society identification of unnecessary tests. The authors advocated the development of new tools and practitioner education aimed at steering current clinical practice away from wasteful prescribing behaviors. The authors described how a poorly designed U.S. health care system reinforced excess and inappropriate use of medical intervention.

Berwick and Hackbarth (2012) recognized that new technology alone fails to reduce costs when delivered in the absence of broader organizational and system change. Recognizing that elimination of all waste advocated disruption to a health care system designed on the basis of occupying hospital beds to capacity, the authors suggested tackling a fraction of waste and thereby reaping meaningful benefits for patients and taxpayers. The authors highlighted unmet opportunities where the application of CDS tools combined with a focused effort by clinical practitioners potentially yields the greatest opportunity for reducing costs and enhancing patient care.

The need for interoperability and standards. Marsolo (2012) discussed the challenges related to implementation and use of current EHRs. Specifically, the author called out the lack of interoperability of EHRs with other clinical applications. The lack of integration with hospital activities such as clinical research limited the utility of the EHR reinforcing the need for multiple data storage locations. The author cited statistics that four of every ten patients in the U.S. have a medical record in Epic. The proprietary and closed systems provided by Epic and Cerner dominated the U.S. market. Rather than patient data becoming widely accessible through a higher number of applications and

programs, the vendors limited incorporation of outside tools further restricting the longitudinal view of each patient's record.

The author participated in two research initiatives that faced substantive limitations as a result of the lack of interoperability across EHR systems. Data collected in population research studies could not be imported or extracted from the EHR system. Although Epic agreed to develop a data collection form to support the research initiative, the other vendors did not collaborate forcing participating hospitals to either abandon the research or develop expensive stand-alone solutions. Marsolo (2012) recommended greater collaboration between the informatics community and the EHR vendors coupled with an Apple-like environment for software developers to share applications in support of robust data sharing.

Researchers such as Rea et al. (2012) and Kuperman (2011) discussed design limitations of current EHRs preventing seamless data exchange. These authors identified the need for improved software tools, standards, and platforms. Rea et al. (2012) described a HIT research project sponsored by the Office of the National Coordinator (ONC). ONC's Strategic Health IT Advanced Research Projects (SHARP) Program funded several projects supporting the adoption of HIT. In the specific research project described by the authors, both structured and unstructured data from 10,000 patient records were transmitted to a specially designed open source platform supporting data retrieval from two large U.S. health care systems, the Mayo Clinic and Intermountain Healthcare. The researchers planned to access and analyze patient data from multiple locations with expectations for improving the management of chronic diseases across

large patient populations. While the project demonstrated some success with respect to normalizing data, the authors noted several challenges. A lack of standardized terminology represented a significant challenge in supporting large-scale population health management approaches (Rea et al., 2012).

In contrast to these approaches, Yasnoff, Sweeney, and Shortliffe (2013) countered the solution to interoperability extends beyond addressing the known limitations of EHRs. The authors advocated enhancements to health information exchange through the adoption of a national patient record bank. The authors contended that achieving a scalable approach to managing population health requires the collaboration of all stakeholders toward realistic goals.

Summary. Numerous authors highlighted the need for collaboration across the health care industry and government in addressing known EHR limitations. Voicing a commonly expressed opinion, Kellermann and Jones (2013) identified a lack of standards as a primary contributor to the lack of interoperability of EHR systems. Expressing the concern of many in regard to the billions invested in HIT, the authors reinforced the importance of a patient centric health care model supported with appropriate payment models. Kellermann & Jones called for the active participation of vendors and health care providers in redesigning care processes for the optimal use of health care information technology.

Similarly, Kuperman (2011) reviewed the history of interoperability issues in patient data exchange with current HIT solutions identifying requirements for interoperable data exchange. Describing another ONC sponsored program, Kuperman

identified the goals of the Direct Program as identification of challenges in the electronic exchange of patient data and potential solutions. Participants of the Direct program and the ONC anticipated EHR and software vendors aligning product development efforts with the use cases the program identified. The authors concluded a need for greater collaboration across industry stakeholders with more focused research and development effort.

Future CDS Research Opportunities

HIT researchers identified a lack of patient engagement as an emerging need for enhancing software tools for shared clinical decision-making. McGinn et al. (2012) conducted a qualitative Delphi study exploring the perspectives of actual and future EHR users in Canada. The authors anticipated informing future quantitative research related to EHR deployments. Their study conducted via the internet provided expert panels with a link to a survey requiring completion within 48 hours. After the first survey, sharing of respondent answers supported consensus building during subsequent survey rounds. A framework identified by McGinn et al. (2012) highlighted consensus along a continuum of agreement as (a) strong, (b) moderate, (c) partial, or (d) missing. A significant limitation of the research stemmed from the perceptions of future users identifying concerns in the absence of experience. Attempts to include a patient panel failed due to lack of participation. McGinn et al. (2012) identified an area for future research focused on improving the health care provider's understanding of the patient's perspective during episodes of care delivery.

Patient and family focused. Fleurence et al. (2013) discussed the remit of the Patient Centered Outcomes Research Institute (PCORI) mandated by legislation to address the research interests of patients and caregivers. New research aims to place greater significance on outcomes that matter to the majority of patients and their families. Many clinical studies excluded elderly patients and those with complex conditions despite the higher cost of care associated with caring for these patient populations. An additional goal of PCORI includes improving access to evidence-based sources of information for use by patients and caregivers.

Several proposed and unfunded PCORI studies identified the need for CDS equipping patients and caregivers for discussions regarding best treatment options with their doctors. The organization created a prioritization process by assigning a unique "conceptual value" to the information potentially garnered from the proposed research. The discussion by the authors raised a novel aspect to future design of CDS tools. Should new tools supporting ACO clinical software end-users incorporate features enhancing the direct interaction with patients and caregivers?

Genomics based CDS. Several researchers pointed toward emerging fields such as genomics and advances in machine learning or artificial intelligence opening new paths for better capture and synthesis of clinical and nonclinical data. Caceres (2013) reiterated the emerging value of EHRs supporting patient-centric care and genomic medicine. Overcoming the lack of interoperability remains central to realizing these benefits and opportunities for patients to easily share and exchange data with providers. Caceres envisioned connecting patient and clinical data to other information sources

specific to employment history, housing, and education facilitating improvements in population health management. Pakhomov et al. (2011) identified opportunities for new research leveraging unstructured data. Current EHRs contain patient and clinical data entered as unstructured free text and structured text adding complexity to searches or queries. Heightened complexity stems from the lack of tools permitting identification and grouping of similar terms or concepts. The authors described their efforts in developing a computerized framework establishing a common set of standards supporting future categorization and mapping of like terms. Setting open source standards permits other researchers access resulting in anticipated improvements and expansion of the proposed framework.

Improving CDS through artificial intelligence. Derived from artificial intelligence software programming, Pakhomov et al. (2011) exposed the results of their mappings to outside human raters experienced with medical coding and informatics. Higher agreement of terms occurred by human raters although the machine derived matching achieved a moderate level of agreement. Their research points toward the potential for future development efforts in automating term mapping for improved data queries within the EHR.

Murdoch and Detsky (2013) described "Big Data" use cases and limitations supporting improvements in the cost, quality, and efficiency of care delivered. Recognizing the immense sets of data residing within deployed EHRs, the authors discussed the nature of unstructured clinical and patient data as a significant challenge in applying typical analytical approaches. Potentially, only 20% of data stored in the EHRs

stems from nontext based data. A potential avenue toward unlocking unstructured text-based data hinges on the use of advanced software applications such as artificial intelligence, machine learning, and natural language processors. The authors anticipated greater use of real-time CDS tools prompting clinicians based on contextual patient data combined with other data sources.

A big data CDS landscape. The landscape for new and improved types of CDS remains robust with future applications of genomics and artificial intelligence supporting patient and family centric applications. A connected environment capturing data sources from personal devices lends further possibilities for patient and family engagement (Atkins & Cullen, 2013). The inclusion of a patient's genetic data and integration of laboratory values retrieved from fitness applications and other devices opens up new areas for future research. Murdoch and Detsky (2013) described adoption of EHRs as only an initial step in the transformation of care. Caceras (2013) also discussed the emerging value of EHRs supporting patient-centric care and genomic medicine. Overcoming the lack of interoperability remains central to realizing these benefits and opportunities for patients to easily share and exchange data with providers. Eventually connecting patient and clinical data to other information sources specific to employment history, housing, and education may offer important advancements in population health management. Future research exploring the application of nonclinical data with patient contextual clinical data may enable earlier identification of at risk patient populations and inform improvements in software tools for those purposes (Atkins & Cullen, 2013).

Pathak, Kho, and Denny (2013) affirmed ideas expressed by Murdoch and Detsky (2013) through the identification of genomics as an emerging research use case in HIT and population health management. The authors identified that minimal research existed exploring ways to extract patient data from EHRs specific to furthering the science of genomics. The future use and application of data search standards enables the identification of new patient cohorts thereby advancing research in areas of population health previously deemed inaccessible (Atkins & Cullen, 2013). The authors suggested the use case for integrating patient data captured from digital applications or mobile technology enabling advancement in patient-contextualized research.

Waitman, Aaronson, Nadkarni, Connolly, and Campbell (2014) described an early research initiative formed through the collaboration of more than 20 hospitals and 70 clinics across seven states encompassing more than ten million patients. The Greater Plains Collaborative (GPC) selected one common disease and one rare disease as the basis for exploration of sharing data and supporting interoperability for the exchange of common data elements across all EHRs and HIT systems participating in the GPC.

The collaborators viewed establishment of a research network as potential proof that U.S. investments in HIT supported a favorable return on the billions of dollars spent on EHRs. Focused initially on Epic System installed EHR's the GPC expects to include other EHR vendor systems. Waitman et al. (2014) proposed future CMS MU Stage Two and Stage Three criteria supporting further development of population management tools. These authors in addition to Agha (2014) suggested future research consider the affect of

MU requirements and health care reform models on the use of HIT and effects on cost and care quality.

Summary. As suggested by these authors, an advanced requirement for demonstration of MU necessitates evolution in EHR design including the need for ongoing research in CDS software tool development. The promising applications of genomics coupled with the use of artificial intelligence and machine learning keeps HIT researchers hopeful in regard to overcoming current EHR limitations. Whether through the adoption of new standards or an accelerated move to cloud and open based platforms, the opportunity to continue studying and improving the types and timing of workflow integrated CDS remains compelling.

Summary

McGowan, Cusack, and Bloomrosen (2012) shared four components comprising the American Medical Informatics Association (AMIA) conference recommendations for reducing the potential for patient harm with HIT use. Their recommendations spanned the technical, human, organizational, financial, and regulatory aspects of HIT implementation and adoption. The recommendations from these medical informatics experts underscored the need for extensive collaboration across stakeholders engaged in the development of HIT systems and their deployment. McGowan et al. (2012) also emphasized the importance of the U.S. government in overseeing and directing HIT adoption from a national health care perspective. Given the acceleration of HIT adoption, the authors concluded that the risk for patient harm as a byproduct of EHR adoption remains a potential threat. The authors suggested that mitigating the risk of patient harm

required conducting additional research studies. Correctly harnessing EHR data and consolidating appropriate data sources represents a new frontier in health care for the realization of improvements in the cost and quality of care (Murdoch & Detsky, (2013); Pathak, Kho, & Denny, (2013). The results from the proposed research study may partially address the need for enhanced collaboration of software vendors with physician end-users in design of improved CDS tools.

Transition and Summary

The literature review revealed opportunities for improvements in CDS tools supporting the goals of ACOs. Given recent government investments in HIT and legislation supporting the formation of ACOs, interest in enhancing physician use of CDS tools remains high. While research exists related to CDS alerts, none of the previously published studies included a quantitative analysis of the sociotechnical factors in alert design and physician perceptions of better adherence with ACO quality measures.

