An Institutional Theory Perspective on EHR Engagement: Mandates, Penalties, and Enforcement

Mark J Keith
Brigham Young University
mark.keith@gmail.com

Elina Chun Stewart
University of Washington
elinacs@uw.edu

Tevin Stewart
University of Washington
tcstewart95@gmail.com

Mitchell Josephson
Health Data Management Group
mitchell.josephson@hdmgroup.org

Bob Cash
KLAS Research
bob.cash@klasresearch.com

Connor Bice
KLAS Research
connor.bice@klasresearch.com

Abstract

Electronic Health Record (EHR) systems are the predominant information system (IS) used by healthcare clinicians and have been the source of both great success and pain. User engagement with EHR systems is unique from traditional IS contexts in significant ways. Prior research explains EHR usage and success primarily on traditional technology acceptance research (i.e., TAM, UTAUT). However, these models assume that EHR engagement is no different from IS systems in general business domains. Yet, the healthcare context is far more regulated than most. Based on qualitative focus group sessions with a leading healthcare analytics firm (KLAS Research), we identify the role of mandates, penalties, and enforcements from government, organizations, associations, and insurance companies in explaining EHR engagement. We validate a measurement instrument for these factors and demonstrate that their inclusion can improve model fit five times over a traditional UTAUT-based model (R^2 = 54.8% versus 10.2%).

1. Introduction

The $27.7 billion industry of electronic health record (EHR) systems has been a source of great success and pain for administrators, clinicians, and technicians [1]. As a result, researchers from many domains have been greatly interested in explaining EHR success to improve a variety of outcomes for providers (e.g., burnout [2, 3], job satisfaction [4]), patients (e.g., safety and quality of care [5]), and the healthcare industry [6].

With notable exceptions, researchers have primarily drawn from prior theory on technology acceptance or continuance to explain EHR end-user behaviors; most prominently the technology acceptance model (TAM) [7] and the unified theories of acceptance and use of technology (UTAUT) [8] (for a review, see [9]). However, these theories were originally developed for general organizational information systems (e.g., enterprise resource planning systems, accounting systems, human resources systems, and marketing and sales systems, etc.) in contexts that are quite different from healthcare. When theories are ported from other disciplines, there may be important assumptions and conditions that do not apply well to the new context leaving opportunities for ground truth theorizing [10].

For example, healthcare informatics researchers have identified additional factors to add to TAM- or UTAUT-based models such as EHR training [4], EHR self-efficacy [11], and trust in IT and EHR vendors [12]. Yet, despite hundreds of academic research papers, the EHR is still arguably the most hotly contested information system among end-users [13].

Besides a potential theory misalignment, there are also measurement problems with EHR research. The standard outcome measure used in these studies is *intent to use* an EHR and/or *actual use*. However, usage and intentions are fundamentally different with EHR systems than others. For example, EHR end-users, specifically physicians, nurses, and other healthcare professionals, do not use these systems in their primary roles (providing healthcare). Rather, EHR usage is a secondary role and considered a hurdle or roadblock (whether technically or referring to time spent) to clinicians' primary responsibility [14]. As such, *intent to use* an EHR system is not entirely motivated by a desire to better perform one's perceived primary job function.

As a result, we posit that there is room to retheorize our understanding of EHR success; leading to our first research question, “What are the antecedents that explain EHR end-user engagement?” To answer our research question, we performed two studies in a mixed-methods approach. First, we conducted a qualitative grounded theory study that revealed new and critical EHR engagement factors that aligned relatively well with an *institutional theory* perspective [15, 16]. The results of this study led us to a second research question, “How do institutional regulations, standards, and

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pressures, impact EHR engagement." To address this question, we performed a second study to generate and validate new measurement items and tested our normative theoretical model with a final survey.

In summary, the purpose of this research is to develop and test a theoretical model explaining EHR end-user engagement that is more reflective of the underlying assumptions in the healthcare context which is deeply impacted by institutional forces. Our model explained the variance in EHR engagement over five times greater than a traditional UTAUT-based model when measuring engagement based on perceived time spent on the most relevant EHR use cases (R^2 = 54.8% versus 10.1%) as recommended by recent research [17].

