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The Development of an Integrated Model of EMR Adoption: Incorporating the Organization Artifact

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Abstract:

The information systems (IS) field has studied information technology (IT) adoption for several decades to, among other things, make it easier for organizations to derive value from IT by helping them to more effectively and efficiently use it. Extant IT adoption work has traditionally focused on a single type of structural form: the form in which the purchasing decision maker does not represent the end user of the innovation. While this structure may have adequately represented the predominant corporations historically, a greater number of organizations now contain employees who represent both the purchasing decision maker and the end user. We begin to investigate alternative structural forms by focusing on organizations in which the IT purchasing decision maker also represents the end user. Thus, we investigate the factors what physicians in a hospital setting versus those in private practice find important in adopting EMR systems. Our results demonstrate that the context of adoption matters, and we discuss the additional opportunities that exist in this area for researchers to examine this new theoretical lens for adoption research.

Keywords: IT Adoption, Organization Artifact, Electronic Medical Records, Healthcare Information System, Structural Equation Model.

Monica Tremblay was the Senior Editor for this paper.

1 Introduction

Researchers have studied information technology (IT) adoption for several decades to, among other things, make it easier for organizations to derive value from IT by helping them to more effectively and efficiently use it (Venkatesh, Thong, & Xu, 2012). Much research has assumed that individuals base their decision to use an IT based on their intention to adopt it and personally use it. As a result, adoption research has focused in large part on emerging IT innovations in an attempt to understand individual-level user intentions. Early IT adoption research focused on core models such as the technology acceptance model (TAM), the perceived characteristics of innovations (PCI), and task-technology fit (TTF). Over the course of the past decade and a half, research into the adoption of IT has consolidated into more unified understandings of this type of individual user adoption, which the unified theory of the acceptance and use of technology (UTAUT) exemplifies (Venkatesh, Thong, & Xu, 2016; Venkatesh et al., 2012; Venkatesh, Morris, Davis, & Davis, 2003). The theoretical approaches that UTAUT adopts address the "micro-level" adoption intention or decision and focus on explaining individual users' behavioral intention through their perceptions about using IT.

While UTAUT has focused on the drivers of the individual-level intention to use, we posit the adoption in a typical small practice healthcare context requires one to consider additional factors (Gagnon, Ngangue, Payne-Gagnon, & Desmartis, 2015; Gagnon et al., 2012). For example, a separate strand of work has focused on organizational "macro-level" decisions (Lo, Wu, Morra, Lee, & Reeves, 2012) such as healthcare policies (Gagnon et al., 2016) and outsourcing (Schwarz, 2014; Gorla & Somers, 2014; Cronk & Sharp, 1995). In the outsourcing decision, a healthcare organization decides whether it should use an external vendor to implement a new technology (i.e., outsource its implementation) (Avgar, Tambe, & Hitt, 2013)—in other words, a macro-level decision. Most organizations contain a distinction between the people involved in the macro and the micro levels of decision making with regard to technology adoption; the decision maker who decides whether or not to outsource the new IT's implementation and the individual who "adopts" and will regularly use the new IT (e.g., clinicians) often differ (Dutta, Gwebu, & Wang, 2017; Shaha et al., 2015).

Thus, current IT-adoption approaches assess organizational context factors as omnibus effects if they consider them at all. However, a new context has begun to emerge since more than 60 percent of physicians in the US work in practices with 10 or fewer physicians (Hawkins, 2016), and small organizations in the US employ more than half of all workers (Larrucea, O'Connor, Colomo-Palacios, & Laporte, 2016) and have begun to take the lead in creating new jobs (Dilger, 2018). What about cases in which the technology adopter represents the outsourcing decision maker? We posit that a gap in the literature exists regarding the role of the organizational artifact in explaining behavioral intention and use—in other words, that variance in the organizational degree of macro-micro overlap may 1) elicit a distinct set of salient factors that influence the adoption decision and 2) impact the strength of influence certain factors exert in explaining user behavior. While other scholars have previously suggested that unique factors impact small businesses (Thong, 1999), we propose and examine the relationship by applying applicable constructs from multiple theories using a micro-macro approach to the EMR adoption context. Therefore, in this paper, we apply micro and macro levels of theory to develop an integrated model that incorporates the organizational artifact and conceptualizes its specific effects on adoption behavior in a healthcare context. Accordingly, this study advances our understanding of complex, difficult adoption domains, such as healthcare IT in small practices.

Contribution:

This paper identifies and tests a full model of 21 factors important for physicians in private practice adopting EMR systems. For policymakers, this research offers insight into how they can best support private practice physicians who have yet to implement EMR systems (almost 50% as of 2018 according to the adoption dashboard kept by the US Office of the National Coordinator for Health Information Technology). For researchers, it shows how they can include both individual and organizational (macro and micro) factors when considering adoption decisions in similar settings.

In the healthcare information technology (HIT) domain in particular, researchers have noted both successes and shortcomings of current micro approaches for explaining IT use (Chau & Hu, 2002; Gagnon et al., 2012; Holden & Karsh, 2010). Thus, the healthcare context provides an emerging opportunity to explore what we term the "micro-macro divide", which refers to the confluence of micro and macro factors that simultaneously influence IT adoption. The HIT domain represents an appropriate context to study such adoption because this context features an abundance of small businesses whose owners also use the HIT that the businesses employ. By using theories that explain how the micro and macro factors that influence IT adoption intersect, we incorporate the role of the organizational artifact in IT adoption. In this study, we report on physicians' decisions to adopt electronic medical record (or EMR) technology. We investigate how the micro and macro factors that influence IT adoption intersect by contrasting physicians in private practice versus those in a hospital system. Before doing so, however, we discuss organizational context and our work's theoretical foundations.

2 Theoretical Development

2.1 Organizational Form

Structural contingency theory has a long history in the organizational science domain and the information systems (IS) literature (Burton, 2004; Donaldson, 2001; Weill & Olson, 1989). According to this theory, the environment puts requirements (e.g., for efficiency or innovation) on organizations in order to survive and prosper (Hage & Aiken, 1970). As a result, they employ a strategy that reflects these pressures (Christensen-Szalanski, 1978). This strategy, along with the available resources, leads organizations to adopt differing types of technology, which structural contingency theory considers a *contingency* variable (Blau, 1970; Chandler, 1962; Perrow, 1967; Pugh & Hickson, 1976; Woodward, Dawson, & Wedderburn, 1965). In the 1970s, adoption research began to extend this work by examining end users separate from other structural contingency factors to determine what drove their intention to adopt technologies.

Though structural contingency theory indicates that we should consider a variety of organizational forms in adoption research (Brown & Bostrom, 1994), perhaps for research expediency or convenience's sake, previous work in IT adoption has focused upon a single type of structural form: the form in which the purchasing decision maker and the end user differ. While this structure may have adequately represented the predominant corporation historically, a greater number of organizations now contain employees who represent both the purchasing decision maker and the end user. By limiting our understanding to one structural form, we inhibit our ability to understand alternative organizational forms and, specifically, that structural form in which the decision maker also represents the end user. We posit that adoption research should address variation in the macro structure (i.e., the strategic effects and contingency reasoning that occurs in adoption contexts). In this study, we investigate alternative structural forms by focusing on organizations in which the IT purchasing decision maker also represents the end user.

As UTAUT exemplifies, the micro level focuses on individual-level adoption and how an individual will experience and gain value from using a technology (Venkatesh et al., 2012, 2003). We expect that, in many technology adoption contexts, this view will adequately represent the key factors that influence adoption. However, in organizations where the technology purchasing decision maker also represents a primary end user, we postulate that the micro-level adoption view will be inadequate. In such contexts, the decision maker considers factors beyond the technology itself, such as the organization and the environment. We believe these factors will likely influence how such individuals perceive the technology and what adoption decision they make.

As such, with this study, we address a gap in knowledge about the relationship between the environmental considerations, the organizational structure, and individual-level attitudes and decisions about adopting an innovation. Accordingly, we illustrate how the limitation in the literature impacts how we theorize adoption. To do so, we present the findings from an empirical study of actors in two types of organizations: organizations where the environmental and organizational characteristics have much influence in the adoption decision and organizations where the environmental and organizational characteristics have less influence in the adoption decision. We conducted our study in a specific industry to ensure that all organizations under investigation experienced the same industry pressures.

Specifically, we conducted our study in the context of the medical industry in the United States (US), which today faces much pressure to adopt EMR technologies. Given that contingency theory argues that requirements from the environment exert pressure on strategic change, this context suits our focus on

understanding what impact organizational structure has on adoption decisions. In Section 2.2 we discuss the empirical context before we theorize about the impact that structure has on the adoption decision.

2.2 Empirical Context: EMR Adoption by Physicians

Healthcare organizations have begun to adopt electronic medical record (EMR) technology in the US due to pressure from both the federal and state governments to encourage (or mandate) such adoption. Indeed, the EMR reimbursements program in The American Recovery and Reinvestment Act (ARRA) of 2009, which allocated almost US$20 billion to help healthcare organizations widely adopt and use HIT, exemplifies this pressure (Moriya & Simon, 2016; Blumenthal, 2009). The funding provided incentives to organizations if they adopt interoperable HIT early on, but it also enacted penalties in future years for physicians who have not demonstrated that they have "meaningfully used" EMRs (Miller, 2011). In terms of IT adoption theory, these pressures were coercive (in the case of the payments/penalties) and mimetic (in the case of interoperable network technologies among physician organizations). The macro-level institutional theory applied to technology adoption clearly identifies these pressures (Sinha & Van de Ven, 2005; Robey & Boudreau, 1999; Scott, 1987). Interestingly, although physicians have known about these incentives and recognized the potential penalties for non-adoption, they have been slow to adopt the technology (Noteboom, Hafner, & Wahbeh, 2017; FitzGerald, Rorie, & Salem, 2015; DesRoches et al., 2008). As of 2017, just over 60 percent of small practice physicians had adopted an EMR system (a change of about 20% during the preceding eight years), while over 95 percent of hospital-based physicians had adopted an EMR system (a change of almost 50% over the preceding eight years) according to the U.S. Government's Office of the National Coordinator for Health Information Technology (2018). These results demonstrate that the institutional theory drivers (i.e., coercive pressures) implemented along with policy imperatives did not adequately motivate small practices to adopt HIT.