The next section includes details regarding the research study design. I share details specific to the study population, sampling, and handling of data. Section Two concludes with explanations for conducting data analysis and plans for ensuring the validity of the survey instrument. The third section includes the results from the research analyzed in a manner consistent with quantitative correlation studies. I hope the results of the research will add to the existing body of work specific to the use of workflow integrated CDS. I will share any additional insights gleaned from the analysis for use by third-party software developers seeking to address the sociotechnical needs of physician end-users. Section Three concludes with my suggestions as to how the results of the

research may be applied to future research endeavors including the business and social implications of my research findings.

Section 2: The Project

Quantitative, correlation research supports the extrapolation of findings from a sample to a population. To collect data for the planned research, I developed a survey instrument and vetted the questions with experts in the field of CDS software use. The research participants included in the study bring with them the relevant EHR and CDS experience to adequately address the survey questions. Using a correlation study design permits examining clinical software user needs for improved CDS tools. Specifically, the methodology enables examining a relationship, if any exists, between the design and timing of alerts with physician perceptions of improved adherence to reportable ACO quality measures.

Purpose Statement

The purpose of the this quantitative, correlation study was to examine the extent of any relationship between the type and timing of CPOE automated alerts with physician perception for better adherence to reportable ACO quality measures. The independent variables related to sociotechnical attributes included the type of decision support provided and the timing for presenting an alert to physicians in an electronic ordering workflow. The dependent variable tied to reportable ACO quality measures supported analysis of physician perception toward the achievement of ACO quality measures and the cost reduction and performance improvement goals associated with using CDS during electronic ordering.

The study population included U.S. physician executives from integrated health system ACOs using CDS software tools in either a Cerner Corporation or Epic Systems EHR. These two EHR vendors hold the largest U.S. ACO market share supporting their selection as the basis of the study population (Chalasani et al., 2014). Opportunities for enhancing the experience and performance of physicians using CDS tools in an EHR supports the primary social change goal of ACOs in supporting better quality care through the advanced use of HIT (Kuperman & McGowan, 2013).

Role of the Researcher

I am currently employed and have equity in a venture capital funded SaaS firm specializing in the design of EHR integrated CDS tools. My work enables close collaboration with experts in software tool design as well as the physician end-user community across many academic medical centers and community hospitals. Given my professional work experience, I remained cognizant of my potential for influencing the results of the research and the participants' perception of bias related to the survey questions (Klabunde, Willis, & Casalino, 2013).

Using statistical, parametric analysis supports objectivity in presenting the results obtained from Likert-based surveys (Norman, 2010). However, Klabunde et al. (2013) reported surveys administered to physicians frequently yield diminished response rates. The authors suggested physicians concerned about survey data reflecting negatively on their clinical practices increasingly fail to respond to new survey requests. Therefore, I proactively provided research participants with explicit details on my handling of their survey data and the blinding of all study participants to minimize the risk of

nonparticipation. In accordance with the Belmont Report (HHS.gov), I obtained informed consent from all study participants ensuring my proposed research conformed to the principles of conducting ethical research. I used a commercially available web-based survey platform tool for administration of the survey. Physician executives with financial ties to my firm were excluded from participation in the final survey further limiting the risk for unduly biasing the study results.

Participants

I drew from a purposeful sampling of physician executives working at health system directed ACOs using either a Cerner Incorporated or an Epic Systems EHR (Padgett, 2014). This approach provided each physician executive drawn from a homogenous population with an equal opportunity for participation in the survey (Peikari et al., 2013). Physician leaders frequently played an important role in the development of advanced CDS tools for use in EHRs (Berkowitz & Pahira, 2014). After obtaining institutional review board (IRB) approval (No. 06-09-15-0396865), I coordinated communication for inviting participation to the survey with my community partner, the Association of American Medical Directors of Information Systems (AMDIS). This professional society is a nonprofit organization with more than 2,900 physician members. The AMDIS email listserv included the population intended for the research. AMDIS leadership provided a letter of cooperation as a community partner for the study (Appendix C).

The study inclusion criteria restricted many AMDIS members from actively participating in the research. Slightly fewer than one half of an estimated 645 ACOs

obtained sponsorship by an integrated health system (Muhlestein et al., 2014). Of those, nearly one third included the use of an Epic or Cerner EHR (Berkowitz & Pahira, 2014, HIMSS, 2014).

After initiating a request for participation through the AMDIS listserv, I initiated follow up contact with targeted participants through an email directed from my Walden University email account. In a recent analysis of large-scale surveys directed at physicians, the majority of surveys conducted via the internet included an email solicitation from the researcher (McLeod, Klabunde, Willis, & Stark, 2013). My email invitation included details specific to the background and purpose of the study, the blinding of participant data, the benefits of participation, and a link to the survey. The survey included the consent form approved by Walden University's IRB.

Research Method and Design

The design of this quantitative, correlation study explored the extent of any relationship between an alert deployed in an EHR and the timing of deploying an alert with a physician's perceived adherence to reportable ACO quality measures. Both independent variables represented sociotechnical traits specific to the type of CDS tool known as an alert. Independent variable A represented attributes specific to alert content. Independent variable B represented other sociotechnical traits specific to the timing of presenting an alert during computerized physician order entry (CPOE). Other researchers examined associations of CDS use within CPOE applications for their affect on cost and quality (Spaulding & Raghu, 2013). The two independent variables selected provided the basis for assessing whether any relationship existed with physicians' perceptions about

their adherence to CMS reportable ACO quality measures. Physician's anticipating access to better workflow integrated CDS tools for enhancing their patient treatment decisions may attribute the application of these tools as supportive to fulfilling EHR MU requirements in accordance with the objectives of an ACO to improve care quality while safely lowering costs (Beeler, Bates, & Hug, 2014; Berkowitz & Pahira, 2014; Dubois et al., 2014). A detailed explanation of (a) the research methodology, (b) the research design, (c) alternative methods considered, and (d) the justification for the chosen methodology and design follows.

Research Method

Quantitative approaches underscore applications of evidence-based medicine in health sciences research. Moving from evidence-based medicine to evidence-based practice extends a positivist view (Hjørland, 2011). A positivist philosophy aligns with the evidence-based practice of HIT underpinning the selected research method. Others researching the transfer of knowledge in medicine recognized the usefulness of a positivist worldview coupled with quantitative based research methodologies (Walsh et al., 2012). A quantitative methodology permits a deductive approach through objective analysis of the variables and an opportunity to accept or reject a research hypothesis. Further, a quantitative method supports the application of inferential statistics permitting inferences from the sample to an entire population (Bryman, 2012). The selection of a quantitative method extends the utility of the research for an audience comprised of medical practitioners accustomed to an evidence based approach to research.

With substantive qualitative research previously conducted in regard to the software tool needs of physicians, I rejected utilizing that approach (Novak et al., 2013; Lanham et al., 2014). Qualitative researchers explore unstructured phenomena by discovering themes extracted from interviews or observations (Bryman, 2012). Although qualitative case studies deepen the examination for a specific phenomenon, such approaches generate insufficient data required for accepting or rejecting a stated research hypothesis (Bryman, 2012; Constantinides, 2013; Takian, Sittig, Singh, & Barber, 2014). Given the expectations for scientific rigor by leading health care professionals and technology industry stakeholders for whom the proposed research bears interest, I rejected the use of that approach. The aim of the research remained focused on determining whether any correlation existed between CDS alerts presented during a physician's computerized ordering activity and perceptions for better adherence to reportable ACO quality measures. A qualitative methodology precluded a deductive approach thus limiting the usefulness of the findings as applied to future CDS software tool design.

Combining attributes of qualitative and quantitative studies supports a mixed methods approach (Bryman, 2012; Onwuegbuzie, Frels, Leech, & Collins, 2011). The application of mixed methods brings utility to usability and acceptance focused research when investigators seek to uncover themes necessary for informing additional research elements included in usability experiments (Devine et al., 2014). Determining appropriate questions for the Likert-based survey derived from prior published studies on the application of electronic alerts reduced the need for uncovering new themes. When

researchers lack sufficient insights for testing a hypothesis, they include qualitative aspects (Bryman, 2012). By vetting the proposed questions with a small group of subject matter experts prior to conducting the proposed research, the potential benefits associated with a mixed methods study remain marginal in comparison. Rejecting the mixed methods approach in favor of a quantitative study aligns best with the goals of the study while supporting an expedient approach to generate data sufficient to accept or reject the stated hypotheses (Onwuegbuzie, Frels, Leech, & Collins, 2011; Venkatesh, Brown, & Bala, 2013).

Research Design

Quantitative studies incorporate either an experimental or nonexperimental design (Bryman, 2012; Turner, Balmer, & Coverdale, 2013). The use of an experimental design requires the researcher to control the environment and potentially manipulate the variables studied to determine a cause and effect (Bryman, 2012). While lacking randomization of participants, a quasi-experiment includes design aspects similar to a controlled study (Bryman, 2012). Along the continuum of social science research designs accessible to the researcher, survey design provides an optimal fit.

Similar to other researchers studying the relationship of CDS on a specific physician related outcome, I selected the correlation design utilizing a Likert-based, self-administered survey as most suited to the research question (Peikari et al., 2014; Xiao et al., 2012). Turner, Balmer, and Coverdale (2013) stressed the necessity of the research question informing the choice of study design. Examining the relationship between the type and timing of alerts with physicians' perception of improved adherence to reportable

quality measures utilizing an experimental design requires manipulation of variables within an EHR that remain outside the scope of the research.

A descriptive quantitative design provides an approach to generate statistics about the participants and the variables. The use of percentages and frequencies alone fails to support examination of any correlation including the direction or strength of the relationship across the variables studied (Turner et al., 2013). Among the types of quantitative designs available, I selected a correlation study in order to examine the nature of any relationship among the predictor and dependent variables. The use of a Likert-based survey supports an appropriate accumulation of data specific to the variables selected for a multiple regression analysis. Further, the application of correlation through statistical inferences supports the potential extrapolation of the results to the population of physicians from integrated health systems participating in ACOs. The findings from the study may be of interest to the software users and vendors engaged in the development and applicability of CDS tools for use by ACOs.

Population and Sampling

I selected survey participants from a purposively derived sample of physician executives participating in a U.S. hospital or health system sponsored ACO using either a Cerner Incorporated or Epic Systems EHR. Although purposive sampling is frequently attributed to qualitative research methods, the approach aligned best with the need to select participants from a highly homogenous population based on a designated set of inclusion criteria (Bryan, 2012; Peikari et al., 2013). The sample originated from a membership list maintained by my community partner, AMDIS. This professional society

provided access to their physician members through their private email listserv. AMDIS members including physician executive roles such as chief medical information officers, chief medical officers, and medical directors are predominately representative of the study population (AMDIS, 2015).

Muhlestein et al. (2014) identified more than 600 ACOs comprised of both physician and hospital sponsored organizations. In partnership with AMDIS, I invited the participation of the population of physician executives at health systems fulfilling the criteria for inclusion in the study. Data previously licensed and extracted from a 2014 HIMSS Analytics database identified 100 unique health systems with 1,113 affiliated hospitals participating in ACOs (HIMSS, 2014). From this population, I identified 955 hospitals from 90 integrated health systems utilizing a Cerner Incorporated or Epic Systems EHR. With the assistance of AMDIS, the steps I followed in capturing the population included

1. Identify members from health systems participating in an ACO:

(a) Location of ACO=United States.

(b) EHR = Cerner or Epic Systems.