2. IS Theories and EHR Engagement

TAM and *UTAUT* are well-known theories explaining end-user engagement with information systems. In particular, these theories explain general system usage intentions and behaviors based on various relevant factors including performance expectancy, effort expectancy, social influence, and facilitating conditions that are moderated by demographic features like the user's age, gender, and experience [8].

Yet, EHR engagement is unique from traditional IS engagement in fundamental ways. First, traditional technology adoption research assumes that system usage is 1) optional, and 2) that usage would improve performance [18]. The boundaries of these assumptions have long been identified in prior research and have led to incremental revisions over time (e.g., moving from TAM to UTAUT, UTAUT to UTAUT2 [8]).

However, the EHR context is unique in two ways. First, it is arguably more heavily regulated than any other major information system, largely due to the Health Insurance Portability and Accountability Act (HIPAA) [19]. As a result, many EHR use cases are mandated to some degree. Furthermore, these mandates may come from more distinct sources (e.g., the end user's organization, government, industry associations, and insurance companies) than the typical IS.

The importance of mandates, penalties, and enforcement in explaining behavior in organizations may fit best within the boundaries of *institutional theory*. While institutional theory explains the process by which social structures, including norms, routines, informal rules, and schemes become established as guidelines for social behavior in organizations [15, 16, 20]. So to survive, organizations conform to the prevailing rules and belief systems of their environment (e.g., government, insurance companies, and industry associations). These rules and belief systems are impacted, in turn, by the experiences of the organization members, customers, and other stakeholders. This process results in revised formal structures and institutionalized practices (e.g., mandates, penalties, and enforcements) over time [15, 16, 20].

The drivers of change, or "institutionalization," have been characterized in a variety of ways. The most common characterization may be from Powell and Dimaggio [21] who framed change factors as *coercive* (pressure by a more powerful individual), *normative* (informal pressure to conform to the group), and *mimetic* (copying the behaviors of higher-ranking individuals). Because these factors are present in the context of EHR systems, institutional theory may be a better fit than other theories. Institutional theory has already been used in qualitative studies designed to explain how EHR is institutionalized at a society level [22, 23], explain HIPAA compliance [24], and even in our same problem space—to better explain EHR engagement [c.f. 25, 26, 27 among others]. However, the application of institutional theory in this context is still relatively rare compared to TAM and UTAUT. Institutional theory did not appear in a recent literature review of the most common theories to explain EHR adoption or engagement [9].

Second, as discussed above, EHR systems often do not directly help the clinician perform their primary job role (providing care) in the way that, for example, a customer relationship management system helps salespeople find leads or that an accounting system helps an accountant balance ledgers. Exacerbated by the fact that many use cases are mandated, EHR usage is seen as a hurdle rather than a tool [14]. This perception results in an interesting phenomenon: successful EHR engagement may result in *less* rather than *more* time spent by the end user because those with greater EHR skill and desire to perform their primary role better will use the EHR quicker and more efficiently than others. Therefore, traditional outcomes like *intent to use* may be poor measures of EHR engagement because of this phenomenon. This means it is unclear if users would prefer to work with the EHR as little as possible or if they would prefer to integrate features of the EHR with their primary role. Despite these different possibilities, most EHR acceptance studies typically use the measures provided by TAM and UTAUT [9].

3. Study 1: Focus Groups

Prior qualitative research on EHR usage has focused on the perspectives of EHR end-users, namely physicians and nurses [e.g. 28]. This is useful and appropriate because the practitioners have personal experience with EHR systems. However, their experience is typically limited to one of few EHR systems and unique to their context of use.

To further understand how EHR engagement is unique, we looked beyond existing research and theory. Our first study was based on a qualitative, grounded-theory approach [10] and included two focus group discussions with a target audience who were uniquely equipped to inform this topic.

3.1. Methodology

We set out to find an audience with a broader perspective than the typical end-user and formed a relationship with a unique corporate partner. Therefore, the focus groups included the authors of this study and a group of analysts, consultants, and executives at KLAS Research (https://klasresearch.com/)–a firm that provides quantitative and qualitative investigations of EHR users of all types.

KLAS was uniquely equipped to support our investigation of EHR engagement factors because they collect data from major healthcare providers from around the world. KLAS administers surveys from clinicians, technicians, and healthcare administrators to understand the positive and negative success factors of EHR and other healthcare information technology. KLAS professionals have helped the researchers of this study understand factors impacting end-user EHR engagement and success across a wide variety of healthcare organizations, user types, and EHR vendors.