Meta-studies on physicians' EMR adoption also evidence a divide between the small and large practice context. Over a 30-year period, more than 89 EMR adoption studies had almost universally applied UTAUT and similar individual user adoption theories to understand this problem (Najaftorkaman, Ghapanchi, Talaei-Khoei, & Ray, 2015). Two meta-studies in particular provide a clear comparison. First, Castillo, Martinez-Garcia, and Pulido (2010) examined a sample of physicians overwhelmingly taken from large practice settings (i.e., hospitals). With this sample, the authors concluded that adoption factors were heavily weighted to individual job issues such as the user attitude toward technology, workflow impact, interoperability, technical support, and communications with the support team. In contrast, Boonstra and Broekhuis (2010) drew their sample from studies with a much higher proportion of small practice physicians. They discovered that the key adoption factors included the technical categories that Castillo et al. found but included the additional factors of financial, time to implement, legal, and security/privacy. Moreover, the latter study also demonstrated that organizational size represented an important factor in how adoption would proceed, but it did not extend this insight into understanding how the different organizational contexts would impact the weighting of the various factors.

Research into EMRs is eclectic and spans many disciplines, such as public health, sociology, business, epidemiology, economics, and strategy (Najaftorkaman et al., 2015; Schwarz & Schwarz, 2014; Fichman, Kohli, & Krishnan, 2011). Early findings provided a variety of rationales for the adoption and/or non-adoption of technology (which we summarize below in Table 1). Overall, these findings show that EMRs provide significant benefits once adopted, which is great news from a UTAUT perspective. Performance expectancy represents the most salient driver of adoption (Venkatesh et al., 2003). Nonetheless, we see from the analyses of physician adoption that the potential adopters (particularly smaller, private practices) have not adopted HIT at levels that one would predict when observing the overall high performance expectancy (Reardon & Davidson, 2007). Somehow, other factors must influence this situation. Some research suggests that macro-level considerations have a determinate influence in this context. For example, financial considerations, which traditional adoption models do not include, could cause organizations to pause or struggle in their adoption decision (Najaftorkaman et al., 2015; Reardon & Davidson, 2007).

To our knowledge, research has yet to systematically and empirically investigate the differential effects that large versus small contexts have on IT adoption in a way that incorporates both micro and macro factors in an EMR adoption model. We posit that studying EMR adoption in two differing organizational contexts simultaneously contributes to the literature on the role of organizational structures in the adoption process and how the unreconciled macro and micro factors can jointly impact EMR adoption.

Table 1. Summary of Previously Identified Factors of EMR Adoption

Adoption theory base level of analysis (most closely associated IS theory rationale)	Factor	Studies
Macro level: (diffusion of innovations)	Financial barriers	Anderson (2007), Ash & Bates (2005), Bates, Ebell, Gotlieb, Zapp, & Mullins (2003), DesRoches et al. (2008), Gans, Kralewski, Hammons, & Dowd (2005), Miller & Sim (2004), Reardon & Davidson (2007), Simon et al. (2007)
Micro level: (UTAUT: effort expectancy)	EMR technology factors	DesRoches et al. (2008)
Micro level: (UTAUT: facilitating conditions)	Organizational factors (within hospital or practice)	Burt & Sisk (2005), Simon et al. (2007)
Macro level: (Institution theory: normative pressure)	Lack of standards between EMR systems	Bates et al. (2003), Simon et al. (2007)
Micro level: (UTAUT: moderators)	Physician characteristics	DesRoches et al. (2008)
Micro level: (UTAUT: performance Expectancy)	Perceived loss of productivity and time with the patient	Ash & Bates (2005), DesRoches et al. (2008), Gans et al. (2005)
Micro level: (UTAUT: Effort Expectancy)	Concerns over ability to use the EMR system	Gans et al. (2005), Miller & Sim (2004), Simon et al. (2007)
Micro level: (UTAUT: effort expectancy & performance expectancy)	Incompatibility with physician work flow	Miller & Sim (2004)

To address the divide in adoption rationales, we investigated the adoption decision for physicians in private practice and those in a larger hospital context. As we discuss above, we expect that physicians in smaller practices will exhibit a greater concern for environmental and organizational structural characteristics (macro-level factors) compared to those in larger settings.

2.3 Creating the Model of the Adoption Decision

Because we developed a new, blended model for adoption that combined factors from two theory bases (micro and macro), we needed to ensure that our assumptions and inferences accurately reflected the experiences of those individuals we sought to characterize. Moreover, we needed to collect these actual experiences without biasing them toward either theory base. As such, we adopted a four-phased approach to build our model. We developed our four-phased approach to: 1) identify and explore specific factors of the IT that discriminate between adopters and non-adopters in our two distinct organizational structures (completed in phases 1 through 3); and 2) in a new sample, determine the extent to which these factors differentiate adopters and non-adopters and the differences that exist between the two distinct organizational structures (completed in phase 4). Table 2 outlines our approach.

Table 2. Four-phase Process of Empirical Study

	Phase one: factor identification	Phase two: factor refinement	Phase three: theoretical sensemaking	Phase four: theory testing
Objective	To identify the specific factors that differentiate adopters and non-adopters	To categorize our factors through the lens of UTAUT	To create a theoretical model that integrates factors refined through phase two.	To empirically validate the candidate factors in our research model.
Approach	We conducted interviews with 21 physicians that had not adopted EMR technology. We transcribed interviews and conducted a thematic analysis of the texts to identify common themes that existed across cases.	We classified the 36 factors into five categories: performance expectancy, effort expectancy, social influence, facilitating conditions, and novel influences.	Drawing on various research streams, we created an integrated research model.	We used a Web-based survey that 277 physicians in private practice and 169 physicians in hospitals completed.
Outcome	We identified 36 factors that differentiate adopters and non-adopters.	We obtained a theoretical understanding of the factors we identified in phase 1.	We created a theoretical model with 21 first-order constructs, six second-order constructs, and 11 hypotheses.	Hospital and private practice physicians differed in the adoption/non-adoption decision.

2.4 Phase One: Factor Identification

In the first phase, we identified the factors that we needed to include in our model. While we had already obtained micro and macro factors that prior theory and research had identified, we sought to better understand whether and how decision makers/end users experience these factors in combination. When examining extant work on EMR adoption, we realized that this approach was novel. We found that most EMR studies have collected data in one location, such as a hospital (Kim, Lee, Hwang, & Yoo, 2016; Hennington, Janz, Amis, & Nichols, 2009), or with physicians in one specialty (e.g., Baird, Furukawa, & Raghu, 2012; Ayal & Seidman, 2009). Few have examined private practice (Reardon & Davidson 2007), and none have included a comparative sample of different organizational structures. This study fills this gap in the literature.

We used the critical incident technique (CIT) to guide our work in the first phase. The CIT approach calls for an individual to describe a recent incident (i.e., their decision not to adopt EMR) and the circumstances surrounding that incident along with their actions. CIT provides a validated method for eliciting the detailed actions that individuals take and the rationales they employ in a given context (Martin, Tulla, Meltzer, Arora, & Farnan, 2017; Butterfield, Borgen, & Amundson, 2005; Flanagan, 1954). Other IS research has also used CIT: for example, Thomas and Bostrom (2010) used it to examine how individual leaders deal with difficult decision problems regarding technology.

Thus, following an intensity sampling rational (Thomas & Bostrom 2010), we began the first phase of the study by identifying a targeted sample of 21 rejecter physicians who had not adopted EMR technology and did not come from an integrated care setting. We selected physicians across specialties (including electrophysiology, family practice, ophthalmology/retinology, orthopedics, general surgery/medicine, internal medicine, ophthalmology, psychiatry, vascular surgery, dermatology/dermatologic surgery, ENT, occupational medicine, anesthesiology/pain management, psychiatry/geriatrics, bariatric surgery, pediatrics, dermatology) and included physicians both inside hospitals and those involved in private practice (the latter of which included practices with only one physician to larger ones). We conducted structured, qualitative interviews with each physician (see Appendix for the interview structure summary). A typical interview lasted between 30 to 45 minutes. In all, we obtained over 15 hours of interview text to analyze. We collected the data in a state in the Southeastern United States, and we included respondents from all of the diverse regions of the state. In deciding our sampling for this phase, we considered that either the macro or micro factors would have likely influenced adopters. The EMR rejecters (non-adopters who had explicitly considered adoption) would have likely faced a challenge with issues pertaining to one or more of the factors that led them to not adopt the technology (Schwarz, Chin, & Hirschheim, 2014b).

We posit that they would provide insight into key factors involved in inhibiting adoption (Cenfetelli, 2004; Cenfetelli & Schwarz, 2011). We determined the number of interviews we conducted to concur with CIT guidance since we examined aspects of a job's subrole (Flanagan, 1954). The physicians had a range of experience in practice (from nine to 48 years with an average of 25).

To determine the factors that drove rejecters, we used a four-step process that we modeled on prior IS CIT work to analyze each interview (Thomas & Bostrom, 2010):

- **Step one (initially analyze transcripts):** the first author read through each transcript and extracted a quotation every time a respondent mentioned a reason they decided to reject EMR.
- **Step two (formally group factors)**: during this step, the first author analyzed the extracted quotations in a more structured fashion. The author grouped each quotation together with similar quotes and a label and developed a definition for each grouping.
- **Step three (formally review groups):** during this step, the second author and an external academic researcher who conducted research in adoption (who had not yet seen the materials) reviewed the group names, definitions, and corresponding criterion until they came to a consensus.
- **Step four (analyze formal groups)**: the first author and the second author then analyzed the groups to determine their similarity to extant factors that we identified via reviewing the literature on adoption research.