(c) Contact type = Physician Executive such as Chief Medical Officer (CMO), Chief Medical Information Officer (CMIO), Chief Information Officer (CIO), Ambulatory Care Head, Medical Director of Informatics.

(d) Credentials =medical doctor (MD) or doctor of osteopathy (DO).

2. Exclude nonphysician executive AMDIS members.

The entire population of 2,900 physician executives from AMDIS established the purposive sample needed for potential inclusion in the proposed survey (AMDIS, 2015). Contacting the participants through the AMDIS listerv with an introductory email sent from my Walden University email potentially influenced an improved response rate for the survey (Anseel, Lievens, Schollaert, & Choragwicka, 2010; McLeod et al., 2013). The planned, purposive sampling process provided for the equal inclusion of all physician executives fulfilling all inclusion and exclusion criteria for participation.

Sample Size

Criteria-based and non-probability sampling results in the conscious inclusion of data units using an approach other than chance alone (Bryman, 2012). Given the homogenous nature of the population and the expertise required to complete the self-administered survey, utilization of random sampling techniques unduly restricts participation essential for addressing the research question. The application of purposive sampling in related research on physician use of CPOE and the stated need to survey physician executives from ACOs using a specific type of EHR negated the use of other sampling approaches (Bryman, 2012; Peikari et al., 2013).

Based on the criteria established, a search comprising all hospital affiliated ACOs in a HIMSS 2014 database returned a population of 1,113 hospitals. Further refining the selection based on type of EHR used reduced the population of affiliated hospitals to 955. Searching for physician executive titles meeting the remaining requirements yielded a population of 144 units.

To test the null hypothesis that no significant relationship exists between the type and timing of a CDS alert deployed in CPOE and a physician's perception of improved quality measure adherence, I conducted an a priori power analysis using G*Power 3.1 software. A power analysis requires the researcher to consider and select the alpha level for rejecting the null hypothesis (Saffer, 2014). Based on convention, I selected an alpha level of $p < .05$ (Bryman, 2012).

The determination of sample size requires an assumption of effect size for the test statistic. The *F* test statistic supports a multiple regression analysis for understanding whether a relationship exists between the predictor and dependent variables (Green & Salkind, 2011; Saffer, 2014). Other researchers quantified only modest effects of CDS use on physician ordering behaviors (McCullough et al., 2014; Munn, McArthur, & Moola, 2010; Shaikh et al., 2014). A specific limitation of prior research on alerts concerned the lack of associating design characteristics with an EHR type (Munn, McArthur, & Moola, 2010). The final study design with a focus on alert use in integrated health system ACOs using only two types of EHRs provided sufficient focus for addressing that gap. Powering the study at 80% with the selection of a medium effect size (.15) aligns with guidance provided to novice researchers (Green & Salkind, 2011; Saffer, 2014).

Table 1 contains the data values obtained from the power analyses and the G*Power results showing the required sample size for a modest effect size. G*Power results indicated the need for 68 completed surveys for a medium effect size ($\omega = 0.15$) and a power level of .80.

Table 1

*Sample Size Calculation for Proposed Study Using G*Power 3.1 Software*

F tests - Linear multiple regression: Fixed model, R^2 deviation from zero.	
Effect size (f^2)	.15
α err prob	.05
Power (1-β)	.80
Number of predictors	2
Noncentrality parameter λ	10.20
Critical *F*	3.13
Numerator *df*	2
Total sample size	68
Actual power	.80

Note. Analysis: A priori: Compute required sample size.

Survey response rates by physicians while potentially declining persist in reported rates > 50% (Klabunde et al., 2013; Peikari et al., 2013;). With expectations for a minimum response rate of 50%, at least 138 physician executives must attempt to complete the survey (136 × .50 = 68). Applying the criteria based and purposeful sampling approach, I solicited all AMDIS physician executives participating on the AMDIS email listserv ensuring all physicians sampled maintained an equivalent chance for participation. The CEO of AMDIS released my survey invitation on the listserv on June 29, 2015, with a second request on July 13, 2015. During the next 3 weeks, I sent

247 additional requests for participation to physician executives who had shared their personal contact details with me through prior professional interactions. Ensuring adequate rigor to the study design, I utilized SPSS in all post hoc testing of the survey data for verification the study achieved the planned statistical power greater than .80.

Ethical Research

The Belmont Report issued by the National Commission for the Protection of Human Subjects provides researchers with specific guidance ensuring the protection of research participants from harm (Mahon, 2014). The underlying concepts from the Belmont Report of courtesy, advocacy, and protection for all research participants remain at the forefront of IRB processes (Lewis, Gonzalez, & Kaufman, 2012). The potential for harm to research participants arises from multiple sources such that researchers must rely on established processes to obtain informed consent, maintain the confidentiality of all data, and ensure subjects are treated with respect and dignity (Bryman, 2012). The nature of an online survey necessitates additional consideration in the procedure for obtaining informed consent (Mahon, 2014).

The use of SurveyMonkey® for the administration of an Internet-based survey allows for the inclusion of a statement of acceptance of voluntary participation by each participant (Survey Monkey, 2014). The informed consent statement included a brief description of the study purpose. All participants acknowledged they received no compensation in exchange for their participation. Participation was voluntary. Participants understood they could suspend their involvement at will as outlined in the informed consent statement (see Appendix C). Further, each participant received details

for contacting me with any questions or concerns in regard to the research study. Through provision of my Walden contact details, participants may request the published study results. Ensuring the capture of informed consent preceded the answering of any survey questions aligning with current best practices in the conduct of digital based research (Mahon, 2014).

Data Privacy

Compliance with Walden University's IRB process necessitated appropriate measures for ensuring the privacy and confidentiality of research participants. AMDIS maintains direct control of the member listserv. With the cooperation of AMDIS managing the invitation process through their listerv, no deidentification of their database containing the sample of physician executives with their associated health system affiliations was required. All data obtained from the survey-hosting site remained encrypted with IP protocol identification turned off ensuring the anonymity of the results obtained and stored (Mahon, 2014). Only general demographic data was collected confirming each participant's professional credentials, participation in an ACO, and type of EHR utilized consistent with the research study inclusion requirements.

Internet-based research necessitates more than a single layer of security protocols (Mahon, 2014). The use of SurveyMonkey® conforms to current requirements for data encryption (Survey Monkey, 2014). Upon completion of the study, I transferred all data to an encrypted external hard drive. The stored drive remains locked in a fire-safe file cabinet for the 5-year retention period. I maintain sole access to the data files. During the period of storage, the study results will be made available to all participants upon written

request. At the conclusion of the 5-year storage period, I will destroy the external hard drive.

As physicians, the participants are not representative of a protected or vulnerable class. No inducements were provided anticipating that a shared professional interest in improving CDS tools for ACOs merited the active and honest participation of the participating physician executives. Conducting research intended to improve the CDS tools used by ACOs supports an ethical intention of conducting quality research through the provision of generating valuable information (Bryman, 2012).

Data Collection

The use of a self-administered survey hosted on the Internet provided the mechanism for data capture. In combination with solicitations for survey participation disseminated by AMDIS through their email listserv, I sent 247 personalized electronic invitations from my Walden email account to the purposeful, criteria-based sample of 2,900 physician executives (Appendix C). The email invitation provided an opportunity to describe the purpose of the survey with the request for each subject's voluntary participation. Including a link to the SurveyMonkey® Internet hosting site provided an efficient approach to securing survey responses. Maintaining brevity in the design of the survey supported potentially higher response rates with less risk for methodology associated bias (Hohwu et al., 2013, Kaplowitz, Lupi, Couper, and Thorp, 2012; Podsakoff, MacKenzie, and Podsakoff, 2012). Embedding the informed consent form with an electronic review and affirming an acknowledgement process preceding the first survey questions ensured compliance to Walden University IRB processes. The CEO of

AMDIS reminded members to participate resending the invitation to participate in the research to the listserv approximately two weeks after the initial request was issued.

SurveyMonkey® provides encrypted storage of survey data for subsequent retrieval. Based on the a priori power analyses for determining sample size, 68 completed surveys supported a statistically valid outcome (Lan & Lian, 2010). Use of a purposive sampling approach potentially enhances generalizability of the results (Polit & Beck, 2010). With a sufficient number of surveys completed upon the close of the survey period on July 23, 2015, I migrated all survey data from SurveyMonkey® to my personal computer using the secure and routine data download processes provided by SurveyMonkey®. All study data stored in my computer is contained within a password protected and encrypted disk. Following the completion of all statistical analyses using SPSS, I exported the study data to an external disk drive kept in a fireproof, locked file cabinet for the mandatory 5-year retention period. Throughout this period, the research data will be provided to other researchers upon written request. No identifying information regarding participant names, email addresses, and participant affiliated hospitals and health systems will be released. At the conclusion of the retention period, all data stored electronically and on paper will be destroyed.

I selected SurveyMonkey® as the hosting service based on their known capabilities in providing appropriate safeguards ensuring participant data remains protected based on password protected and permission-based protocols (SurveyMonkey, 2014). SurveyMonkey® protects participant data from unauthorized access through the use of firewalls. The use of data encryption protocols coupled with a Secure Socket Layer

(SSL) ensures each participant's data remains protected and secure from external threats. By using a suite of design tools provided by SurveyMonkey® all participant e-mail addresses and their IP locations remain confidential, as SurveyMonkey® will not store that data. To further safeguard the data stored at SurveyMonkey®, I created an account with a unique password that was not shared with anyone else. All survey data remains confidential and anonymous through use of the specific settings that prevented the collection of email and IP addresses. The participant data extracted from SurveyMonkey® and compiled for analyses in SPSS does not include the names, email addresses or affiliated organizations of the participants (SurveyMonkey, 2014).

Instruments

Although no previously validated instrument supported the research study, sufficient material from the academic literature on CDS alerts deployed in CPOE informed the development of the survey questions (Koopman et al., 2011; McCoy et al., 2012; McCullough et al, 2014; Peikari et al., 2013; Smith et al., 2013). The survey included four sections (Appendix A). The first survey question in section one of the instrument required confirmation of the informed consent process. The next three questions in section one confirmed the inclusion criteria of the participant. The remaining sections of the survey included three self-developed Likert-type scales designed for analyzing each study construct. I developed these constructs in alignment with the predictor and dependent variables from the synthesis of the peer-reviewed literature coupled with feedback obtained from academic and industry experts in the field of EHR-integrated CDS tools. Content validation of a survey frequently involves obtaining expert

feedback on each survey item and scale (Etchegaray & Fischer, 2010; Rickards, Magee, & Artino, 2012). The use of expert feedback provides an opportunity to examine the wording of each item for potential bias (Fan & Yan, 2010). Good survey design requires isolating construct items within a single scale. Difficulties in data interpretation arise with the use of scales containing mixed constructs (Etchegaray & Fischer, 2010). All survey items following section one supported a range of answers based on a 5-point Likert-type scale requiring a participant response as: *Strongly Agee, Agree, Neutral, Disagree,* and *Strongly Disagree*. Likert-based scales although ordinal by nature support interval, parametric-based analyses through the summation of multiple items (Norman, 2010). Grouping a minimum of three items in the generation of scales for composite scoring improves instrument validity and reliability by demonstration of consistent scoring across related items (Bryman, 2012; Etchegaray & Fischer, 2010). Drawing from the academic literature on the design of CDS alerts and sociotechnical considerations of EHR workflow informed the development of items underpinning the constructs for the two independent variables. A summary of the instrument items included in each scale is provided in Table 2.