The first focus group included three academic researchers and three KLAS professionals. The focus group occurred at the researcher's university in October 2019 and lasted approximately one hour. Detailed discussion notes were taken. At the beginning of the meeting, and before, discussions began, the researchers briefly reviewed the primary theories used in prior research to explain EHR engagement such as UTAUT2 and satisfaction theory based on an expectations-disconfirmation model [29]. The researchers then shared examples of several research papers in the healthcare context that had applied these models to explain EHR engagement. After this literature and theory review, the researchers then laid out the purpose of this study with a single question: *What do you believe—from your experience—are the primary factors that explain EHR end-user engagement success?*

The initial priming (i.e. the theory and literature review) and subsequent question led to a discussion about how accurately prior theory and research truly captured the unique characteristics of the EHR engagement problem. Participants discussed each of the factors in these prior and agreed that there were additional issues that needed broader input from a wider variety of participants. Additionally, it was recognized that measurement of EHR engagement was debatable.

Therefore, a second focus group was scheduled for December 2019. This focus group included the primary investigator and 11 KLAS professionals and occurred in the KLAS offices over 2.5 hours, though not all participants attended the entire time. The meeting was audio recorded and diagrams photographed.

3.2. Results

As mentioned above, due to priming—the discussion of the first focus group centered around several factors relevant to UTAUT (primarily effort and performance expectancies), but it departed in two interesting ways. First, there was a greater emphasis on maintaining compatibility across systems and clinicians than is typically found in general IS-based adoption studies. For example, if assistants (scribes) perform charting, it is critical that assistants document in such a manner that nurses and doctors can quickly and easily digest the information. Second, participants emphasized the importance of meeting HIPAA, Joint Commission, and other regulations. Though regulatory requirements will dictate what an EHR needs to do, they will not indicate exactly how to do it nor force every staff, technician, or clinician to follow the spirit of those requirements. As a result, EHR vendors are left to their own devices to creatively meet those regulations when new regulations are approved. KLAS professionals suggested that this topic was worth further discussion and arranged another focus group.

In the second focus group, the role of regulation and governance was highlighted and discussed at length. Although the participants understood the importance of UTAUT constructs, they believed those factors only mattered if the particular use case for the EHR was 1) mandated, penalized, and enforced and 2) that governance could come from the provider's own organization, government regulation, industry associations that the clinician or provider belonged to outside of their organization (e.g., the American Medical Association), and insurance companies. This discussion revealed the matrix in Table 1, which will be defined separately for each relevant use case of the EHR (e.g., charting, ordering prescriptions, etc.).

Table 1. Governance Matrix

	Mandated	Penalized	Enforced
Provider's organization	?	?	?
External associations	?	?	?
Government	?	?	?
Insurance companies	?	?	?

Note: This data could be unique for every EHR use case

The differentiation among entities and governance factors is vital for a variety of reasons. For example, an insurance company may mandate a certain type of documentation that must be performed in the EHR system to receive reimbursement. However, if that mandate is not penalized or the penalty is not enforced, then the provider will likely ignore it. This scenario is a reality as insurance providers sometimes consent to make payments even when certain mandates are not followed. However, that likelihood is moderated by the degree to which their organization enforces the insurance company's mandate for them.

Additionally, there are two principles at play in this scenario. First, the "closeness" of the governing body to the end-user can explain EHR engagement. This factor is demonstrated in social network research. Workers who are socially closer to their stakeholders are more likely to comply and perform in the expected way [30]. Essentially, because the insurance company is "further" from clinicians than their own organization, clinicians are less likely to use the EHR for the insurance company's mandated purpose *unless* their organization penalizes and enforces the mandate. Closeness implies a greater ability to monitor and socially influence users, which is a critical factor in achieving compliance (see principal-agent theory [31]).

Second, mandates will only lead to compliance with "some of the people some of the time" if not penalized and enforced. This is evidenced in many healthcare scenarios, including vaccinations [32], patient information privacy [33], and insurance coverage [34].