The four-step analysis approach yielded 36 factors that contribute to discriminating between adopters and non-adopters. As Table 3 displays, the findings confirm existing theory's influence since nine of UTAUT's factors emerged in addition to six macro factors (or factors more likely to pertain to a physician-owner). Moreover, we identified seven new factors (i.e., novel to adoption theory) that repeated across interviews. By the end of the interviews, we did not see any new factors emerge in the last three interviews, which indicated that we had reached theoretical saturation (Thomas & Bostrom, 2010). We then sought but did not identify any factors that appeared only in a given demographic, specialization, practice size, or practice context.

2.5 Phase Two: Factor Refinement

From phase one, we obtained a set of factors that drive an EMR rejection decision. Next, we theoretically analyzed the constructs beginning with the 36 factors that we identified in phase one. We categorized each factor while using the UTAUT as a lens and grouped the factors that adoption studies had not previously identified. Employing the definitions of the high-level constructs, we placed each of our 36 factors into one of five categories:

- **Performance expectancy**: the degree to which individuals believe that using the system will help them to attain gains in job performance.
- **Effort expectancy**: the degree of ease associated with using the system.
- **Social influence**: the degree to which individuals perceive that important others believe they should use the new system.
- **Facilitating conditions**: the degree to which individuals believe that an organizational and technical infrastructure exists to help them use the system.
- **Novel influences**: factors that UTAUT has not previously captured.

In addition, if we found that other constructs theoretically captured factors that we identified in phase one, we eliminated them. As a result, 22 factors remained. Table 3 lists and defines the 22 remaining factors that we obtained after the refinement process. Table 4 highlights the duplicative factors from phase one that we rejected in creating the integrated model.

Table 3. Driving EMR Rejecters

Construct	Construct definition	Citation	Group (source)
Performance expectancy: the degree to which an individual believes that using the system will help the individual to attain gains in job performance.			
Relative advantage	The degree to which an individual perceives the innovation as being better than the other options.	Compeau, Meister, & Higgins (2007)	Performance expectancy (UTAUT)
Outcome expectancy: patient interaction	The performance-related consequences of the behavior; specifically, the consequence of a negative change in the interaction with the patient.	Compeau & Higgins (1995)	
Outcome expectancy: number of patients seen	The performance-related consequences of the behavior; specifically, a reduction in the number of patients seen.	Compeau & Higgins (1995))	
Outcome expectancy: decreased patient care	The performance-related consequences of the behavior; specifically, a decrease in patient care.	Compeau & Higgins (1995)	
Effort expectancy: the degree of ease associated with using the system.			
Systems quality	User perceptions of the interaction with the quality of the system.	Nelson, Todd, & Wixom (2005)	Effort expectancy (UTAUT)
Ease of use	The degree to which an individual perceives an innovation as being easy to use.	Compeau et al. (2007)	
Complexity	The degree to which an individual perceives an innovation as being difficult to use.	Thompson et al. (1991)	
Reliability of systems quality	The dependability and consistency of access and uptime of systems.	Goodhue & Thompson (1995)	
Facilitating conditions: the degree to which an individual believes that an organizational and technical infrastructure exists to help the individual use the system.			
Compatibility with preferred work style	The degree to which an individual perceives the innovation as being consistent with the way the individual would like to work, even if that is not the way the individual works now.	Compeau et al. (2007)	Social influence (UTAUT)
Novel influences: factors UTAUT has not previously captured			
Integration			
Integration of systems quality	The degree to which a system facilitates the combination of information from various sources internal to the firm.	Nelson et al. (2005)	Integration (this paper)
Extra-organizational integration	The degree to which a physician is concerned that other organizations the physician needs to share information with will be unable to integrate with the physician's EMR systems.	New concept	
Situational normality			
Situational normality: benevolence	In general, EMR vendors are benevolent (i.e., the vendor works in the best interest of the customer).	McKnight, Choudhury, & Kacmar (2002)	Situational normality (consistent with McKnight et al., 2002)
Situational normality: integrity	In general, EMR vendors have integrity (i.e., the vendors are honest and keep their promises).	McKnight et al. (2002)	
Situational normality: competent	In general, EMR vendors are competent (i.e., the vendors can do what the physician needs).	McKnight et al. (2002)	

Table 3. Driving EMR Rejecters

Distrust			
Distrust of government	The degree to which a physician distrusts the government, including whether the government will continuously alter EMR requirements in a malicious manner, the government's true reasons for requiring EMR adoption, and whether the government will use the data collected from EMRs to monitor the physician's work practices.	New concept	Distrust (this paper)
Distrust of insurance companies	The degree to which a physician distrusts insurance companies, including whether the insurance companies will using the data collected from EMRs to monitor the physician's work practices and penalizing doctors for certain practices.	New concept	
Security and legal issues			
Security of private data	The degree to which a physician possesses fear of intrusion or disturbance regarding an individual's personal information as a result of using an EMR system.	New concept	Security and legal issues (this paper)
Legal	The degree to which a physician is concerned that laws have not yet been developed and updated to account for issues pertaining to EMRs.	New concept	
Vendor issues			
Vendor uncertainty	The extent to which a physician is uncertain about the viability of vendors in the current EMR marketplace.	New concept	
Vendor complexity	The degree to which a physician perceives the vendor marketplace to be too complex.	New concept	
Mimetic and coercive pressures			
Mimetic pressure	The prevalence of a practice in the focal organization's industry and the perceived success of organizations in the focal organization's industry that have adopted the practice.	Scott (1987)	
Coercive pressures	Formal or informal pressures exerted on organizations by other organizations that the former depends on (which includes regulatory agencies).		

Table 4. Constructs Not Included in our Research Model

Construct	Construct definition	Citation	Rationale for elimination
Subjective norm	The person's perception that most people who are important to him think he should or should not adopt an EMR.	Venkatesh et al. (2003)	Subjective norm is captured by mimetic pressure.
Measurability	The degree to which the impact of the innovation can be assessed.	Compeau et al. (2007)	Measurability is captured by relative advantage.
Distrust of administration	Within hospitals, the degree to which a physician does not trust the hospital administration's decisions about EMRs.	New concept	We are interested in a broader model – not all physicians operate inside of a hospital.
Lack of time for physician	An insufficient resource of time relative to that required for mastery of the technology for the physician.	New concept	We theorize that all cost and time issues are not assessed strictly in terms of the financial outlay, but in terms of the cost relative to what is gained and argue that cost is captured by relative advantage.
Cost: initial	The degree to which a physician is concerned about the initial cost of the EMR technology.	New concept	
Cost: maintenance	The degree to which a physician is concerned about the maintenance cost of the EMR technology.	New concept	
Cost: future upgrades	The degree to which a physician is concerned about the cost of future upgrades to the EMR technology.	New concept	
Employee retraining	The degree to which a physician is concerned about having to retrain their staff to use the EMR system.	New concept	
Additional employees	A perception that additional employees will need to be hired to support an EMR (i.e., a scribe, an IT specialist, a person to scan documents).	New concept	
Network effects	The degree to which a physician desires to wait until EMRs are more pervasive and data can be exchanged more easily, so they can receive the full benefits from the EMR systems.	New concept	We theorize that network effects and normative pressures are captured by extra-organizational integration.
Normative pressures	The degree to which a focal organization has direct or indirect ties to other organizations that have adopted an innovation and is able to learn about that innovation and its associated benefits and costs, and is likely to be persuaded to behave similarly.	Scott (1987)	
Job change	The likelihood that a physician will be leaving their current job (i.e., moving to a new practice/hospital or changing career paths) in the near future.	Ferratt, Agarwal, Brown, & Moore (2005)	We suggest that the potential for job change is not generalizable across all physicians and represents a minority of the theorized population.
Loyalty	An individual's faithful commitment to their current technology whereby the individual does not consider alternative options.	Carraher-Wolverton, & Cenfetelli (2019)	We suggest that loyalty is captured by compatibility.
Personal innovativeness in the IT domain	The willingness of an individual to try out any new information technology.	Agarwal & Prasad (1998)	PIIT has traditionally been used to understand the adoption of a specific, rather than a class, of technologies.

2.6 Phase Three: Theoretical Sensemaking

In phase two, we examined the constructs through the lens of UTAUT. We found support for some UTAUT constructs and identified other ones to create a new integrated model for an individual's decision to adopt EMR. With our final set of constructs complete, we next focused on understanding our underlying theory. We began with the assumption that each construct identified in phase two contributes to the adoption/rejection decision. Based on this theory, we created a proposed research model (see Figure 1) that comprises 11 hypotheses and six second-order constructs. In Sections 2.6.1 to 2.6.11, we discuss each hypothesis and explain how each construct contributes to the adoption/rejection decision.