Table 2

Survey Scales by Question and Supporting Literature

Survey questions	Construct and composite variable	Literature sources
E, F, G, J	Alert content, independent variable A	Koopman et al. (2011), McCoy et al. (2012), Smith et al. (2013), Bell et al. (2014), McCullough et al. (2014), Shaikh et al. (2014)
L, M, N	Alert workflow timing, independent variable B	Kawamoto et al. (2005), McCoy et al. (2012), Anderson et al. (2013), Bowman (2013), Jung et al. (2013)
H, I, K, O, P, Q	ACO Goals and Quality Measure Adherence, dependent variable C	Baysari et al. (2012), Xiao et al. (2012), Grace et al. (2013), Chukmaitov et al. (2014), CMS, (2014), Dubois et al. (2014), McCullough et al. (2014)

The first Likert-type scale in the survey instrument contained four items pertaining to the content of a CDS alert displayed in the EHR. These four questions are identified in the survey as E, F, G, and J (Appendix A). These items supported the capture of data specific to the independent variable A alert content. The second Likert-type scale consisted of three questions providing the basis for capturing data relevant to the independent variable B alert timing. The second Likert-type scale contained only those items pertaining to the timing for presenting CDS alerts during physician ordering sessions within an EHR. The third and final Likert-type scale in the survey instrument

comprised of six questions pertains to the construct associated with the dependent variable in capturing physician perceptions related to ACO goals of improved outcomes. Each Likert-type scale contained only those items that directly supported the central research question and hypotheses.

Data Collection Technique

As previously discussed, an online survey hosted by SurveyMonkey® supported the administration of a self-administered survey for the purpose of collecting data and subsequently transferring data to SPSS™ software for analysis (Alessi & Martin, 2010). Incorporating survey design recommendations from Etchegaray and Fischer (2010), I limited the survey to 17 questions estimating survey completion times less than15 minutes prior to the capture and validation of pilot study results post IRB approval (Appendix A). The use of a brief set of questions potentially supports improved response rates while potentially limiting bias related to the methodology (Hohwu et al., 2013; Kaplowitz et al., 2012; Podsakoff et al., 2012).

The first four survey questions A through D confirmed the completion and acceptance of the informed consent integrated with the survey (Appendix A). Key inclusion criteria such as practice credentials, participation in an ACO, and use of an Epic Systems or Cerner Incorporated EHR comprised the set of questions designed for capture of descriptive statistics. For these first two questions, yes responses were coded as a *1* and all no responses as a *0.* Coding of the results in this manner permitted subsequent frequency calculations. For EHR type, a response indicating the use of Cerner was coded as a *1* and the use of Epic as a *2.* Coding EHR type responses supported a subset analysis

related to the underlying research question. Further, the application of a frequency distribution analysis for a small number of categories permits subsequent display of the findings in a bar or pie chart (Green & Salkind, 2011).

Upon IRB approval, I piloted the survey with five physician executives in order to validate the usability of the survey and assess the ability to collect representative data supporting quantitative analysis. Piloting the online survey supports the evaluation of each item for determination of construct reliability (Bryman, 2012; Rickards et al., 2012). Pilots provide researchers with opportunities to improve participant instructions with insights regarding the ease of use of the instrument and the participant's understanding of survey items (Bryman, 2012).

No definitive guidance exists with respect to the determination of an appropriate sample size for pilot studies (Johanson & Brooks, 2010; Thabane et al., 2010). Other researchers conducting online surveys piloted instruments with a number of physicians equating to approximately 3% of their final respondents (Jung et al., 2013; Peikari et al., 2013). Quantitative survey research examining the relationship of physician use of CPOE and rates of prescribing errors conducted by Peikari et al. (2013) included survey pilot testing with five physicians over three stages of review. Results from 166 completed surveys supported their research findings. Similarly, the assessment of physicians' attitudes toward alerts designed with patient-contextualized data included pre-testing of the survey with seven physicians and final survey results obtained from 223 physicians (Jung et al., 2013). Based on the approach taken by previous researchers in the field of CDS alerts, I piloted the survey with five physician executives representative of the study

population. The number of physicians for the pilot equates to 7% of the calculated sample size of 68 physician executives and 3.5% of an estimated 144 physicians planned for inclusion as mitigation for nonresponse.

The pilot survey was conducted from June 8 to June 13, 2015. A primary objective of the pilot study included analysis of the instrument reliability and validity. Table 3 includes Cronbach's alpha coefficient for each scale. The application of Cronbach's α supports the assessment of the interrelatedness of each subscale item (Green & Salkind, 2011). Of note in Table 3, the reliability analysis conducted for the ACO quality construct resulted in deleting question O for purposes of obtaining a satisfactory alpha coefficient. The value generated by including this question was revisited in the analysis for the final survey. Based on the obtainment of a satisfactory coefficient alpha for each scale, I proceeded with data collection for the final study.

Table 3
Analysis of Cronbach's Alpha Coefficients in a Pilot Study

Construct	*n*	*M*	*SD*	Cronbach's alpha
Alert content	4	17.60	3.21	.880
Alert workflow timing	3	7.00	2.44	.750
ACO Quality and Cost Goals	5	21.80	2.28	.697

I sent a personalized invitation from my Walden email account to the Chairman of AMDIS for dissemination to the AMDIS listerv (Appendix D). My email contained the link to SurveyMonkey®. Survey participants completed the informed consent process through mandatory completion of the first question in the survey (Appendix E). At the close of the survey on July 24, All data migrated from SurveyMonkey® remains secure and confidential (SurveyMonkey, 2014). I entered coded data into SPSS™ software for analysis maintaining all data on a password-protected computer. In addition, I migrated the data and all study related documentation to an encrypted and password protected external disk that will be kept under lock and key for five years.

Data Organization Techniques

Access to the survey via the link embedded in the participant's invitation remained active for a period of three weeks. At the end of the second week, a second email soliciting participation was sent from my Walden email account (Appendix F). At the end of week three, I deactivated the survey link. All data collected in SurveyMonkey® was exported to SPSS™ for analysis based on complete coding of all categorical variables and the creation of composite scores for the scaled items. No personal identifiers in SurveyMonkey® were accessible and all cookies in the online platform remained disabled (SurveyMonkey, 2014). Upon completion of the retention period, all raw study data and related documents previously stored in a locked, fireproof cabinet will be destroyed.

Data Analysis Technique

Upon data extraction from SurveyMonkey®, I used SPSS™ for quantitative analysis of the data obtained. Descriptive statistics such as frequencies, counts and percentages apply to the demographically focused questions. Data obtained from the 13 Likert-based questions enables the use of the Pearson correlation, multiple linear regression tests. Compiling and analyzing survey responses supported assessment of the extent of any relationship between the content of an alert deployed in an EHR and the timing of deploying an alert with a physician's perceived adherence to reportable ACO quality measures. I utilized the following survey to address the research question and hypotheses as follows:

13 survey questions adhered to a 5-point Likert-type scale where 5 = *Strongly Agree*, 4 = *Agree*, 3 = *Neutral or No Opinion*, 2 = *Disagree*, and 1 = *Strongly Disagree*. Three distinct scales supported the construction of a composite score associated with each study variable. Independent variable A associated with alert content characteristics were measured based on responses to four questions. Independent variable B associated with alert timing characteristics were measured based on responses to three questions. The dependent variable associated with physician perception of meeting ACO goals with improved ACO quality measure adherence was measured in the third scale comprised of six questions:

Scale 1: Alert Content Characteristics

1. Alerts triggered during physician order entry for an ACO patient should account for the context provided by patient specific data contained in the patient's medical record.

2. Pop-up alerts triggered while placing orders for ACO patients should always include pre-populated, evidence-based override reasons.

3. Alerts specific to the selection of a patient intervention (medication, lab, test, or procedure) for an ACO patient should include links to patient education materials when available.

4. Alerts triggered while ordering any intervention for any ACO patient should contain links to additional peer-reviewed information when available.

Scale 2: Alert Timing and Settings:

5. All alerts should be suppressed until the last order in a session for an ACO patient is entered by the physician.

6. Alerts triggered by current ordering activity for an ACO patient should be presented immediately as orders are entered.

7. Alerts should be non-intrusively displayed (not requiring any user interaction) as a passive reminder during all order entry sessions for chronically ill ACO patients or those ACO patients at risk for diabetes, heart failure, or cardiovascular disease.

Scale 3: ACO Quality Measure Compliance

8. Alerts triggered by a physician during computerized order entry for an ACO patient should include substitution recommendations for appropriate, lower-cost interventions if available.

9. Alerts triggered while ordering an intervention for chronically ill ACO patients or those ACO patients at risk for diabetes, heart failure, or cardiovascular disease should contain links to published guidelines, peer-reviewed literature, or other supportive documentation such as a published quality metrics.

10. Alerts specific to chronically ill ACO patients or those ACO patients at risk for diabetes, heart failure, or cardiovascular disease should require a user-documented override reason when the provider decides to not follow the recommendation contained in the alert.

11. Pop-up alerts triggered while placing orders and contextualized by patient age and condition enhance compliance with ACO reportable quality measures.

12. Passive or non-intrusive alerts visible during electronic ordering consisting of general reminders for at risk ACO patient populations enhance compliance with ACO quality measures.

13. Alerts whether non-intrusive or requiring action by the user should be placed in the provider's ordering workflow to improve adherence to ACO quality measures

Testing the discriminant validity of each subscale item required a correlation analysis of each item on a scale with the total score obtained for that scale. The application of Cronbach's α supports the assessment of the interrelatedness of each subscale item (Green & Salkind, 2011). Bivariate linear regression analysis utilizes the Pearson Correlation Coefficient. This analysis was applied to determine how well each of the independent variables predicted the dependent variable (Green & Salkind, 2011). Both the multiple correlation coefficient R and the squared correlation coefficient R^2 provide sufficient information for determining the strength of any relationship necessary for rejecting the null hypothesis (Green & Salkind, 2011). Use of these statistical methods aligns with prior research conducted on physician acceptance of alerts with frequent use by health sciences researchers (McCullough et al., 2014; Peikari et al., 2013; Rickards et al., 2012).

Reliability and Validity

For researchers, the work to improve the reliability and validity of a study's findings continues beyond the single use of a research instrument (Rickards et al., 2012). The researcher's concerns ultimately surround the meaning extracted from the analysis supported by the use of a particular instrument. Thus, the researcher considers (a) the nature of the evidence used in constructing the instrument, and (b) whether the survey

items convey the intended meaning to the research participants, and (c) when scored, whether the items contained in the instrument related appropriately to the constructs supporting the hypotheses (Rickards et al., 2012).

Reliability

Reducing the risk of obtaining unreliable scores necessitates thorough review and pilot testing of the survey instrument. Although no prior survey instrument existed, I developed the questions supporting each scale through careful review of the published literature. Other researchers in the field of CDS developed new instruments adapted from their review of the literature coupled with input from physician experts (Peikari et al., 2013; Xiao et al., 2012). While substantive qualitative research exists with respect to the sociotechnical challenges associated with physician electronic ordering workflows, sufficient empirical findings remain scarce (Cresswell & Sheikh, 2013; Meeks et al., 2014; Peikari et al., 2013). I reviewed the content with experienced physician executives and leading experts in the field of computerized CDS. The use of cognitive interviewing remains a common practice among researchers seeking confirmation that survey items convey the meaning intended (Overby et al., 2013; Rickards et al., 2012). Upon IRB approval, I conducted the pilot with five physician executives providing confirmation that scores obtained upon use of the instrument remain reliable. As applied by other researchers, the use of descriptive statistics and Cronbach's coefficient α provided further means for ensuring the internal consistency reliability of each scale within the instrument (Peikari et al., 2013; Rickards et al., 2012).