The COVID-19 pandemic is an example of these principles. Despite mandates from state and local governments, citizens refused to wear masks [35]. Compliance is achieved in two ways. First, the "closer" the governing body is to the end-user, the more likely they are to comply. For example, the retail chains Target and Costco each mandated mask-wearing in their stores. Because these entities are closer to the consumer than the state or local government, they were more likely to achieve compliance. As soon as customers left the stores, they were no longer governed by those bodies and were more likely to remove their masks. Second, the cities, states, and countries who actually penalized (e.g., issued a citation) and enforced (e.g., citations) achieved greater compliance [36].

Finally, it was generally agreed that measuring EHR engagement based on *intent to use* (c.f. UTAUT2 [37] and theory of planned behavior [38]) was not sufficient but that more objective measures of actual usage are required.

3.3. Discussion

Armed with these grounded theory results, we realized that one theory was inadequate to understand successful EHR engagement. While theories based on planned behavior such as UTAUT theory [25] were clearly relevant to explain factors such as ease of EHR usage and usefulness of the EHR, they do not explain these factors of mandates, penalties, and enforcements. These factors are, however, supported by both our grounded theory results and prior theory on institutionalization [20]. This finding gave us the opportunity to develop an integrated theory from both.

We next sought literature applying institutional theory to EHR adoption and found several valuable studies [22, 24, 26, 27, 39]. Yet, after a careful review of these important contributions, we discovered certain limitations offered opportunities for us to further contribute to this line of research. First, some of these earlier studies designed to build theory are entirely theoretical and/or qualitative in order to initially identify the application of institutional theory to EHR adoption [e.g., 23, 26]. While useful, these studies do not measure or test a theoretical model empirically. Thus, we can contribute by developing a valid measurement scale. Second, the paper that most closely aligns with our study by Bozan, et al. [25] frames the causal factors of institutional theory—coercive, normative, and mimetic—as types of social influence based on a UTAUT model (see Figure 1 adapted from [25]).

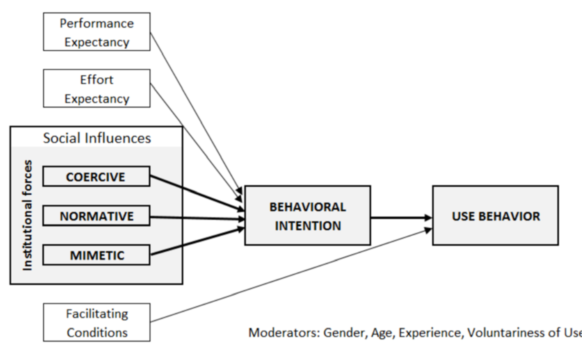

Figure 1. Model Adapted from [25]

Their findings revealed that coercive institutional factors were better modeled having a direct effect on user behavior than behavioral intention [25, p. 3311]. Based on our qualitative findings from Study 1, we agree that this in an important revision to their model and proceeded to test it more explicitly in Study 2.

Finally, these prior studies continued to focus on behavioral intention which was identified in the focus groups as a potential problem because staff, technicians, and clinicians can be easily persuaded to claim (in an academic survey) that they intend to use an EHR appropriately, but then decide not to do so "in the moment" when time is short and pressures are high. Therefore, the importance of various antecedents of EHR engagement may be misestimated.

3.4. Combined Theoretical Model

In summary, our data from Study 1 and review of institutional theory lead to our theoretical variance model in Figure 2.

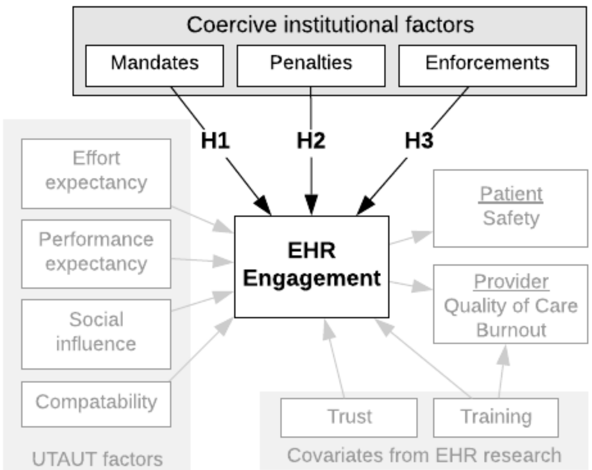

Figure 2. Combined Theoretical Model

Similar to the few and more recent studies on EHR engagement [23, 25, 26], our model is based on an integration with traditional UTAUT theory [37] with institutional theory [20]. *Effort expectancy* refers to the time spent learning and using the EHR. *Performance expectancy* refers to the degree to which the end-user expects it to make them faster, more efficient, and more effective in their job role. *Social influence* refers to the informal social structures that encourage EHR engagement. Conceptually, this maps to the *mimetic* and *normative* factors identified in institutional theory [25]. Although the UTAUT-based measure does not differentiate between the group (normative) and higher-ranking individuals (mimetic) as social influencers, we did not find that differentiation relevant in Study 1 based on the very different job roles and EHR uses among healthcare workers with different licenses.