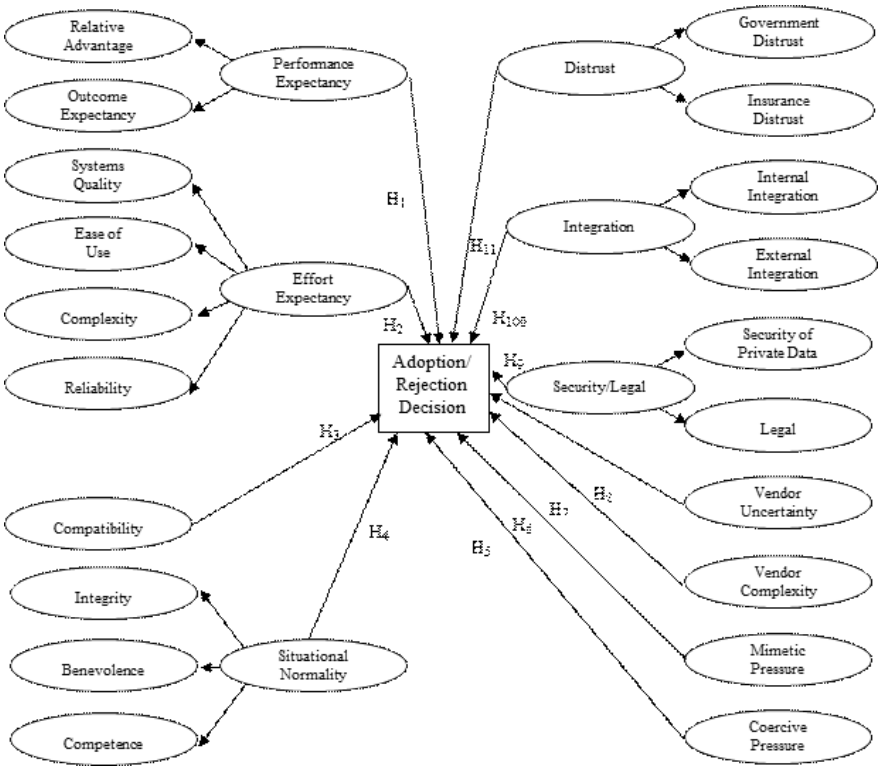

Figure 1. Research Model

2.6.1 Performance Expectancy

H1a: The more physicians believe that using an EMR system will help them to attain gains in job performance, the more likely they will be to adopt the EMR system.

Consistent with UTAUT, we theorize that, if physicians perceive that an EMR solution will help them to attain gains in job performance, the more likely they will be to adopt the EMR solution. As Venkatesh et al. (2003) note: "The performance expectancy (PE) construct within each individual model is the strongest predictor of intention and remains significant at all points of measurement in both voluntary and mandatory settings, consistent with previous model tests" (p. 447). However, while UTAUT collapses all of the various dimensions of performance expectancy down to a first-order construct (that includes usefulness, relative advantage, job fit, and outcome expectations), we found support in the qualitative study for only two of the constructs (namely, relative advantage and outcome expectations).

As such, we conceptualize performance expectancy as a second-order construct that includes the dimensions of relative advantage and outcome expectancy. Unlike UTAUT, we model performance expectancy as a second-order construct because we believe that relative advantage and outcome expectancy represent two distinct dimensions of our higher-order construct and that they tap into different aspects of performance expectancy. We postulate that relative advantage focuses on the workflow aspects of usage (i.e., whether the system performs better than its precursor), while outcome expectancy provides insight into the outcome of that usage (i.e., whether the system provides positive outcomes through its use). While we expect that performance expectancy will play a significant role in explaining a physician's decision to adopt or not adopt an EMR, we theorize that PE will have more influence for doctors in a hospital because they will have more support from colleagues and management as examples and aids in integrating the system into their productive workflows and routines. Thus, we hypothesize:

H1b: Performance expectancy is higher in physicians in a hospital setting than in a private practice.

2.6.2 Ease of Use

H2a: The more physicians perceive an EMR system as easy to use, the more likely they will be to adopt the EMR system.

Consistent with UTAUT, we theorize that the less effort that physicians have to employ in order to operate an EMR system, the more likely they will be to adopt the system. As Venkatesh et al. (2003) note: "effort-oriented constructs are expected to be more salient in the early stages of new behavior" (p. 450), which corresponds with subsequent work. Drawing from UTAUT, we theorize that ease of use and complexity represent two dimensions of effort expectancy. Specifically, if physicians perceive that an EMR system will be free of effort, they will adopt the EMR to assist in their practice. Similarly, they will be less likely to adopt an EMR system the more complex they perceive it.

Based on our qualitative interviews, we theorize that one should include two additional constructs as dimensions of effort expectancy in the EMR context: systems quality and reliability. In the first case, when physicians perceive that an insufficient number of EMR products exist (definition of systems quality), then they must assess the amount of effort they would need to expend to find a system of acceptable quality. Thus, we extend UTAUT by adding system quality as the third dimension of effort expectancy.

In the second case, we propose that, when a physician has concerns about losing data or time due to a system failure (e.g., computer crashes, a common factor in the qualitative interviews), they need to employ more effort to ensure that they will be able to access the data. Thus, we extend UTAUT by adding reliability as a fourth dimension of effort expectancy.

While we expect that effort expectancy will play a significant role in explaining a physician's decision to adopt or not adopt an EMR, we theorize that effort expectancy will exert a greater impact on physicians in a private practice because they have fewer colleagues and managers able to assist them with operating the system and to help solve the various operational problems that may occur. Thus, we hypothesize:

H2b: Effort expectancy is higher in physicians in a private practice than physicians in a hospital setting.

2.6.3 Compatibility

H3a: The more physicians perceive that an EMR is compatible with their work style, the more likely they will be to adopt the EMR system.

Drawing on UTAUT and extant adoption research on task and technology fit (TTF), we theorize that physicians who perceive an EMR system to fit with their preferred work style will be more likely to adopt an EMR system. Unlike a more objectively measured TTF construct, compatibility taps into the *perception* of workflow: that the technology does not negatively disrupt the user's preferred workflow. Compatibility has long represented a determinant of technology acceptance, and, in this study, we focus the perceived "work" aspect of compatibility as opposed to the objective features and values embedded in the EMR system. Specifically, we postulate that a positive perception of compatibility will lead to adoption and a negative perception of compatibility to rejection. While we expect that compatibility will play a significant role in explaining a physician's adoption decision, we theorize that compatibility will have greater significance for doctors in a hospital setting. Our initial phase interviews indicated that hospital settings are likely to have more standardized procedures (structures), and we propose that, as a result, a hospital setting provides an anchor from which a physician can assess the workflow requirements of a proposed innovation. Therefore, the more formal the structure of the organization, the more likely that compatibility will matter. Thus, we hypothesize:

H3b: Compatibility exerts a greater impact on physicians in a hospital setting than physicians in a private practice.

2.6.4 Vendor Characteristics

H4a: The more physicians believe that, in general, EMR vendors possess competence, benevolence, and integrity, the more likely they will be to adopt an EMR system.

In phase one, we found support for the assertion that situational normality influences adoption. According to the theory of situational normality, a buyer assesses their environment to understand if it matches their understanding of what should be happening from prior stories or observations. To the degree that they experience a match, they perceive the situation to be in "proper order" and are more likely to proceed (Hsieh, 2015; Garfinkel, 1963; Lewis & Weigert, 1985). In our context, we suggest that a physician who believes that vendors that offer products in the marketplace are in proper order will be more likely to adopt an EMR system. Note that this view does not concern one vendor specifically but rather the overall context. Drawing from previous work (McKnight et al., 2002), physicians who possess positive views

towards situational normality believe that, in general, vendors that offer EMR systems are competent, benevolent, and have integrity. These three dimensions characterize perceptions of vendors in terms of situational normality in our EMR context. Specifically, we postulate that a positive perception of situational normality will lead to adoption and a negative view to rejection.

We expect the situational normality vendor characteristics (i.e., competence, benevolence, integrity) to play a more significant role in a private practice. We also suggest that the locus of decision making in a private practice requires a physician to assess a technology that includes characteristics beyond the technology itself, while, in more a centralized structure where physician does not directly participate in the decision making process (i.e., a hospital), the characteristics of the vendor will have less salience. Thus, we hypothesize:

H4b: Vendor characteristics are more important to physicians in a private practice than physicians in a hospital setting.

2.6.5 Coercive Pressure

H5a: The more coercive pressure physicians perceive, the more likely they will be to adopt an EMR system.

Coercive pressures refer to formal or informal pressures exerted on organizations by other organizations that the former depends on (Kreuzer, 2017; Son & Benbasat, 2007; DiMaggio & Powell, 1983). Drawing from institutional theory, we posit that institutions that physicians depend on can coercively exert pressure on them in order to influence adoption. In phase one, we identified two sources of coercive pressure: the government and insurance companies. By linking reimbursement rates for performing services with a physician's EMR adoption decision, both government and insurance companies rely on formal, financial pressure to influence adoption. Thus, we theorize that these forms of coercive pressure will lead physicians to adopt an EMR system. Specifically, we postulate that a positive perception of coercive pressure will lead a physician to adopt an EMR system and a negative perception to rejection.

While we expect coercive pressure to play a significant role in explaining physicians' EMR adoption decisions, we theorize that coercive pressure will play a more significant role with physicians in a private practice. We posit that the locus of decision making in a private practice requires a physician to assess technology that includes characteristics beyond the technology itself, while, in a more centralized structure where physician does not directly participate in the decision making process (i.e., a hospital) about what technology the hospital adopts, coercive pressures will have less salience. Thus, we hypothesize:

H5b: Coercive pressure is a larger concern for physicians in a private practice than physicians in a hospital setting.

2.6.6 Mimetic Pressure

H6a: The more mimetic pressure physicians perceive, the more likely they will be to adopt an EMR system.

Mimetic pressure "exist[s] when an organization imitates the actions of other structurally equivalent organizations because these organizations occupy a similar economic network position in the same industry" (Sherer, 2010). In our context, physicians will adopt an EMR system when they imitate the actions of other similar physician organizations. Institutional theory suggests that the imitation behavior enables an actor to reduce search costs and typically occurs more when questions of relative advantage exist (Shi, Shambare, & Wang, 2008; Son & Benbasat, 2007; Teo, Wei, & Benbasat, 2003; Urgin, 2009). Given the concerns over the advantages that physicians derive from EMR systems and the high degree of costs they incur when searching for a suitable EMR technology, we theorize that the presence of mimetic pressure will lead physicians to adopt an EMR system. Specifically, we suggest that a positive perception of mimetic pressure will lead to adoption and a negative view to rejection.

We expect mimetic and coercive pressure to act in a similar fashion. Just as in the case of coercive pressure, we theorize that mimetic pressure will play a more significant role with doctors in a private practice. We propose that the locus of decision making in a private practice requires a physician to assess technology that includes characteristics beyond the technology itself, while, in more centralized structures where the physician does not directly participate in the decision making process, mimetic pressure will have less salience. Thus, we hypothesize:

H6b: Mimetic pressure is a larger concern for physicians in a private practice than physicians in a hospital setting.