Validity

Validity requires confirmation that the research instrument enables the generation of meaningful data supporting the acceptance or rejection of a hypothesis (Etchegaray & Fischer, 2010). I focused on obtaining the face validity of the instrument through capture of feedback by experts as I developed and refined the questions pertaining to each scale. Other means for ensuring content validity involve the establishment of a validity score for each construct prior to piloting the instrument with experts. Computing a mean validity index for each scale approximating 70% post pilot testing further mitigates the validity risk associated with the use of a new instrument (Etchegaray and Fischer, 2010). Validity, once obtained, supports the researcher in drawing extrapolations from the research to the larger population (Dekkers, Elm, Algra, Romijn, & Vandenbroucke, 2010). The potential for generalizability of the results to a larger population remains predicated on obtaining results from the intended sample of 68 physician executives per the previously calculated *a priori* power sample size. Given the homogenous focus of the study, such generalizations would be limited to the population of physician executives using a Cerner or Epic systems EHR within a hospital integrated ACO.

Transition and Summary

Section 2 contained core elements of the research project including (a) the description of my role as the researcher, (b) the contents of the survey instrument, (c) the calculation of the sample size, and (d) the efforts I employed to safeguard the rights of the research participants as well as the security and confidentiality of the raw data. I reviewed the final study design and methodology identifying the means for collecting,

organizing, and analyzing the data. Lastly, I reviewed my approach to mitigate risks associated with the validity and reliability of using a new survey instrument.

In Section 3: Application to Profession Practice and Implications, I provide the research findings and share how the results relate to the current field of practice. Moreover, I consider the application of the study findings to society and any affect for change such findings may support. Last, I revisit the limitations associated with my study while offering suggestions for additional research that may extend my work and support even greater business and societal benefit.

Section 3: Application to Professional Practice and Implications for Change

The results of the study are presented in this section with my interpretation of the findings. In seeking to answer the research question outlined in Section 1, I surveyed physician executives to obtain their perceptions on the relationship of the content and timing of a computerized order entry alert on improving adherence to ACO quality measures. The specific business problem was that third-party software developers lack an understanding about physicians' preferences for integrated alerts supporting adherence to ACO quality measures while placing their electronic orders. With the completion of this research study, I provide suggestions for additional research that could support improvements in software design. Clinical software users, firms developing software solutions, and ultimately patients may benefit as these research findings add to a body of knowledge supporting business and social cases for positive change.

Overview of Study

The purpose of this quantitative, correlation study was to examine the nature of any association between physician preferences for CDS alerts and perceptions of improved adherence to ACO quality measures during electronic ordering. With billions of dollars invested in adopting EHRs, questions surfaced with regard to achieving a return on this important national investment pointing to the need for improved software tools (Beeler et al., 2014; Rudin & Bates, 2013). As U.S. health care reform shifts reimbursement from a fee-for-service model toward reimbursement based on outcomes,

ACOs are considered part of the national strategy for achieving health care's triple aim of providing better and safer care at lower costs (Berwick, 2011; Burwell, 2015).

Improvements in the design of software tools continue to be identified as an ongoing need in the successful adoption and use of EHRs as hospitals and health systems participating in ACOs rely on advanced HIT for shared decision making (Kuperman & McGowan, 2013; Meeks et al., 2014; Shortell et al., 2014). Third-party software developers often lack an understanding of the sociotechnical needs of clinical software users. Software tools that fall short of the end-user's expectations may negatively affect the quality and cost of care (Sittig & Singh, 2010; Smith et al., 2013; Meeks et al., 2014; Novak et al., 2013).

In alignment with the stated purpose of this study to establish whether any significant relationship exists between the content and timing of an integrated alert and physician perceptions for improved ACO quality measure adherence, I surveyed physician executives participating in a hospital or health system associated ACO while using a Cerner Incorporated or Epic Systems EHR system. The empirical evidence supported the rejection of the null hypothesis H_{O_1}: A significant relationship does not exist between the content of an alert deployed and a physician's adherence to ACO quality measures. However, the empirical evidence supported the acceptance of the null hypothesis H_{O_2}: A significant relationship does not exist between the timing of when an alert is deployed in a physician's electronic ordering workflow and a physician's adherence to ACO quality measures. These findings are discussed in detail in the following section.

Presentation of the Findings

The overarching research question underpinning this research was: To what extent do sociotechnical factors addressed in the design of CDS software tools affect physician ordering behavior? A significant correlation was found between independent variable A (alert content) and the dependent variable (quality measure adherence). No significant correlation was identified between the independent variable B (alert timing) and the dependent variable.

The purpose of the this quantitative, correlation study was to examine the extent of any relationship between the type and timing of CPOE automated alerts with physician perception for better adherence to reportable ACO quality measures. The independent variables related to sociotechnical attributes included the type of decision support provided and the timing for presenting an alert to physicians in an electronic ordering workflow. The dependent variable tied to reportable ACO quality measures supported analysis of physician perception toward the achievement of ACO quality measures and the cost reduction and performance improvement goals associated with using CDS during electronic ordering.

Descriptive Statistics

No previously validated instrument supported the combination of variables intended for examination. Therefore, I developed a survey instrument using a 5-point Likert-type scale incorporating feedback from industry experts and findings from the published academic literature on CDS. The survey included demographic questions pertaining to physician credentials (MD or DO) and type of EHR system used (Cerner or

Epic). The instrument included 13 5-point Likert-type questions supporting data collection for a standard linear multiple regression analysis. Prior to data capture for the final study, a brief pilot with five physician executives supported testing for reliability and validation of ease of completion. With the assistance of AMDIS as my community partner and email invitations sent to physician executives within my professional network, 126 physicians attempted to complete the online survey with 55% meeting all inclusion criteria. As depicted in Table 4, the required sample size of 68 was achieved with valid responses from $N = 69$. Table 4 includes the descriptive statistics and the number of survey participants for the questions pertaining to each composite variable.

Table 4

Descriptive Statistics on Composite Scores

Variable	*M*	*SD*	Cronbach's α	Number of items	*N*
Alert content	16.478	2.330	.631	4	69
Alert timing	7.608	2.492	.628	3	69
Quality	23.797	3.265	.627	6	69

Produced using SPSS 22.0, the average score of all respondents on the composite variables of alert content, alert timing, and quality was 16.47, 7.60, and 23.79 respectively. Although descriptive statistics do not affect the regression analysis, the provision of this data is useful in the characterization of the data underpinning the variables in the research study (Green & Salkind, 2011). In contrast to reliability statistics identified previously in Table 3, Cronbach's alpha as depicted in Table 4 declined to 63%

for each composite variable. Many researchers considered the use of previously validated instruments with alphas < .70 as questionable (Pallant, 2013). In the case of a new research instrument, alphas > .60 are generally accepted (Churchill & Peter, 1984). As depicted in Figure 2, approximately two thirds of physicians had access to an Epic Systems EHR with one third identifying their hospital or health system provided access to a Cerner Incorporated EHR. Potential generalization of the research findings to the population of physicians at hospital or health system affiliated ACOs using market leading EHR systems was an important objective of the research study.

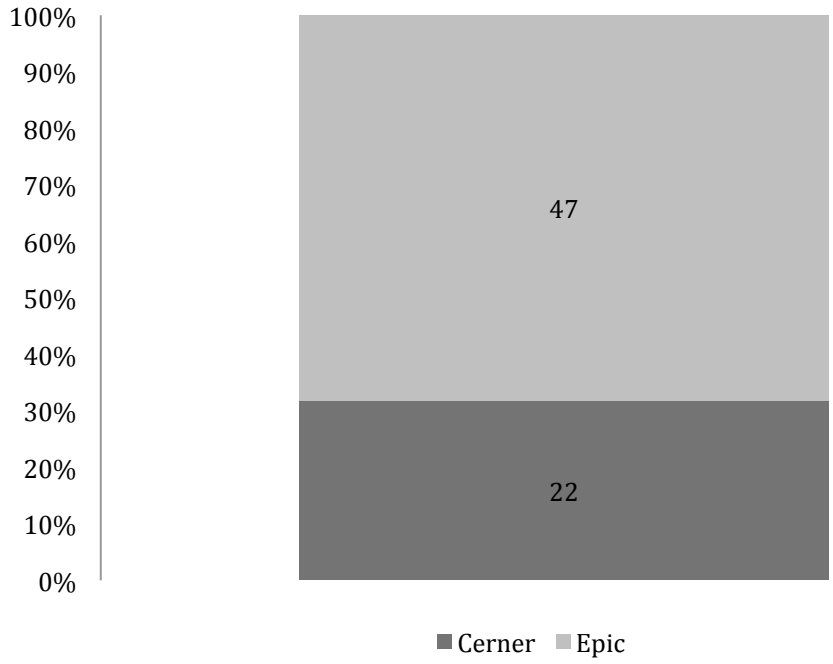

Figure 2. EHR type by respondent ($N = 69$).

The application of descriptive statistics includes an analysis of Pearson's correlation coefficient. Statistically significant values indicate whether or not the coefficient will be represented in the population from which the sample was derived

(Bryman, 2012). Table 5 contains the correlation matrix including Pearson's correlation coefficient values, the number of cases pertaining to each correlation, and the 1-tailed significance for each correlation. From Table 5, only one correlation was statistically significant. The correlation between the predictor variable alert content and the dependent variable quality was significant ($r = .326$, $p < .003$) indicating rejection of the null hypothesis that no significant relationship existed between the content of an alert and physician perception of improved ACO quality measure adherence. The correlation of $r = .037$ and $p > .05$ indicated less than 4% of the variation might be explained by characteristics of alert timing on physician perception of improved ACO quality measure adherence. Because the 1-tailed significance value was .381, the null hypothesis was accepted. No significant relationship was identified between this predictor variable and the dependent variable. The results of this analysis supported the underlying sociotechnical characteristics of an integrated alert's content as meaningful to physician perceptions of improved ACO quality measure adherence. The sociotechnical attributes associated with the timing of presenting the alert in the physician's ordering workflow was not meaningfully correlated with physician perceptions for improving quality measure adherence.

Table 5

Correlations

		Quality	Content	Timing
Pearson's correlation	Quality	1.00	.326	.037
	Content	.326	1.000	−.013
	Timing	.037	−.013	1.000
Sig. (1-tailed)	Quality		.003	.381
	Content	.003		.458
	Timing	.381	.458	
N	Quality	69	69	69
	Content	69	69	69
	Timing	69	69	69

Parametric Assumptions and Tests for Normality

Testing for the normality of data prior to conducting multiple regression analysis remains a standard practice of field researchers (Pallant, 2013). I confirmed assumptions of the linearity, normality, and collinearity of the data. Table 6 provides the Tolerance and the Variance Inflation Factors (VIFs) for each independent variable. All of the values of Tolerance were > .10 with no VIF values exceeding 10.0. Thus, the independent variables met the normality and collinearity assumption test.

Table 6

Tests for Tolerance and Collinearity (VIF values)

Composite variable	Tolerance values	VIF values
Content	1.00	1.00
Timing	1.00	1.00

Inspection of the residual statistics table permits identification of outlier data negatively affecting the regression model (Pallant, 2013). I used the Mahalanobis value and Cook's distance in the residual statistics table to confirm the assumption that no outliers affected the regression model (Appendix G). For Cook's distance, a value >1.0 is considered problematic and likely to influence the regression model. From the table in Appendix G, the maximum value calculated for Cook's distance was (.196) <1.0. A maximum Mahalanobis distance of 12.23 at $p < .05$, $N = 50$ was previously established as a guideline for field research (Stevens, 1984). With a maximum Mahalanobis distance calculated of 11.196, $N = 69$, the analysis confirms no outlier influence on the model.