We included additional covariates of *trust* and *training*. Based on EHR engagement research findings, *trust* [12]—both in the provider's organization and the EHR vendor—leads to greater engagement. Similarly, *training* is an important indicator of EHR usage and provider outcomes like burnout and quality of care [4].

We also included two general types of EHR engagement outcomes identified in prior research, provider outcomes and patient outcomes. Provider outcomes refer to those directly related to the clinician, such as job satisfaction, burnout, and patient care. *Burnout* is a more relevant provider outcome that has received significant recent attention in EHR research [3] and is included in our study. Burnout is generally defined as a "state of vital exhaustion" which results from extended organizational stress [2]. *Patient care* is included because this is the provider's primary goal in their workplace [5]. We also included the patient outcome of *safety* [2] in our model. Although EHR engagement outcomes are not necessary to explain engagement, we include these in our model to help validate our measure of engagement.

4. Study 2: Normative Model Testing

4.1. Methodology

Our next step was to quantitatively validate the theoretical model developed in Study 1. To do this, we administered a 31-question survey to various healthcare clinicians and technicians from January 24, 2021 to March 7, 2021. First, we generated an initial draft of the survey by using measurement items from a combination of prior research and a survey already in production by KLAS Research. Then, KLAS reviewed this survey and gave feedback on the measures and particularly on our new measures of EHR engagement, mandates, penalties, and enforcements.

4.1.1. Measures. Much of the prior EHR engagement research is based on high-level, indirect measures that imply EHR user acceptance [e.g., 27, 39]. Recent research has shown that EHR engagement is best measured when observed as time spent on specific EHR use cases based on log data [17]. Particularly, it should be measured as the number of hours within an eight-hour work period spent on particular EHR use cases. However, marketing theory has long demonstrated that consumer behavior based on time spent with a product is more accurately reflected when based on the perception of time as opposed to actual time [40]. Therefore, rather than using EHR log files, we ask participants to state how many hours they *believe* they are spending on each use case. In other words, EHR engagement is measured by perceived time spent. This creates a formative measure of EHR engagement.

The 12 use cases measured include a broad range of activities with varying relevance to technicians, nurses, and doctors, including medical charting, scheduling inpatient services, scheduling outpatient services, order placement, managing patient care plans, patient education, e-prescriptions, workflow management, health records output, coding and billing, and service requests. These use cases were selected based on recent research [17] and a review of those encouraged or prescribed by the US government on HealthIT.gov [41].

Similarly, EHR features can be uniquely *governed* (i.e., mandated, penalized, and enforced) separately by each *source* or governance type—in this case, organizations, associations, governments, and insurance companies. Therefore, we measure a matrix for each EHR use case based on the regulatory measures conceptualized in Table 1. All use cases for a particular source load together as a formative first-order factor for each source. This first-order source factor is then modeled in a second-order formative factor for each governance type. Figure 3 visualizes how penalties are modeled as a second-order formative factor based on the four sources that are each first-order formative factors based on each use case. For example, in our questions regarding mandates, penalties, and enforcements, respondents were directed to *"Please indicate whether misuse (or lack of use) of each feature is mandated by each entity,"* and respondents were asked to check a box indicating whether *charting* was *penalized* by the *government* in a matrix table.

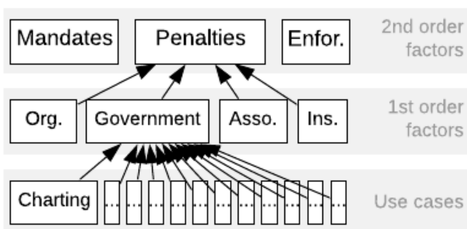

Figure 3. Model of Institutional Factors

The remaining measures were either drawn or adapted from prior research on UTAUT [37], EHR trust [12], EHR training [4], patient safety [2], patient care [5], and burnout [3]. This survey was first pilot tested with 90 participants, and the measurement model was checked before proceeding. Upon satisfactory results from this first test, the survey was then administered to the remaining 131 participants.