2.6.7 Vendor Marketplace Complexity

H7a: The more complexity that physicians perceive to exist in the vendor marketplace, the more likely they will be to reject an EMR system.

Research into human behavior (under the umbrella of economics and behavioral finance) has examined individuals' difficulty in making decisions under complex market conditions. For example, the formal processing model (De Palma, Myers, & Papageorgiou, 1994) and other models (Schwarz & Schwarz, 2014; Gonçalves & Villa, 2016; Heiner, 1983) suggest that market complexity leads humans to make suboptimal decisions. Theoretically, one can trace the roots of market complexity that affect human behavior back to the argument of bounded rationality (Foss & Weber, 2016; March, 1978). Despite the empirical evidence outside of IS that market complexity influences human choice, to our knowledge, little work has examined the impact of market complexity on adoption. We theorize that, if physicians, due to bounded rationality, perceive the EMR vendor marketplace to be complex, they will reject an EMR system. Bounded rationality requires volition in order for one to fully exercise it. Therefore, we expect that, in organizations with more volition (i.e., private practices), a physician would focus more on the vendor marketplace. Thus, we hypothesize:

H7b: Vendor marketplace complexity is a larger concern for physicians in private practice than physicians in a hospital setting.

2.6.8 Vendor Viability

H8a: The more uncertain that physicians are about the viability of vendors in the current EMR marketplace, the more likely they will be to reject an EMR system.

A significant body of research has investigated the topic of IT implementation. Researchers have long understood the importance of an individual being able to assess a vendor's viability in order to influence adoption (e.g., Fleischmann, Amirpur, Grupp, Benlian, & Hess, 2016; Lucas, Walton, & Ginzberg, 1988). Consistent with this line of research, we postulate that a physician will assess the business viability of vendors in the EMR marketplace and that, based on this assessment, will decide to adopt or reject an EMR system. We theorize that, if a physician perceives the EMR vendors as unviable, the physician will reject an EMR system. Similar to the logic of vendor marketplace complexity, we would expect that, in organizations with more volition (i.e., private practices), a physician would focus more on the vendor marketplace. Thus, we hypothesize:

H8b: Vendor viability is a larger concern for physicians in a private practice than physicians in a hospital setting.

2.6.9 Security

H9a: The more physicians perceive EMR systems to lack security and have related legal implications, the more likely they will be to reject an EMR system.

In H4, we hypothesize that situational normality influences adoption/rejection behavior. Similarly, structural assurance represents a second aspect of institution-based trust (Wu, Cheng, & Yen, 2014; McKnight et al., 2002). Structural assurance refers to a belief that sufficient structures (e.g., guarantees, regulations, promises, legal recourse, or other procedures) that promote success exist (Malhotra, Sahadev, & Purani, 2017; Shapiro, 1987; Zucker, 1986). In our context, we found two types of structural assurances from our interviews in phase one: a legal structure and a security structure. We hypothesize that structural assurances, in an EMR context, comprise these two dimensions and, thus, that we can theorize structural assurances as a second-order construct. We argue that a physician in a hospital will not have to examine how the EMR fits in the security and legal framework that currently exists in the organization. Thus, we hypothesize:

H9b: Security and legal concerns are a larger concern for physicians in a private practice than in a hospital setting.

2.6.10 Data Integration

H10a: The more physicians perceive that an EMR system will integrate data in and outside of their practice, the more likely they will be to adopt an EMR system.

Researchers and practitioners have long recognized the need for organizations to integrate data both internal and external to them (Goodhue, Quillard, & Rockart, 1988; Goodhue, Wybo, & Kirsch, 1992). In the context of physicians, integrating data has been a significant issue and plagued with challenges of accuracy, consistency, and integrity (St-Maurice & Burns, 2017; Kisilowska, 2006; Alshawi, Missi, & Eldabi, 2003; Goodhue et al., 1992). Thus, we hypothesize that perceptions about the degree to which an EMR system can integrate data in and outside of a practice will influence EMR system adoption. Specifically, we posit that a positive perception of integration will lead to adoption and a negative view to rejection. Similar to compatibility and workflow considerations, we theorize that a physician in a hospital setting will be more likely to consider workflow than physicians in a private practice. Thus, we hypothesize:

H10b: Data integration factors are a larger concern for physicians in a hospital setting than physicians in a private practice.

2.6.11 Institutional Distrust

H11a: The more physicians distrust the institutions that pressure them to adopt an EMR system, the more likely they will be to reject an EMR system.

Organizational theorists have historically recognized that distrust and suspicion present reoccurring problems in organizations (Gago-Rodríguez & Naranjo-Gil, 2016; Sitkin & Roth, 1993; Fox, 1974). Suspicion, a central cognitive component of distrust (Deutsch, 1958), refers to a psychological state that "actively entertain[s] multiple, possibly rival, hypotheses about the motives or genuineness of a person's behavior" (Fein & Hilton, 1994, p. 168). In interviews in phases 1 through 3 of this research, we encountered quite a few physicians who had deep suspicions regarding the motivations of the institutions that put pressure on them to adopt an EMR system. Thus, we hypothesize that this distrust will lead to rejection behavior. We further identify two institutions that physicians distrust: insurance companies and the government.

Drawing on institutional theory, we theorize about the impacts of mimetic and coercive pressure. Similarly, we theorize that the distrust in the institutions that attempt to exercise the mimetic and coercive pressure will operate similarly. Specifically, as in the case of coercive and mimetic pressure, we theorize that institutional distrust will play a more significant role with doctors in private practice. We postulate that the locus of decision making in a private practice requires a physician to assess technology to include characteristics beyond the technology itself, while, in more centralized structures where the physician does not directly participate in the decision making process, institutional distrust will have less salience. Thus, we hypothesize:

H11b: Institutional distrust is higher in physicians in a private practice than physicians in a hospital setting.

2.7 Phase Four: Theory Testing

With a proposed research model, we entered phase four: that is, we tested our integrated model with physicians. First, we created items to measure the constructs we identified in our previous phases. Where possible, we used previously published scales to measure each construct. In Table 5 below, we outline the construct, the definition of the construct, the items we used to measure each construct, and the source of the measurement.

Table 5. Construct Definitions and Items

Construct	Definition	Items	Source
Relative advantage	The extent to which a physician perceives that the adoption of an EMR will decrease his/her efficiency across patients	Using EMR systems enables me to accomplish tasks more quickly Using EMR systems improves the quality of work I do Using EMR systems simplifies my work tasks Using EMR systems improves my job performance Overall, I find EMR systems to be advantageous in performing my job Using EMR systems reduces my effectiveness on the job Using EMR systems gives me greater control over my work Using EMR systems makes me more productive	Compeau et al. (2007)
Outcome expectancy	The degree to which a physician perceives that their interaction with the patient will be negatively influenced by the introduction of EMRs	My interaction with the patient will be negatively influenced [R][1]	Compeau & Higgins (1995)
	The extent to which a physician perceives that he/she will see less patients due to the adoption of an EMR	I will not be able to see as many patients [R]	
	The degree to which a physician believes that an EMR would reduce the quality of care provided to a patient	The quality of care that I deliver to my patients will be reduced [R]	
Systems quality	The extent to which a physician perceives there is a lack of good EMR products available	In terms of systems quality, I would rate EMR systems highly Overall, EMR systems is of high quality Overall, I would give the quality of EMR systems a high rating	Nelson et al. (2005)
Ease of use	The extent to which a physician believes EMRs are easy to use	I believe that EMR systems are cumbersome to use [R] It is easy for me to remember how to perform tasks associated with using EMR systems When I use EMR systems, it requires a lot of mental effort [R] Using EMR systems is often frustrating [R] I believe that it is easy to get EMR systems to do what I want it to do Overall, I believe that EMR systems are easy to use Learning to operate EMR systems are easy for me EMR systems are user friendly	Compeau et al. (2007)
Complexity	The extent to which a physician perceives that EMR will decrease his/her efficiency for seeing a specific patient	Using an EMR system takes too much time from my normal duties during a patient visit [R] Working with an EMR system is so complicated, it is difficult to understand what is going on during a patient visit [R] Using an EMR system involves too much time doing mechanical operations (e.g., data input) during a patient visit [R] It takes too long to learn how to use an EMR system during a patient visit to make it worth the effort [R]	Thompson, Higgins, & Howell (1991)

Table 5. Construct Definitions and Items

Reliability	The degree to which a physician is concerned about losing data due to a system failure (i.e. - computer crash)	I can count on EMR technology systems to be "up" and available when I need it EMR technology systems are subject to unexpected or inconvenient downtimes which makes it more difficult to do my work [R] EMR technology systems are subject to frequent problems and crashes [R]	Goodhue & Thompson (1995)
Subjective norm	A physician's perspective of whether their colleagues believe they should adopt an EMR, including stories of a colleague's experiences with adoption of an EMR	People who influence my behavior think that I should use the system. People who are important to me think that I should use the system	Venkatesh et al. (2003)
Compatibility with preferred work style	The extent to which the EMR systems are not designed in a way to facilitate processes that occur in the practice of medicine	Using EMR systems fits with my preferred work style Using EMR systems fits well with the way I like to work Using EMR systems lets me work the way I would like It is hard to employ my preferred work style when using EMR systems [R]	Compeau et al. (2007)
Situational normality	The extent to which a physician distrusts vendors offering EMR technology	Situational Normality-Benevolence (IB) I feel that most EMR vendors would act in a customers' best interest. If a customer required help, most EMR vendors would do their best to help. Most EMR vendors are interested in customer well-being, not just their own wellbeing. Situational Normality- Integrity (II) I am comfortable relying on EMR vendors to meet their obligations. Most EMR vendors generally fulfill their agreements. I always feel confident that I can rely on EMR vendors to do their part when I interact with them. Situational Normality-Competence (IC) In general, most EMR vendors are competent at serving their customers. Most EMR vendors do a capable job at meeting customer needs. I feel that most EMR vendors are good at what they do.	McKnight et al. (2002)
Coercive pressures	Formal or informal pressures exerted on organizations by other organizations upon which they are dependent (DiMaggio & Powell, 1983). This includes regulatory agencies.	Penalties from the federal government for not adopting an EMR by the deadline will play a critical role in whether or not I adopt an EMR Penalties from the state government for not adopting an EMR by the deadline will play a critical role in whether or not I adopt an EMR Penalties from insurance companies for not adopting an EMR by the deadline will play a critical role in whether or not I adopt an EMR	None
Mimetic pressures	The prevalence of a practice in the focal organization's Industry and the perceived success of organizations within the focal organization's industry that have adopted the practice.	Physicians in my area that offer services similar to mine that have adopted EMR: have benefited greatly are perceived favorably by other physicians in the same industry are perceived favorably by patients	None
Vendor complexity	The degree to which a physician perceives the vendor marketplace to be too complex	The EMR marketplace has too many vendors The EMR marketplace is too complex Consolidation needs to occur in the EMR marketplace in order to make it simpler for physicians to select an EMR vendor	None