Researchers test for the normality of data using P-P plot graphs. The finding of a fairly straight diagonal line when evaluating the cumulative probability regressed by the expected variability supports the assumption for normally distributed data (Pallant, 2013). Figure 3 supports the assumption of normality with the diagonal line viewed from bottom left to the upper right in the graph. Assessing linearity with scatterplots, I found all data was distributed in a linear fashion as illustrated in the P-P plots for both independent variables (Figures 4 and 5).

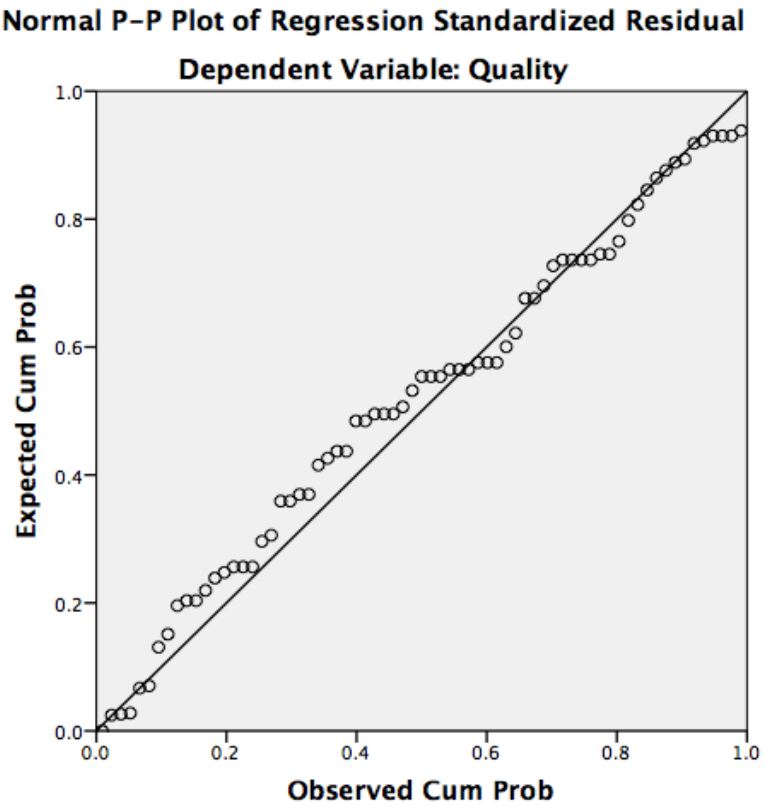

Figure 3. Normal P-P plot of regression standardized residual of dependent variable, quality.

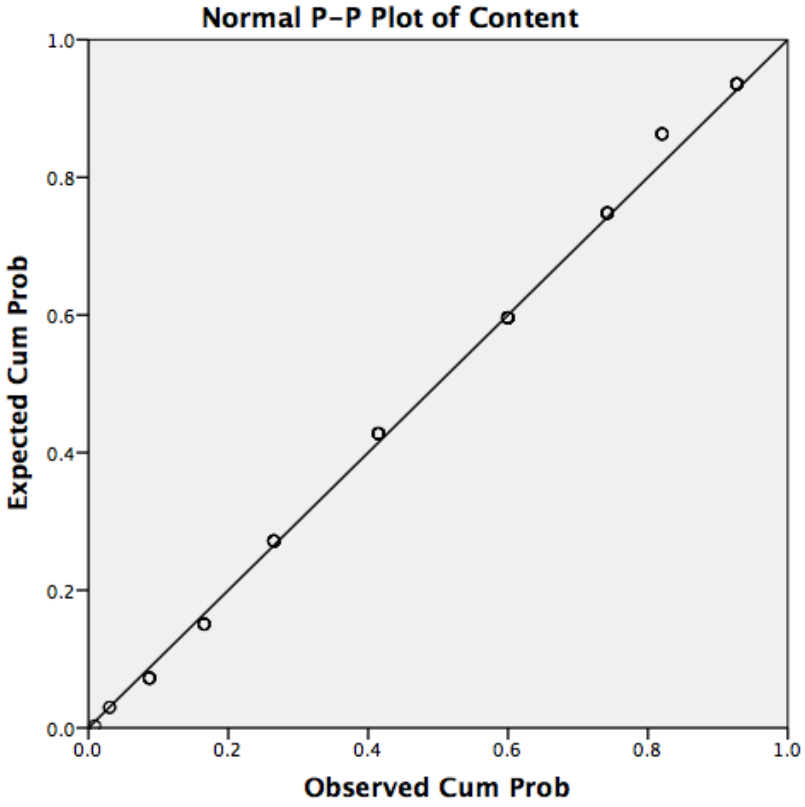

Figure 4. Normal P-P plot of regression standardized residual of independent variable, content.

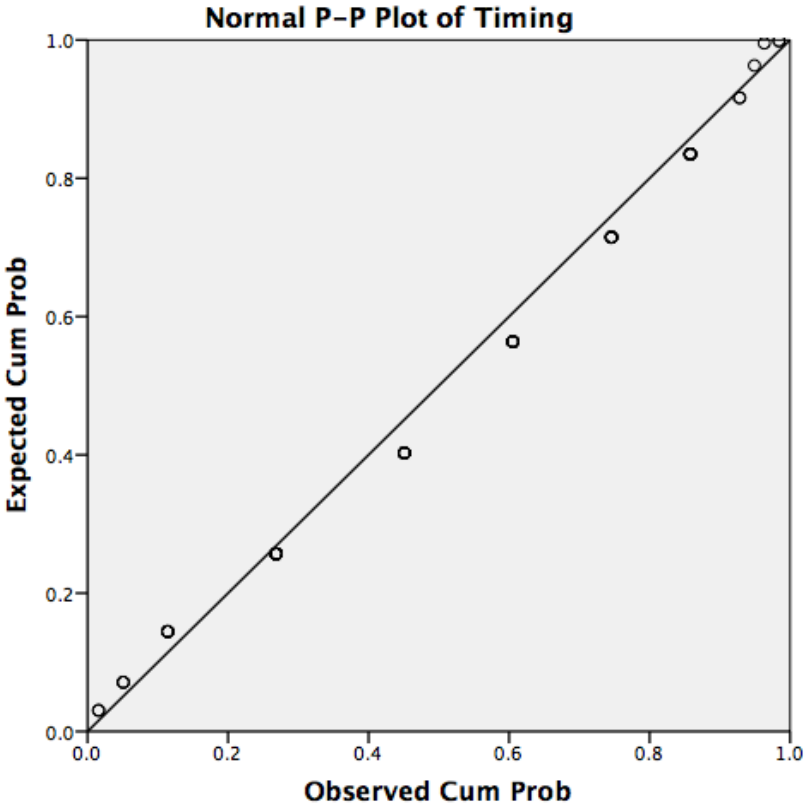

Figure 5. Normal P-P plot of regression standardized residual of independent variable, timing.

Discussion

The results of the multiple regression analysis were significant, $R^2 = .108$, $F(2,66) = 3.99$, $p = .023$. The analysis was performed to determine if any relationship existed between the sociotechnical characteristics of alerts determined by their content and timing within the physicians' computerized ordering workflow with their perceptions for improved adherence to ACO quality measures. The sample correlation coefficient was .33 with approximately 11% of the variation in the sample attributed by the strength of the linear combination of the alert content and timing characteristics. As identified and

shown in Table 7, the relationship between the predictor variable timing and the dependent variable was not statistically significant with $p = .724$. Given the results of these correlations, the hypothesis of a relationship between alert timing and quality necessitates acceptance of the null hypothesis. With respect to the hypothesis of a relationship between alert content and quality, the null is rejected. The results of the multiple regression analysis are provided in Table 7.

Table 7

Characteristics of Alert Content and Timing Supporting Improved ACO Quality Measure Adherence

Source	*B*	*SE*	*β*	*t*	*p*	*95%LB*	*95%UB*
Content	.458	.163	.327	2.81	.007	.132	.783
Timing	.054	.152	.041	.355	.724	-.250	.358

Note. $R^2 = .108$, $F(2,66) = 3.99$, $p = .023$.

These findings lend further support to certain aspects of sociotechnical theory. Specifically, a previously published sociotechnical framework guides software developers in addressing complex systems through an improved understanding of the communication patterns, workflows, and tools required by users across the system. Among the dimensions identified in their framework, Sittig and Singh (2010) included technical components such as content and software as well as social dimensions such as software users and processes. Organizational processes include an understanding of required clinical workflows, internal policies, and procedures (Menon et al., 2014; Murphy, Singh, & Berlin, 2014). Many hospital and health system procedures are

established with an aim toward achieving specific outcomes such as reporting on measures to meet MU criteria and CMS quality measures tied to the performance of ACOs.

In this study, a technical dimension in software design specific to alert content was highly correlated with the physician software user's perception of improved quality measure adherence. In the current body of published literature, much has been written about physician nonadherence to alerts due to issues of alert fatigue and information overload (Bowman, 2013; Menon et al., 2014; Smith et al.). Previous research identified that primary care physicians saw more than 60 alerts per day requiring nearly an hour of their clinic time to manage (Murphy, Reis, Sittig, & Singh, 2012). In a follow up survey, physicians claimed nearly 90% of alerts were unwarranted with 2/3 of the physicians reporting they could not manage the volume of alerts they triggered daily (Singh, Spitzmueller, Petersen, Sawhney, & Sittig, 2013).

The results of the correlation for alert content and quality seem to reinforce the need for software developers to remain mindful of the context of alerts in the design of new software tools. The physicians surveyed for this study found certain attributes of alert content when aligned with evidence and specific to a patient's clinical and medical status as beneficial. With no significant correlation found between the timing of when an alert was presented during an ordering session and the perception of improved quality measure adherence, there is less support for the provision of guidance to third-party software developers. Only three questions in the survey supported the construct for workflow timing. Further, the alert timing window was limited to the ordering session

with an emphasis on presenting alerts automatically in a synchronous fashion with ordering. Such a narrowly defined construct for workflow timing likely biased the results obtained. For developers, the sociotechnical dimension related to understanding clinical workflow is frequently cited as a significant and complex challenge in the design and adoption of software tools (Beeler, Bates, & Hug, 2014; Perna, 2012; Sittig & Singh, 2010; Takian, Sittig, Singh, & Barber, 2014).

Applications to Professional Practice

The adoption of EHRs in the U.S. supported by government funding and regulations supports a new era of health care reform relying on improvements in the cost and quality of care delivered through technology enabled systems (Burwell, 2015). A primary benefit of EHRs arises with the ability to consolidate vast amounts of patient and clinical data for purposes of supporting better-informed clinical decisions. However, in gaining access to voluminous data in an EHR system, software vendors created solutions that fatigued physicians increasing the risk for patient harm (Menon et al., 2014; Murphy, Singh, & Berlin, 2014).

My research efforts focused on capturing software user needs for improved and workflow compatible EHR integrated CDS tools. The application of sociotechnical theory supported definition of variable constructs. The development of new constructs aided the process of assessing the extent of any significant relationship between alert content and timing specific to provider perceptions of better adherence to ACO quality measures. The study findings contribute to the current business application of developing improved CDS software tools in four ways.

First, the significant correlate of alert content with improved perceptions for quality measure adherence underpins the need for robust clinical algorithms in the design of alerts. Alert design focused on content containing patient specific factors and latest evidence may be perceived as more beneficial than the vast majority of alerts primary care physicians currently manage in their daily practice (Singh et al., 2013). Second, the lack of correlation between workflow timing and quality underscores the importance of conducting further research in this sociotechnical dimension. Software developers who lack access to an EHR environment for testing new CDS tools rely on the published literature for insights in regard to addressing potential gaps and unmet client needs. Increasingly, software tools developed and tested in collaboration in an EHR test environment permit more extensive usability testing (Smith et al., 2013).