4.2. Results

4.2.1. Descriptive Statistics. Overall, 221 participants completed the entire survey. Our sample was drawn from two primary sources: 1) Master workers from Amazon Mechanical Turk (MTurk) that were filtered to only include those who worked in the healthcare industry, and 2) an online panel purchased from Qualtrics, LLC of active healthcare workers across the US. Notably, the MTurk sample included only those who were declared as healthcare workers in the MTurk system. In other words, their profession was verified and not self-declared. The final sample included 62% females, 37% non-White ethnic and racial minorities, and were an average age of 35 years. Of those respondents who reported their professions (n=204), our sample contained 44 nurses, 62 mid-level providers (nurse practitioners, physician assistants, etc.), 20 physicians, 38 allied health professionals, and 40 others, including administrators, technicians, and others who use EHR as part of the daily job routine. Table 2 summarizes the demographics.

Table 2. Study 2 Participant Demographics

Characteristics	
Age (Mean, Standard Deviation)	35(12.8)
Female	62%
Male	38%
Race/Ethnicity	
Asian	12%
Black or African American	9%
Hispanic/Latino	4%
White	63%
Other	12%
Background	
Allied Health Professional	17%
Midwife	2%
Nurse Practitioner	19%
Nurse, Administrative	6%
Nurse, Clinical	16%
Physician Assistant	7%
Practicing Physician (MD/DO)	11%
Other	19%

Table 3 summarizes the perceptions of coercive institutional factors by indicating the percentage of participants who perceived that one or more of the use cases is mandated, penalized, and/or enforced.

Table 3. Coercive Institutional Factors

Body	Mand	Pen	Enf	None	Unsure
Organization	49%	27%	35%	1%	0%
Government	19%	20%	18%	5%	1%
Association	17%	14%	13%	6%	0%
Insurance	14%	13%	12%	6%	1%

Note: Mand = Mandated, Pen = Penalized, Enf = Enforced

4.2.2. Measurement Model. To ensure the accuracy of our hypothesis testing, the scales used in this study were assessed for measurement model reliability, validity, covariance, and common methods bias. Table 4 indicates that each scale had sufficient reliability [42]. Convergent validity is sufficient when composite reliability (CR) is over 0.7 and the average variance extracted (AVE) is over 0.5 for each scale [43]. This was met by every scale except for CSP which was just slightly under 0.5. However, it passed the composite reliability test, so we retained each item. Covariance was tested by calculating the variance inflation factor (VIF) for each exogenous construct. Every VIF score was below the recommended cutoff of 10.0 [44].

Table 4. Reliability and Convergent Validity

Variable	α > .7	CR > .7	AVE > .5	VIF
CSP	0.78	0.79	0.49	1.66
EE	0.91	0.94	0.84	1.84
PE	0.82	0.84	0.57	2.07
PaOC	0.89	0.92	0.74	n/a
PaOS	0.85	0.89	0.62	n/a
SI	0.76	0.29	0.26	1.28
Train	0.83	0.90	0.74	2.28
TRUO	0.90	0.94	0.83	1.54
TRUV	0.90	0.91	0.78	1.98

Notes: CSP = compatibility with systems and people, EE = effort expectancy, PE = performance expectancy, PaOC = patient outcome: quality of care, PaOS = Patient outcome: safety, SI = social influence, Train = training, TRUO = trust in the healthcare professional's organization, TRUV = trust in the EHR vendor

Discriminant validity is sufficient when the square root of the AVE for each reflective construct is greater than that construct's correlation with every other factor. Table 5 demonstrates validity as each number in the diagonal (bolded and underlined) is greater than each of the values below it. In summary, we conclude that the data exhibit sufficient measurement model quality.