Table 5. Construct Definitions and Items

Vendor uncertainty	The extent to which a physician is uncertain about the viability of vendors within the current EMR marketplace	I believe that the EMR vendors I have seen will be viable for the foreseeable future I have concerns about the viability of the vendors offering an EMR product [R] I feel that there is a great deal of uncertainty in the EMR vendor marketplace [R] I feel that EMR vendors have not yet proven themselves to be stable [R]	McKnight et al. (2002)
Legal	The degree to which a physician is concerned that laws have not yet been developed and updated to account for issues pertaining to EMRs.	The legal system has not yet addressed issues related to EMR adoption More work needs to be done to examine the legal issues surrounding EMR	None
Security	The degree to which a physician is concerned about the ability to keep private data secure with EMRs	I am concerned about the security of my patient's personal information when using an EMR I am concerned about the potential for my patient's personal information to be abused or misused if the data is stored in an EMR I do not want to give up control of my patient's personal information to an EMR vendor I am concerned about my patient's privacy when using an EMR I am concerned that using an EMR will make my patient's data less secure	None
External integration	The degree to which a physician is concerned that other organizations they need to share information with will be unable to integrate with their EMR systems	At this point in time, EMR systems will enable me to effectively share data with physicians outside my practice/hospital At this point in time, EMR systems will allows me to obtain information from physicians external to my practice/hospital At this point in time, EMR systems will facilitates the sharing of information between physicians from different practices/hospitals	None
Internal integration	The degree to which a physician is concerned with the data from their EMR integrating with other systems used within the office	EMR systems effectively integrates data from different areas of the practice EMR systems pulls together information that used to come from different places in the practice EMR systems effectively combines data from different areas of the practice	None
Distrust of insurance companies	The degree to which a physician distrusts insurance companies, including the insurance companies potentially using the data collected from EMRs to monitor the physician's work practices and penalizing doctors for certain practices	I distrust the motivation of insurance companies for encouraging EMR adoption I distrust how insurance companies will use the data collected from the EMR I distrust how insurance companies will use the EMR to monitor my work practices I believe that insurance companies will use EMRs to penalize physicians for engaging in certain practices	None
Distrust of government	The degree to which a physician distrusts government, including whether they will continuously alter their EMR requirements in a malicious manner, the government's true reasons for requiring EMR adoption, the government potentially using the data collected from EMRs to monitor the physician's work practices	I distrust the motivation of the government for requiring EMR adoption I distrust how the government will use the data collected in the EMR I distrust how the government will use the EMR to monitor my work practices I believe that the government will alter EMR meaningful use criteria often	None

[1] [R] denotes reverse-coded items.

After developing our items, we then pre-tested our survey instrument with the 21 physicians from phase one. We provided each physician with a link to the Web-based survey that asked them to provide feedback on the items. These respondents provided minor suggestions for rewording the instructions. Subsequently, we proceeded to conduct our full empirical study.

2.8 Sample

In order to test our research model, we conducted a survey with physicians in a state in the Southeastern United States. Our survey targeted physicians who were knowledgeable about EMR and had either adopted or rejected an EMR system. Through a partnership with a local medical society, we identified 3,295 physicians in the state as the target population and sent them an invitation to participate in the research study. We incentivized physicians to participate with a copy of the research results and with a draw for two prizes.

From our invitations, 915 physicians expressed interest in completing the survey, and 462 ended up actually completing it (50.5% completion rate). Since we cared about comparing physicians in a hospital versus a private practice setting, we restricted our analysis to these two contexts. Of the 462 physicians, 169 physicians worked in a hospital (with 72 adopters and 97 rejecters) and 277 worked in a private practice (with 151 adopters and 126 rejecters). None of the physicians worked in an integrated care setting. Our physician sample had more males and 20.2 years of experience in practice on average. During a typical week of practice, the physicians saw 94 patients on average. Table 6 provides the remaining demographic information for the respondents. Data on the state's physician population indicated that we had a fairly representative sample of the practicing physicians at the time.

Table 6. Profile of Respondents

Specialty	Hospital	Private practice	Specialty	Hospital	Private practice
Allergy/immunology	0.0	1.8	Neurology	0.6	1.1
Anesthesiology	2.4	0.4	OB-GYN	4.1	9.7
Cardiology	1.2	1.4	Occupational medicine	0.0	0.4
Cardiothoracic surgery	0.6	0.0	Oncology	1.2	0.0
Cardiovascular surgery	1.2	0.0	Ophthalmology	0.0	5.1
Dermatology	0.0	2.5	Oral & maxillofacial surgery	0.0	0.4
Emergency/urgent/critical care	12.4	0.0	Orthopedic surgery	0.6	2.9
ENT/otolaryngology/otorhinolaryngology	3.6	4.7	Orthopedics	0.6	2.5
Family medicine/practice	6.5	15.2	Pathology	1.8	0.7
Gastroenterology/hepatology	0.0	0.7	Pediatrics	3.6	6.1
General surgery	6.5	6.9	Physical medicine & rehabilitation	1.8	1.4
Infectious disease	0.6	0.0	Plastic surgery	0.0	0.7
Internal medicine	16.6	15.9	Psychiatry	0.6	3.2
Neonatal/perinatal medicine	2.4	0.0	Radiology	2.4	0.7
Nephrology	0.6	0.7	Urology	1.8	1.4
Neurological surgery	1.2	0.0	Declined	25.4	13.4
Payment source	**Average percent**	**Average percent**	**Gender**	**Hospital**	**Private practice**
Medicare	25%	25%	Male	70%	80%
Medicaid	19%	12%	Female	21%	15%
Insurance	23%	40%	Declined to answer	9%	5%
Patient	6%	11%			
Other	27%	12%			

3 Data Analysis

3.1 Common Method Bias

We began with a test of common method bias (specifically, Harman's one-factor test). Harman's one-factor test determines whether either 1) a single factor will emerge from the factor analysis or 2) one factor will explain a majority of the covariance of the variables (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003; Schwarz, Rizzuto, Carraher-Wolverton, Roldan, & Barrera-Barrera, 2017). The factor analysis did not reveal that a single factor explained a majority of the total variance; the highest single factor accounted for only 37 percent of the variance. The results from this analysis demonstrate that the single-factor model does not fit the data well, which indicates that common method variance likely does not pose an issue.

3.2 Structural Model Analysis

We used the structural equation modeling tool AMOS (version 20) to analyze the data. We loaded each of the items on to their respective construct with the dependent variable as adoption or rejection of an EMR system. We then proceeded with analyzing the measurement and structural models.

3.3 Measurement Model

The measurement model analyzes the relationships between the latent constructs and their associated items. First, we examined the adequacy of the measures. We did so by examining the individual item reliabilities, which the loadings to their respective construct represent (see Table 7). Based on our analysis, we eliminated 17 items (RA6, RA7, MEAS1, MEAS2, MEAS3, EOU1, EOU2, EOU3, EOU7, CPT4, CMPLX1, REL1, INRT1, VEND3, UNCERTAIN1, GOVTRUST4, and HMOTRUST4). With these items eliminated, all of the remaining items met the 0.70 criteria for their respective construct.

While the first analysis demonstrated that the items loaded appropriately on their respective construct, this result does not indicate the reliability of the items as a whole. Using the loadings from the constructs, we created composite reliabilities for all constructs. Nearly all of the constructs were above 0.90, which evidences their composite reliability.