Third, the survey completed by physician executives of technology enabled ACO affiliated hospitals and health systems using a leading commercial EHR system supports generalizability of the sample findings to the population. The recently published goals of CMS to tie nearly 30% of current fee for service payments to alternative models such as ACOs by the end of 2016, heightens the need for improved CDS tools in the EHR (Burwell, 2015). Fourth, this research underscores the value of collaboration between software vendors and clinical software users in applying the sociotechnical framework in software development and design efforts. These sociotechnical considerations are well established in the peer-reviewed literature and vital to the successful undertaking of any new software tool development initiative (Smith et al., 2013).

Implications for Social Change

An estimated 6 million patients receive care from an ACO (CMS, 2014). The decision by CMS to shift half of all payments to this type of an alternative payment model by 2018 suggests that number will increase over the next few years (Burwell, 2015). This research was undertaken in an effort to add to the body of evidence related to CDS software tool use within commercial EHRs at ACO affiliated hospitals.

The findings from this research might inform software design improvements. Specifically, the focus on the content of alerts provided to physicians during electronic order entry might alleviate concerns of alerts contributing to physician fatigue. Physicians overburdened with information and managing an excessive volume of inconsequential alerts may neglect to respond to an alert that is crucial to the health of the patient (Menon et al., 2014; Murphy, Singh, & Berlin, 2014). Providing physicians with alert content that is clinically relevant and grounded in the evidence might support better decision-making thereby improving patient care.

ACOs potentially provide a vehicle for achieving health care's triple aim (Berwick, 2011). Increasingly, health care systems rely on EHRs as a technology platform for managing care delivery with more than 90% of hospitals using a certified EHR system (Burwell, 2015). Improving the decision support tools for physicians managing ACO patients might support the vision of a technology enabled health care system that transforms clinical data for active decision making for the benefit of health care providers, patients, and their families. Enabling physicians to deliver care more efficiently and more safely might be an outcome of improving CDS software tools. The

significant relationship identified between alert content and physician perception of improved adherence with ACO quality measures, suggests the design of CDS software tools might support improvements in the management of high-risk patients enrolled in ACOs (Kuperman & McGowan, 2013. The findings from this study when applied to improving CDS tools might enable organizations with significant investments in HIT to realize clinical and financial benefits through improved ACO performance and CMS reimbursement.

Recommendations for Action

The study findings in conjunction with the related academic literature provided several recommendations for action. When undertaken by the software vendors and health care stakeholders engaged in the design and implementation CDS tools, these ideas might contribute to the realization of desired improvements in both the business application and positive social change areas. Although the survey participants represented physician executive software users of two commercial EHR systems, the proposed next steps should apply more broadly to physician users of EHRs supporting care delivery for complex patient populations.

The significant correlate of alert content and quality measure adherence aligned with previous findings that well designed CDS supports improvements in the quality and safety of care when applied in EHRs with advanced capabilities to support CDS (Bloomrosen et al., 2011; Horsky et al., 2012). The findings of Peikari et al. (2013) reinforced the importance of information quality provided to physicians during CPOE as a significant precursor to improving patient safety. I recommend that (a) software

developers collaborate extensively with internal physician teams and end-users on all CDS development efforts, and (b) focus on translating static evidence and best practice guidelines into actionable and understandable point of care recommendations, while (c) maximizing the interrogation of relevant patient and clinical data in the process of designing CPOE alerts.

Although no significant relationship was found between alert timing and quality, the findings aligned with concerns expressed by other researchers in regard to the complexity and consideration of placing interruptive alerts in the ordering workflow (Perna, 2012; Smith et al., 2013). The construct I created to measure alert timing provided examples of synchronous alert delivery during the period of order entry. I recommend CDS developers explore the asynchronous timing of alert delivery that might lessen concerns of alert fatigue during order entry while supplying meaningful information supporting improvements in patient care (Perna, 2012).

Collaboration between software developers, software users, and health care stakeholders involved in the delivery and management of CDS tools remains a key consideration in improving CDS tools. Sociotechnical factors underpin software content, usability, and organizational processes (Menon et al., 2014). I made no distinction in my research between ambulatory and in-patient physician executive subjects. The ability to tailor CDS by treatment venue and specialty provides an opportunity for software developers to apply these sociotechnical factors more fully. I recommend the careful consideration and application of a sociotechnical framework in CDS software development efforts.

Recommendations for Further Study

The research study was powered at .80 with a medium effect size requiring a sample of $N = 68$. The limited demographic data I captured included the identification of type of EHR system used. Of 69 valid subjects, 22 used a Cerner Incorporated EHR system, and 47 subjects used an Epic Systems EHR. The study was not powered for a subset analysis on the effect of EHR type with the regression model. A larger study powered for this type of subset analysis might generate additional insights to guide third-party software development efforts. While the findings are potentially generalizable to the population of physician executives using EHRs with advanced CDS capabilities, there might be important differences in the perceptions of end-users with experience gained from a single EHR system.

The research focused on physician executives working in advanced, technology enabled health care hospitals and systems participating in ACOs. These organizations generally commit to improving the quality and cost of care for patient populations with chronic conditions such as diabetes and heart failure (Shortell et al., 2014). The research lacked participation by other software users such as nurses, allied health professionals, and patients. With the opportunity to manage ACO patients longitudinally from their homes, to a hospital, physician office, rehab, or skilled nursing facility, a need persists for additional research on the design and applicability of CDS tools by venue of care and by stakeholder (Balka, Tolar, Coates, & Whitehouse, 2013).

Discussions with subject matter experts from industry and academia along with insights taken from the published literature on CDS informed the design of the instrument

used in the research. The pilot survey results obtained from five physician executives included physicians familiar with my professional work. The reliability statistic calculated for each scale at the time of the pilot was $\alpha > .70$; however, the reliability statistic fell below this threshold at the conclusion of the full study with an average of $\alpha = .63$. The opportunity remains for further refinement of the instrument. In addition, qualitative research might supplement these findings with exploration of end-user attitudes toward alert design attributes of (a) workflow timing, (b) organizational processes by care venue, and (c) the synchronous versus asynchronous delivery of an alert.

Reflections

My interest in pursuing this research arose with my professional employment in a SaaS firm focused on the development of CDS tools. The concept of actionable CDS guides the development work at my firm. It is possible I biased the results of the pilot survey with the participation of physician executives inclined toward the use of interruptive, clinical algorithm derived alerts.

I was gratified; however, to have the participation of AMDIS as my community partner. I knew from the literature the challenges associated in obtaining responses to an online survey. Obtaining the number of responses needed would not have occurred without the support of AMDIS and numerous industry and academic professional colleagues. Exclusion criteria eliminated 57 physician executives who attempted to participate resulting in $N = 69$ complete responses. A few participants emailed me in follow-up to let me know they had taken the survey. They remarked positively on the

effort and the importance of the research. Those email responses from busy physician executives invigorated my efforts to successfully complete this research effort and provide some level of contribution to the field.

In deciding on the design of the study, I considered the professional interests of health care researchers for an evidence-based approach in generating data sufficient to accept or reject a stated hypothesis. A mixed-methods study combining qualitative exploration of stakeholder attitudes with a quantitative or experimental design was not feasible in the context of my DBA studies. However, the opportunity to expand the findings from this research with the application of those methods remains a worthy pursuit after my graduation from Walden University.

Summary and Study Conclusions

The findings from this research supported the alternative hypothesis for the relationship of alert content and perceptions of improved quality measure adherence. No significant correlation was found between alert timing and perceptions of improved quality measure adherence requiring acceptance of the null hypothesis. These results underscored the importance of examining sociotechnical theory in the context of CDS software design efforts.

Prior research validated the application of a sociotechnical framework to such initiatives (Sittig & Singh, 2010; Smith et al., 2013). With billions of dollars invested in the United States in HIT during a significant climate of health care reform, obtaining a return on this investment necessitates leveraging the data captured in EHRs for efficient and effective clinical decisions. Poor use of technology coupled with poor design of CDS

tools contributed to problems of information overload and alert fatigue. Rather than empowering physicians, these deficiencies in tools contributed to patient harm (Menon et al., 2014; Murphy, Singh, & Berlin, 2014).

Software vendors, health care providers, the government, and patients are all vested stakeholders in the successful adoption of HIT (Denham et al., 2013). Applying the insights from this research in conjunction with the existing field of knowledge might support improvements in CDS software tools. Those tools, in turn, might contribute to the achievement of health care's triple aim.

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Appendix A: Survey Questions Presented to Online Participants

A. I have read, and I fully understood the Informed Consent Information. My participation in this survey is voluntary. I acknowledge I have not received any compensation or inducement to participate in this research.

1) Yes.

2) No.

B. My professional credentials include (check one)
1) Medical Doctor (MD)
2) Doctor of Osteopathy (DO)
3) None of these

C. My hospital or health system has access to an EHR from (Check all that apply)
1) Cerner Incorporated
2) Epic Systems
3) None of these

D. My hospital or health system participates in an ACO
1) Yes
2) No

Items E-T are scored on a 5-point Likert-type scale where 5= *Strongly Agree*, 4= *Agree*, 3= *Neutral or No Opinion*, 2= *Disagree*, and 1= *Strongly Disagree*

E. Alerts triggered during physician order entry should account for the context provided by patient specific data contained in the patient's medical record.

F. Pop-up alerts triggered while placing orders should always include pre-populated, evidence-based override reasons.

G. Alerts specific to the selection of a patient intervention (medication, lab, test, or procedure) should include links to patient education materials when available.

H. Alerts triggered by a physician during computerized order entry should include substitution recommendations for appropriate, lower-cost interventions if available.

I. Alerts triggered while ordering an intervention for chronically ill patients or those at risk for diabetes, heart failure, or cardiovascular disease should contain links to published guidelines, peer-reviewed literature, or other supportive documentation such as a published quality metrics.

J. Alerts triggered while ordering any intervention for any patient should contain links to additional peer-reviewed information when available.

K. Alerts specific to chronically ill patients or those at risk for diabetes, heart failure, or cardiovascular disease should require a user-documented override reason when the provider decides to not follow the recommendation contained in the alert.

L. All alerts should be suppressed until the last order in a session is entered by the physician.

M. Alerts triggered by current ordering activity should be presented immediately as orders are entered.

N. Alerts should be non-intrusively displayed (not requiring any user interaction) as a passive reminder during all order entry sessions for chronically ill ACO patients or those ACO patients at risk for diabetes, heart failure, or cardiovascular disease

O. Pop-up alerts triggered while placing orders and contextualized by patient age and condition enhance compliance with ACO reportable quality measures.

P. Passive or non-intrusive alerts visible during electronic ordering consisting of general reminders for at risk ACO patient populations enhance compliance with ACO quality measures.

Q. Alerts whether non-intrusive or requiring action by the user should be placed in the provider's ordering workflow to improve adherence to ACO quality measures.