Table 5. Discriminant Validity

	CSP	EE	PE	PaOC	PaOS	SI	Train	TRUV	TRUO
CSP	**0.70**								
EE	0.39	**0.92**							
PE	0.50	0.60	**0.76**						
PaOC	0.51	0.48	0.51	**0.86**					
PaOS	0.54	0.50	0.49	0.72	**0.79**				
SI	0.09	0.32	0.29	0.03	0.12	**0.51**			
Train	0.51	0.48	0.50	0.40	0.44	0.17	**0.86**		
TRUV	0.32	0.24	0.37	0.30	0.36	0.12	0.50	**0.91**	
TRUO	0.35	0.45	0.42	0.31	0.38	0.29	0.61	0.49	**0.88**

4.2.3. Hypothesis Testing. Hypothesis testing was performed using the partial least squares (PLS) structural equation modeling (SEM) technique available from SmartPLS 3.3.3 [45]. This form of modeling was appropriate because of several formative constructs in our model [46]. For example, while trust in the EHR vendor and provider's organization are reflective sub-constructs, we assume those factors do not covary. Therefore, the second-order trust factor is formative. More importantly, both EHR engagement (the central factor in our model) and each type of coercive institutional factor—mandates, penalties, and enforcements—are each formative based on Boolean measures. Therefore, PLS was required as opposed to a covariance-based SEM technique. Path coefficients are estimated with the PLS algorithm while p-values are generated using a bootstrapping procedure based on 5000 sub-samples. To understand the difference between a traditional UTAUT model and our model, we analyzed both models. Figure 4 visualizes relationship significance based on a UTAUT model without mandates, penalties, and enforcements. (Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$)

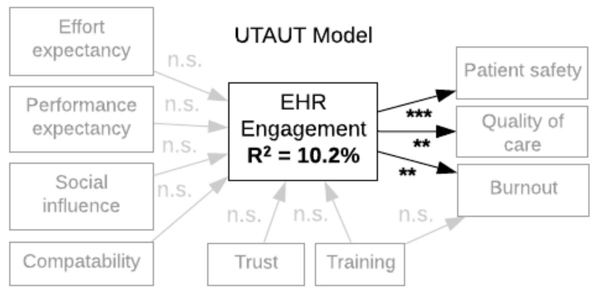

Figure 4. UTAUT Model

Table 6 summarizes the coefficient values for these relationships.

Table 6. Path Coefficients for UTAUT Model

Exogenous	Endogenous	β	t-stat	p-value
EE	Engagement	-0.005	0.048	0.481
PE	Engagement	-0.115	0.851	0.198
SI	Engagement	-0.042	0.226	0.411
CSP	Engagement	0.200	1.106	0.134
Training	Engagement	-0.091	1.064	0.144
Trust	Engagement	0.145	1.071	0.142
Engagement R^2 = 10.2%				
Engagement	PaOC	-0.274	2.677	**0.004**
Engagement	PaOS	0.331	4.723	**0.000**
Engagement	Burnout	0.206	2.734	**0.003**
Training	Burnout	0.092	0.803	0.211

The R squared value of EHR engagement is significantly lower than similar prior research [37]. As stated above, our EHR engagement measure is not based on *intent to adopt*, but rather, a measure of the number of hours per day a healthcare professional uses each feature [17] based on perceived time spent [40]. With this measure, none of the traditional UTAUT antecedents or covariates had a significant relationship with EHR engagement. However, EHR did have a very significant effect on relevant outcomes for patient safety, quality of care, and clinician burnout.

Figure 5 visualizes the relationship significance of our expanded institutional theory model and Table 7 summarizes the coefficients, t-stats, and p-values of our analysis. Mandates, penalties, and enforcements each had significant effects on EHR engagement while traditional UTAUT antecedents were still insignificant. The only other change from the UTAUT model is that the effect of training became partially significant (p <

0.10). The effect of EHR engagement on burnout also became slightly more significant. However, this is only due to randomness in the bootstrapping procedure since the data for that relationship is the same for both models.