Table 7. Item Loadings and Composite Reliability

Construct	Item	Hospital		Private practice	
		Loading	Composite reliability	Loading	Composite reliability
Benevolence	BENTR1	0.899	0.936	0.878	0.917
	BENTR2	0.903		0.861	
	BENTR3	0.93		0.919	
Complexity	CMPLX2	0.866	0.887	0.879	0.901
	CMPLX3	0.88		0.826	
	CMPLX4	0.804		0.897	
Competence	COMPET1	0.96	0.967	0.971	0.971
	COMPET2	0.961		0.976	
	COMPET3	0.936		0.927	
Compatibility	CPT1	0.982	0.982	0.979	0.982
	CPT2	0.995		0.992	
	CPT3	0.944		0.952	
Ease of use	EOU4	0.813	0.923	0.836	0.925
	EOU5	0.809		0.907	
	EOU6	0.936		0.843	
	EOU8	0.905		0.887	

Table 7. Item Loadings and Composite Reliability

External integration	ExtInt1	0.802	0.919	0.824	0.923
	ExtInt2	0.907		0.925	
	ExtInt3	0.952		0.93	
Government trust	GovTrust1	0.886	0.958	0.927	0.969
	GovTrust2	0.978		0.967	
	GovTrust3	0.955		0.971	
HMO trust	HMOTrust1	0.951	0.977	0.953	0.972
	HMOTrust2	0.991		0.973	
	HMOTrust3	0.956		0.954	
Loyalty	INRT2	0.872	0.913	0.846	0.909
	INRT3	0.791		0.783	
	INRT4	0.904		0.845	
	INRT5	0.833		0.904	
Integrity	INTEG1	0.936	0.961	0.937	0.958
	INTEG2	0.938		0.944	
	INTEG3	0.959		0.938	
Internal integration	IntInt1	0.963	0.971	0.944	0.968
	IntInt2	0.95		0.939	
	IntInt3	0.96		0.978	
Legal	Legal1	0.979	0.945	0.956	0.937
	Legal2	0.913		0.922	
Outcome expectancy	Outcome1	0.925	0.877	0.857	0.867
	Outcome2	0.822		0.746	
	Outcome3	0.765		0.875	
Coercive Pressure	Penalty1	0.934	0.954	0.941	0.957
	Penalty2	0.968		0.982	
	Penalty3	0.902		0.89	
Systems Quality	QUAL1	0.967	0.979	0.965	0.984
	QUAL2	0.959		0.98	
	QUAL3	0.98		0.987	
Relative Advantage	RA1	0.893	0.974	0.863	0.967
	RA2	0.909		0.918	
	RA3	0.951		0.922	
	RA4	0.96		0.953	
	RA5	0.959		0.958	
	RA8	0.894		0.843	
Reliability	RELI2	0.857	0.895	0.827	0.909
	RELI3	0.942		0.992	
Security	Secure1	0.948	0.975	0.926	0.977
	Secure2	0.978		0.958	
	Secure3	0.864		0.909	
	Secure4	0.958		0.976	
	Secure5	0.953		0.955	

Table 7. Item Loadings and Composite Reliability

Mimetic pressure	Success1	0.751	0.906	0.76	0.905
	Success2	0.972		0.903	
	Success3	0.886		0.945	
Uncertainty	UNCERT2	0.86	0.917	0.758	0.853
	UNCERT3	0.889		0.852	
	UNCERT4	0.911		0.825	
Complexity	VEND1	0.753	0.786	0.767	0.790
	VEND2	0.855		0.846	

3.4 Structural Model

After analyzing the measurement model, we next analyzed the structural model. Our first analysis revealed a high degree of multicollinearity between the constructs performance expectancy and effort expectancy. High inter-construct correlations (i.e., three over .9, even though they passed tests of discriminant validity) indicate that multicollinearity presented a significant problem in the proposed model (Hair, Black, Babin, & Anderson, & Tatham, 2006; Kline, 2010; Schwarz, Schwarz, & Black, 2014a), which, in turn, suggests that performance and effort expectancy constitute not two but one second-order construct. After collapsing performance and effort expectancy, however, reliability did not load on the new construct and compatibility was highly correlated with our second-order construct. We resolved the problem when we treated performance expectancy as a single construct that comprised relative advantage, outcome expectancy, systems quality, ease of use, complexity, and compatibility. We separated reliability as its own construct.

With concerns over multicollinearity satisfied, we then conducted a test of discriminant validity. Consistent with prior IS studies (e.g., Segars & Grover, 1998; Thong, Ya[. & Raman, 1996; Vandenbosch & Higgins, 1996), we tested discriminant validity by comparing the variance extracted (VE) (Fornell & Larcker, 1981) of each latent construct to the square of correlations between this construct and every other construct. The results (see Tables 8 and 9) support discriminant validity between our constructs.

Table 8. Discriminant Validity—Hospitals

	AVE	Distrust	Integrate	Loyalty	Mimetic	Performance expectancy	Reliability	Security/ legal	Vendor complexity	Vendor uncertainty
Distrust	0.909									
Integrate	0.854	-0.35								
Loyalty	0.724	-0.241	0.231							
Mimetic	0.765	-0.489	0.333	0.147						
Performance expectancy	0.824	0.517	-0.582	-0.334	-0.519					
Reliability	0.811	-0.27	0.216	0.21	0.327	0.632				
Security/ legal	0.888	0.72	-0.139	-0.028	-0.421	0.43	-0.388			
Vendor Complexity	0.649	0.395	-0.155	-0.098	-0.198	0.35	-0.3	0.193		
Vendor Uncertainty	0.787	0.517	-0.192	-0.17	-0.339	0.54	-0.39	0.483	0.72	
Vendor	0.876	-0.426	0.417	0.421	0.425	-0.642	0.389	-0.317	-0.326	-0.591

Table 9. Discriminant Validity—Private Practice

	AVE	Distrust	Integrate	Loyalty.	Mimetic	Performance expectancy	Reliability	Security/ legal	Vendor complexity	Vendor uncertainty
Distrust	0.917									
Integrate	0.855	-0.287								
Loyalty	0.715	0.107	0.059							
Mimetic	0.762	-0.273	0.467	-0.026						
Performance expectancy	0.819	0.369	-0.583	-0.157	-0.557					
Reliability	0.834	-0.227	0.356	0.164	0.307	-0.692				
Security/ legal	0.890	0.661	-0.332	0.029	-0.386	0.68	-0.522			
Vendor complexity	0.652	0.34	-0.302	-0.101	-0.248	0.274	-0.304	0.288		
Vendor uncertainty	0.660	0.381	-0.399	-0.143	-0.43	0.561	-0.435	0.479	0.674	
Vendor	0.862	-0.275	0.493	0.192	0.38	-0.721	0.599	-0.501	-0.287	-0.562

Table 10 provides the results of our structural model test. Table 11 shows the fit statistics. The χ^2 statistics of 1.593 and 1.635 were within acceptable limits (Byrne, 1998; Carmines & McIver, 1981; Marsh & Hocevar, 1985). The Tucker-Lewis index, also known as the non-normed fit index (NNFI, 0.806 and 0.868) (Bentler & Bonett, 1980), and the comparative fit index (CFI, 0.917 and 0.944) (Bentler, 1990), were close to 1, which demonstrates an excellent fit between the structural model and the data (Gefen, Straub, & Boudreau, 2000). RMSEA was well below the suggested threshold value of 0.08 (0.059 and 0.048) (Browne & Cudeck, 1992). The parsimony-adjusted NFI (James, Mulaik, & Brett, 1982) of the hospital and private practice models were 0.754 and 0.812, respectively. These values significantly exceeded the suggested value .60 (Netemeyer, Johnston, & Burton, 1990; Williams & Hazer, 1986), which indicates highly acceptable levels of parsimony and fit of the overall model. All of these fit indices were excellent, which suggests that the overall structural model provides a good fit with the data for both contexts.

As Table 10 indicates, all of the first-order constructs were significant dimensions of their second-order counterparts. Performance expectancy comprised the dimensions of relative advantage (-0.839 hospital / -0.828 private practice), outcome expectancy (0.818 hospital / 0.810 private practice), systems quality (-0.834 hospitals / -0.845 private practice), ease of use (-0.921 hospital / -0.942 private practice), and complexity (0.866 hospitals / 0.902 private practice). Similarly, situational normality comprised integrity (0.988 for both contexts), benevolence (0.973 hospitals / 0.975 private practice), and competence (0.950 hospitals / 0.926 private practice), which confirms our theoretical arguments for this second-order construct. Further, the second-order constructs security/legal (with security loading 0.838 for hospitals and 0.845 for private practice and legal loading 0.724 for hospitals and 0.666 for private practice), integration (internal loading of 0.682 for hospitals and 0.858 for private practice and external loading of 0.827 for hospitals and 0.602 for private practice), and distrust (government distrust loading of 0.833 for hospitals and 0.894 for private practice and insurance distrust of 0.861 for hospitals and 0.900 for private practice) were also significant.

Furthermore, regarding the predictors of the adoption/non-adoption decision, differences existed between the two contexts. In the hospital context, the factors that differentiated between adopters and non-adopters were data integration (-0.781), security/legal concerns (-0.408), reliability of the EMR system (0.183), mimetic pressure (0.179), and loyalty to the current solution (0.146). In the private practice context, eight of the 11 constructs were significant: data integration (-0.444); security/legal concerns (-0.396), performance expectancy (-0.318), distrust (0.236), characteristics of the vendor (0.231), mimetic pressure (0.137), reliability (0.120), and loyalty (0.094).

Table 10. Path Loadings

	Hospital		Private practice	
	Path	**Significance**	**Path**	**Significance**
Performance expectancy → adopter/rejecter decision	-0.163	ns	-0.318	**
Vendor → adopter/rejecter decision	0.144	ns	0.231	*
Distrust → adopter/rejecter decision	0.220	ns	0.236	*
Security/legal → adopter/rejecter decision	-0.408	**	-0.396	*
Situational normality → adopter/rejecter decision	0.146	***	0.094	***
Reliability → adopter/rejecter decision	0.183	***	0.120	***
Vendor complexity → adopter/rejecter decision	-0.211	ns	0.011	ns
Vendor uncertainty → adopter/rejecter decision	0.274	ns	-0.024	ns
Integration → adopter/rejecter decision	-0.781	*	-0.444	*
Mimetic pressure → adopter/rejecter decision	0.179	**	0.137	**
Coercive pressure → adopter/rejecter decision	-0.054	ns	0.031	ns
Distrust → government distrust	0.833	*	0.894	*
Distrust → HMO distrust	0.861	*	0.939	*
Integration → external integration	0.827	*	0.602	*
Integration → internal integration	0.682	*	0.858	*
Performance expectancy → compatibility	-0.919	*	-0.908	*
Performance expectancy → complexity	0.866	*	0.902	*
Performance expectancy → EOU	-0.921	*	-0.942	*
Performance expectancy → Outcome	0.818	*	0.810	*
Performance expectancy → relative advantage	-0.839	*	-0.828	*
Performance expectancy → systems quality	-0.834	*	-0.845	*
Security/legal → legal	0.724	*	0.666	*
Security/legal → security	0.838	*	0.845	*
Vendor → benevolence	0.973	*	0.975	*
Vendor → competence	0.950	*	0.926	*
Vendor → integrity	0.988	*	0.988	*
Significance: * p < 0.01, ** p < 0.05, *** p < 0.1, ns = not significant				

Table 11. Model Fit Statistics

	Hospitals	**Private practice**
χ^2	3395.69	3485.017
df	2132	2132
χ^2/df	1.593	1.635
Normed fit index (NFI)	0.806	0.868
Tucker-Lewis index	0.911	0.940
Comparative fit index (CFI)	0.917	0.944
RMSEA	0.059	0.048
Lower bound	0.056	0.045
Upper bound	0.063	0.051
Parsimony-adjusted NFI	0.754	0.812

Following the methodology of multi-group analysis (Hair et al., 2006), once one establishes the adequate fit of each group, one should next examine group invariance across the groups. The AMOS model comparison (see Table 12) revealed that the hospital and private practice contexts were *not invariant*, which indicates that they *did* vary. Thus, we can conclude that we found empirical support for our assertion that organizational context and macro-level structures influence micro-level attitudes, perceptions, and behaviors. We discuss the implications of our findings next.