Appendix B: CMS ACO Quality Measures

Table: 33 ACO Quality Measures

Domain	Measure	Description	Pay-for-Performance Phase In R= Reporting P= Performance		
			PY1	PY2	PY3
Patient/Caregiver Experience	ACO #1	Getting Timely Care, Appointments, and Information	R	P	P
Patient/Caregiver Experience	ACO #2	How Well Your Doctors Communicate	R	P	P
Patient/Caregiver Experience	ACO #3	Patients' Rating of Doctor	R	P	P
Patient/Caregiver Experience	ACO #4	Access to Specialists	R	P	P
Patient/Caregiver Experience	ACO #5	Health Promotion and Education	R	P	P
Patient/Caregiver Experience	ACO #6	Shared Decision Making	R	P	P
Patient/Caregiver Experience	ACO #7	Health Status/Functional Status	R	R	R
Care Coordination/Patient Safety	ACO #8	Risk Standardized, All Condition Readmissions	R	R	P
Care Coordination/Patient Safety	ACO #9	ASC Admissions: COPD or Asthma in Older Adults	R	P	P
Care Coordination/Patient Safety	ACO #10	ASC Admission: Heart Failure	R	P	P
Care Coordination/Patient Safety	ACO #11	Percent of PCPs who Qualified for EHR Incentive Payment	R	P	P
Care Coordination/Patient Safety	ACO #12	Medication Reconciliation	R	P	P
Care Coordination/Patient Safety	ACO #13	Falls: Screening for Fall Risk	R	P	P
Preventive Health	ACO #14	Influenza Immunization	R	P	P
Preventive Health	ACO #15	Pneumococcal Vaccination	R	P	P
Preventive Health	ACO #16	Adult Weight Screening and Follow-up	R	P	P
Preventive Health	ACO #17	Tobacco Use Assessment and Cessation Intervention	R	P	P
Preventive Health	ACO #18	Depression Screening	R	P	P
Preventive Health	ACO #19	Colorectal Cancer Screening	R	R	P
Preventive Health	ACO #20	Mammography Screening	R	R	P
Preventive Health	ACO #21	Proportion of Adults who had blood pressure screened in past 2 years	R	R	P
At-Risk Population Diabetes	Diabetes Composite ACO #22 – 26	ACO #22. Hemoglobin A1c Control (HbA1c) (<8 percent) ACO #23. Low Density Lipoprotein (LDL) (<100 mg/dL) ACO #24. Blood Pressure (BP) < 140/90 ACO #25. Tobacco Non Use ACO #26. Aspirin Use	R	P	P
At-Risk Population Diabetes	ACO #27	Percent of beneficiaries with diabetes whose HbA1c in poor control (>9 percent)	R	P	P
At-Risk Population Hypertension	ACO #28	Percent of beneficiaries with hypertension whose BP < 140/90	R	P	P
At-Risk Population IVD	ACO #29	Percent of beneficiaries with IVD with complete lipid profile and LDL control < 100mg/dl	R	P	P
At-Risk Population IVD	ACO #30	Percent of beneficiaries with IVD who use Aspirin or other antithrombotic	R	P	P
At-Risk Population HF	ACO #31	Beta-Blocker Therapy for LVSD	R	R	P
At-Risk Population CAD	CAD Composite ACO #32 – 33	ACO #32. Drug Therapy for Lowering LDL Cholesterol ACO #33. ACE Inhibitor or ARB Therapy for Patients with CAD and Diabetes and/or LVSD	R	R	P

Notes: PY = Performance Year

Appendix C: Letter of Cooperation

Letter of Cooperation

Association of Medical Directors Of Information Systems (AMDIS)

[redacted]

Dear Kimberly,

Based on my review of your research proposal, and on behalf of AMDIS, we give permission for you to conduct the study entitled: Assessing Clinical Software User Needs for Improved CDS Tools within the AMDIS community. As part of this study, I authorize you to invite our membership to participate in the self-completed, anonymous, on-line survey research. The participation of our members will be voluntary and at their own discretion.

We understand that our organization's responsibilities include: Providing access to the AMDIS ListServ containing email addresses of AMDIS physician members. We may elect to encourage participation to your survey by directly sending the URL link to the SurveyMonkey® hosted survey with an invitation to our membership encouraging their voluntary participation in the research study. We may also allow you to provide a follow up email directly to the membership from your Walden University email account with the url link and a reminder invitation to participate including notification to the membership of AMDIS cooperation as your Community Partner. We reserve the right to withdraw from the study at any time if our circumstances change.

I confirm that I am authorized to approve research in this setting and that this plan complies with the organization's policies.

I understand that the data provided and collected by the Researcher will remain entirely confidential and may not be provided to anyone outside of the student's supervising faculty/staff without permission from the Walden University IRB. I understand that survey participants may request access to the research data for five years during the study retention period. I also understand that AMDIS may receive the final published study for dissemination to the member community

Sincerely,

[redacted]

[redacted]

Appendix D: Communication with Community Partner

Jun 28

Kimberly Denney <kimberly.denney@waldenu.edu>

to [redacted]

[redacted]

The AMDIS conference was great, and I did not want to disturb you during such an important time. Before we head into the 4th of July Holiday weekend, I was wondering if we can share the invitation and the link to the final research survey with the AMDIS membership? I really appreciate the support you and AMDIS have provided as my community partner for this research. My email invitation with the link is here for your convenience:

I am seeking your assistance to participate in an IRB approved research study. The survey should be completed by a physician using a Cerner Incorporated or Epic Systems EHR as part of the health care information technology infrastructure used by their organization and associated with its use in an accountable care organization.

Although you know me from my professional work history with Stanson Health and Zynx Health, I am a doctoral student at Walden University. I am conducting this research to fulfill the requirements of a doctoral of business administration degree with a specialization in Technology Entrepreneurship. Your participation may provide new insights into the needs for EHR workflow integrated clinical decision support tools that support improved adherence to ACO quality measures.

The survey automatically concludes if a participant does not satisfy any of the inclusion criteria. A Participant Consent Form is included at the start of the survey. The first survey question requires your acknowledgement that you read and fully understood all of the information provided in the Participant Informed Consent Form. It should take **less than 7 minutes** to complete the survey. All responses are anonymous and the pilot test data will be transferred to a secure and encrypted data storage location protecting the anonymity of every research participant throughout the study and a 5-year data retention period. Your voluntary participation is highly appreciated.

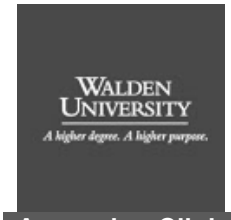
You may complete the brief survey by accessing the link to SurveyMonkey® below.

https://www.surveymonkey.com/r/physician_research_survey

With Kind Regards,

Kimberly Denney
Doctoral Student, Walden University
Kimberly.Denney@waldenu.edu

Appendix E Informed Consent Background and Information



Assessing Clinical Software Users Needs for Improved CDS Tools

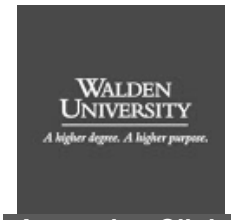
1. Introduction and Informed Consent: DBA Survey

Background

You have been invited to participate in a doctoral study research project. You may have met me professionally through my work in the field of clinical decision support with Zynx Health and Stanson Health. This research is in support of my academic pursuit to earn a doctoral degree from Walden University. Your participation in this study requires the acknowledgement of your informed consent. The purpose of the research and the procedures for study conduct are provided here for your review. As in the case of all research efforts, you should be aware of the benefits and the risks that may accrue to you as a result of your participation. Importantly, understanding your right to terminate your participation at any time from the survey is critical to the protection of your rights. No promises or guarantees are given as to the study outcomes.

Research Study Title: Assessing Clinical Software User Needs for Improved Clinical Decision Support Tools

Researcher: Kimberly Denney, Doctoral Candidate, Walden University



Assessing Clinical Software Users Needs for Improved CDS Tools

2. Informed Consent

Study Purpose: All survey participants are physician executives at health systems participating in an ACO using either a Cerner Incorporated or an Epic Systems EHR. The purpose of the research is to examine the extent of any relationship between the type and timing of CPOE automated alerts with physician perception for better adherence to an ACO quality measure. Opportunities may exist for fulfilling the

"Triple Aim" of health care through ACOs by enhancing the experience of physicians using EHR integrated CDS tools. Your participation may support findings to inform improvements in the design of CDS tools.

Procedure: This study involves completing an Internet-based survey that should take approximately 15 minutes to complete. No compensation is provided in exchange for your time.

Risks and Discomforts: No risks or discomforts are expected from taking the on-line survey.

Benefits: The results obtained from the survey represent the combined opinions of your peers and will be made available for reference once published. The findings from this research will extend the base of current knowledge about CDS use by ACOs using integrated HIT systems. Importantly, the information obtained from this research may inform CDS product development efforts providing third party software vendors with a greater understanding and awareness of physician needs for better workflow integrated tools.

Confidentiality: Every measure is taken by the researcher to ensure the confidentiality of the data provided. All study files are maintained in an encrypted and access-restricted computer file. Aside from me, only my doctoral committee members and the Walden University IRB will have access to the data. A set of survey questions will confirm the participation of your hospital or health system in an ACO and your health system's use of a particular EHR. Other than establishing your medical credentials as a physician (MD or DO), the survey questions do not ask for any other identifying information. Your name and associated health system will not be identified in the data as all survey responses remain anonymous. Once the study has concluded, all survey data will be stored on an external hard drive under lock and key in a fireproof file cabinet for 5 years. After a period of 5 years, the external hard drive containing all of the survey data will be destroyed. Throughout the retention period, all of the survey data will be accessible for the use by other researchers upon written request. At no time will any identifying information (names, e-mail addresses, health system or hospital names) be shared publically.

Withdrawing Your Participation: Your participation in this research effort remains voluntary at all times. At any time during the survey, you can withdraw without prejudice. No penalties are assigned for termination of participation. There is no compensation or incentive of any kind provided for your voluntary participation in this study.

Additional Information: General questions about the study may be directed to Kimberly.Denney@waldenu.edu or Dr. Craig Martin my Faculty Committee Chair at Craig.Martin2@waldenu.edu. All questions regarding your rights as a participant should be directed to Walden University's IRB at irb@waldenu.edu. Walden University's approval number for this study is 06-09-15-0396865 and it expires June 8, 2016.

You are advised to print and retain a copy of this informed consent information.

The first survey question requires an indication that you read and that you fully

understood all of this information.

Appendix F: Personalized Participant Email Invitation

Dear Dr. (XXXXXX),

You are invited to take part in a research study of physician executives using a Cerner Incorporated or Epic Systems EHR as part of the health care information technology infrastructure used by your organization and associated with its use in an accountable care organization.

As the researcher, I am requesting your participation based on your knowledge of clinical decision support tools and understanding of physician workflow associated with computerized order entry. Although you may know me from my professional work history with Zynx Health and Stanson Health, I am a doctoral student at Walden University. I am conducting this research to fulfill the requirements of a doctoral of business administration degree with a specialization in Technology Entrepreneurship. Your participation may provide new insights into the needs for EHR workflow integrated clinical decision support tools that support improved adherence to ACO quality measures.

You may complete the brief survey by accessing the link to SurveyMonkey® below. A Participant Consent Form is included at the start of the survey. The first survey question requires that you acknowledge you have read and fully understand all of the information provided in the Participant Informed Consent Form. It should not take you more than 15 minutes to complete the survey. Your responses will be coded and transferred to a secure and encrypted data storage location protecting your anonymity throughout the study and a 5-year data retention period. Your voluntary participation is highly appreciated.

With Kind Regards,

Kimberly Denney
Doctoral Student, Walden University

Appendix G: Residual Statistics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	20.9076	25.8086	23.7971	1.07315	69
Std. Predicted Value	-2.693	1.874	.000	1.000	69
Standard Error of Predicted Value	.389	1.325	.618	.211	69
Adjusted Predicted Value	20.4366	25.7668	23.7805	1.08256	69
Residual	-12.97233	4.82763	.00000	3.08423	69
Std. Residual	-4.144	1.542	.000	.985	69
Stud. Residual	-4.212	1.581	.003	1.006	69
Deleted Residual	-13.40319	5.07254	.01656	3.21747	69
Stud. Deleted Residual	-4.888	1.599	-.008	1.056	69
Mahal. Distance	.066	11.196	1.971	2.253	69
Cook's Distance	.000	.196	.014	.027	69
Centered Leverage Value	.001	.165	.029	.033	69

a. Dependent Variable: Quality