Table 12. Comparison of Hotel and Private Practice Contexts

Model	DF	CMIN	P	NFI	IFI	RFI	TLI
				Delta-1	Delta-2	rho-1	rho2
Measurement weights	55	98.662	0.000	0.002	0.002	0.000	0.000
Structural weights	65	121.936	0.000	0.003	0.003	0.000	0.000
Structural covariances	131	256.297	0.000	0.006	0.006	0.001	0.001
Structural residuals	146	295.502	0.000	0.007	0.007	0.001	0.002
Measurement residuals	214	574.271	0.000	0.013	0.014	0.005	0.006

4 Discussion

This multi-year, multi-phase study combines a wide variety of factors that the literature has employed to explain why physicians adopt or reject EMR systems and examines them in small, private and large, hospital contexts. Extant literature focuses extensively on performance and outcome expectancy factors as key reasons for adoption; however, in this study, the discriminant validity between these factors' measures was low enough that we joined them. Additionally, the typical micro-level effects from prior studies were largely not supported based on this aggregated construct (H1, H2), though certain individual factors did covary significantly (see Table 13). We found work compatibility, a common prior micro-level factor, to be important (H3a), especially in hospital settings (H3b).

As for macro factors, we found the institutional theory factors to be non-significant with the exception of mimetic pressure (H6a). The vendor characteristics also lacked significance. Security/legal concerns were influential (H9a), but the effect was stronger in hospitals contrary to our hypothesis (H9b). We postulate that, in a hospital setting, security and legal trainings may sensitize physicians to these issues even though physicians in small practices have direct responsibility for developing security and legal processes and compliance. Data integration issues displayed high significance (H10a) with hospital physicians loading higher on external integration as hypothesized (H10b). Institutional distrust mattered only to physicians in private practice (H11b).

Thus, we found significant differences between the hospital and private practice contexts. Moreover, although we used measures from extant work (Table 5), we found that not all measures actually added value in understanding adoption/rejection decisions. Given that organizations and the government have spent a significant amount of money to convince physicians to adopt EMR in addition to the relatively low number of adopters in private practice, a need for further research into the interactions and factors that will improve this process remains.

Table 13. Hypothesis Results

Hypothesis	Result
1a: The more physicians believe that using an EMR system will help them to attain gains in job performance, the more likely they will be to adopt the EMR system.	Not supported
1b: Performance expectancy is higher in physicians in a hospital setting than in a private practice.	Not supported
2a: The more physicians perceive an EMR system as easy to use, the more likely they will be to adopt the EMR system.	Not supported
2b: Effort expectancy is higher in physicians in a private practice than physicians in a hospital setting.	Not supported
3a: The more physicians perceive that an EMR is compatible with their work style, the more likely they will be to adopt the EMR system.	Supported
3b: Compatibility exerts a greater impact on physicians in a hospital setting than physicians in a private practice.	Supported
4a: The more physicians believe that, in general, EMR vendors possess competence, benevolence, and integrity, the more likely they will be to adopt an EMR system.	Not supported
4b: Vendor characteristics are more important to physicians in a private practice than physicians in a hospital setting.	Supported
5a: The more coercive pressure physicians perceive, the more likely they will be to adopt an EMR system.	Not supported
5b: Coercive pressure is a larger concern for physicians in a private practice than physicians in a hospital setting.	Not supported
6a: The more mimetic pressure physicians perceive, the more likely they will be to adopt an EMR system.	Supported
6b: Mimetic pressure is a larger concern for physicians in a private practice than physicians in a hospital setting.	Not supported
7a: The more complexity that physicians perceive to exist in the vendor marketplace, the more likely they will be to reject an EMR system.	Not supported
7b: Vendor marketplace complexity is a larger concern for physicians in private practice than physicians in a hospital setting.	Not supported
8a: The more uncertain that physicians are about the viability of vendors in the current EMR marketplace, the more likely they will be to reject an EMR system.	Not supported
8b: Vendor viability is a larger concern for physicians in a private practice than physicians in a hospital setting.	Not supported
9a: The more physicians perceive EMR systems to lack security and have related legal implications, the more likely they will be to reject an EMR system.	Supported
9b: Security and legal concerns are a larger concern for physicians in a private practice than in a hospital setting.	Not supported
10a: The more physicians perceive that an EMR system will integrate data in and outside of their practice, the more likely they will be to adopt an EMR system.	Supported
10b: Data integration factors are a larger concern for physicians in a hospital setting than physicians in a private practice.	Supported
11a: The more physicians distrust the institutions that pressure them to adopt an EMR system, the more likely they will be to reject an EMR system.	Partial support
11b: Institutional distrust is higher in physicians in a private practice than physicians in a hospital setting.	Supported

4.1 Implications

Our findings have various implications for both research and practice. First, we employed UTAUT in the emerging context of EMR and modeled effort and performance expectancy as second-order constructs. Our results indicate that ambiguity over the structure of these constructs exists because we did not find support for keeping them distinct. Instead, we found support for collapsing them together (while maintaining their original first-order structure). We urge researchers to continue to examine the structure of UTAUT when modeling performance and effort expectancy differently.

Second, the adoption/non-adoption decision formed the dependent variable in our work rather than the traditional DVs of attitude or BI. Thus, our focus shifted to the factors that differentiate adopters and non-adopters. To our knowledge, our work represents the first attempt to create a structural model to ascertain differential factors, and we urge others to continue to examine whether our traditionally studied constructs exhibit the same predictive ability when applied to a differential (as opposed to a predictive) model.

Third, the emerging context of EMR represents an opportunity for adoption researchers to investigate a multitude of research questions. However, work in the area has remained fragmented and lacks a unifying model. We work to bridge this gap by proposing and testing an integrated model of EMR adoption. We urge other adoption researchers to continue to investigate EMR adoption and bring new theoretical lenses to understand this important phenomenon. Especially with adopters such as physicians in small practices, the daunting number of factors they confront may cause information overload. We need to better understand what key elements will most matter to them.

Finally, our work represents the first attempt to begin to understand the role of organizational structure in the adoption decision. While our field has moved beyond calls for the “IT artifact”, we encourage other researchers to begin to investigate the “organizational artifact” in the adoption decision. We suggest that we need to better understand the organizational artifact by examining the macro-level structure of organizations and how it relates to end users’ micro-level attitudes and behaviors. Our overall model tests that compared the hospital to private practice indicated the presence of significant differences, which affirms the core proposition we test in this paper. Future research needs to further explore how these differences operate.

For practice, our findings indicate that the context of adoption matters. Physicians in private practice should care about issues such as vendor reliability, complexity, and uncertainty, although existing trade guidance we reviewed has yet to address these issues. Associations such as the American Medical Association or specialty groups such as the various state organizations for Family Physicians could assist in the adoption process by training physicians on key issues they will face. Decision theory asserts that for complex decisions it will be easier to anchor on factors that they find immediately apparent to them rather than develop an optimized plan due to the level of complexity (Kahneman & Tversky, 1982). For IT executives who seek to deploy an EMR in a hospital context, physician concerns can be addressed primarily by focusing on workflow, security, and reliability. However, in a private practice, driving adoption needs to also focus on the vendor, pressure from similar organizations, and characteristics of the EMR itself.

5 Conclusion

As researchers have coalesced around various models such as the UTAUT when investigating the adoption of innovations, we argue that this focus neglects the organizational context. We postulate that more opportunities exist in this area for researchers to examine this new theoretical lens in IT research, and we urge others to follow our lead to begin understanding the relationship between organizational structure and adoption in healthcare.

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Appendix: Structured Interview Questions

- Describe your educational experience, including where you went to medical school, where you went to residency, and your time between medical school and your current job
- A profile of your current practice, including your specialty, number of patients seen in a given day, and percentage of Medicare/Medicaid patients versus traditional HMO/PPO and self-pay?
- Describe your current views of technology—do you see yourself as an innovator or a laggard? And why?
- What do you believe are the overall benefits of EMR technology? What, if anything, would prevent these benefits from being achieved?
- What are the current experiences of your practice with EMR?
- What is your view of the incentives being offered by the federal and state government to encourage EMR adoption?

About the Authors

Colleen Carraher Wolverton is the Revis & Lorraine Sirmon/LEQSF Regents Endowed Assistant Professor at the University of Louisiana at Lafayette. Her research interests include adoption of new technology, outsourcing, electronic health records, and creativity with IT. Her work has been published in journals such as the *Journal of Information Technology*, *European Journal of Information Systems*, *Communications of the Association for Information Systems*, and *Information & Management*. She has won awards for her research, including the Outstanding Researcher of the Year Award and the Research Excellence Award. She is a Senior Editor at *The Data Base for ADVANCES IN INFORMATION SYSTEMS*. Prior to her career in academia, she was an IT professional, working as a project manager for an IT development firm, an IT analyst for a Fortune 50 oil and gas company, and organizational development in an IT department.

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