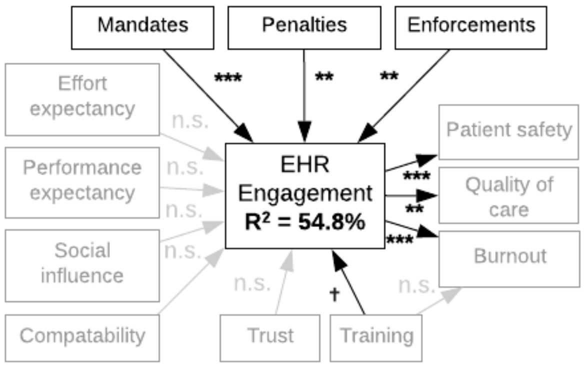

Figure 5. Institution Theory Model

Table 7. Path Coefficients for Enhanced Model

Exogenous	Endogenous	β	t-stat	p-value
Mandates	Engagement	0.270	3.184	**0.001**
Penalties	Engagement	0.237	2.614	**0.004**
Enforcements	Engagement	0.253	2.434	**0.007**
EE	Engagement	-0.064	0.932	0.176
PE	Engagement	-0.089	1.005	0.157
SI	Engagement	-0.074	0.678	0.249
CSP	Engagement	0.037	0.409	0.341
Training	Engagement	0.101	1.452	**0.073**
Trust	Engagement	0.077	1.207	0.114
Engagement	PaOC	0.317	5.535	**0.000**
Engagement	PaOS	0.177	2.290	**0.010**
Engagement	Burnout	-0.284	4.128	**0.000**
Training	Burnout	-0.093	1.121	0.131

5. Discussion

The primary contribution of this study is to demonstrate that institutional theory provides a stronger theoretical lens to understand EHR engagement than TAM, UTAUT, and other theories that have been previously used. This supports prior research on institutional theory in healthcare that is largely qualitative or purely theoretical [15, 22, 24-27]. In particular, all hypotheses were supported; mandates ($\beta = 0.270$, $p < 0.001$), penalties ($\beta = 0.237$, $p < 0.001$), and enforcements ($\beta = 0.253$, $p < 0.001$) each significantly *increased* effect on EHR engagement.

As indicated in Figure 4 and Figure 5, the variance explained in the enhanced model ($R^2 = 54.8\%$) was several times greater than that of the UTAUT model ($R^2 = 10.2\%$). Thus, the improvement effect size between these models (f^2 98.7%; (0.548 – 0.102) / (1 – 0.548)) is considered "large" [47] supporting the addition of institutional theory as stronger explanation for EHR engagement than UTAUT alone.

5.1. Implications

The primary implication of this study is that the efforts of EHR vendors to improve their systems are greatly affected by external forces like regulators, associations, and insurance providers. In addition, successful efforts to improve EHRs make it possible for end users to spend *less* total time and engagement with the EHR rather than more. The importance of effort efficiency is not new and applies to all information systems. However, because 1) EHRs are primarily motivated by the coercive institutional factors of mandates, penalties, and enforcements, and 2) they are not the primary objective of their end users (compared to providing patient care), EHR vendors and researchers should measure engagement and success differently. Our results indicate that it makes sense to assume that EHRs are used as much or as little as needed to meet regulation. Therefore, successful EHRs allow users to spend less total time using them. In contrast, a successful enterprise resources planning (ERP) system, for example, would be used *more* because it allows end users to replace needed tasks performed outside of the system by using the ERP system more.

Although the UTAUT variables and other controls did not have significant relationships with EHR engagement, this is likely only due to the sample size and their relatively smaller effect sizes. Assuming similar coefficients with more data collected, effort expectancy (EE) appears to reduce EHR engagement ($\beta = -0.064$). This is logical since greater effort to use the EHR would cause clinicians to use it less.

The effects of performance expectancy (PE) and social influence (SI) may seem curious at first. Traditional research posits that greater effectiveness would cause clinicians to use an EHR more. However, our results (again, assuming the coefficient remains the same when more data is collected) indicate that greater PE led to *less* engagement ($\beta = -0.089$). This effect is due to the secondary role that EHRs play in a healthcare professional's workday. Because their primary job role is to provide patient care, an effective EHR is one that can be used less, rather than more, to accomplish the same tasks. Therefore, our measure of EHR engagement based on a perceived number of hours used should have a *negative* relationship with PE as it did in our case.

SI had a negative relationship with time spent using the EHR. In other words, the more that a clinician's colleagues expect them to use the EHR, the fewer hours they use it ($\beta = -0.074$). We expect this result has a similar explanation as PE in that SI leads a clinician to use the EHR more efficiently; thus, leading to fewer hours spent on the same tasks.

These findings illustrate the importance of measuring EHR engagement less ambiguously than intent to adopt, which could mean either more or less time spent depending on how the respondent interprets the concept. For example, one clinician may believe that a stronger intention to adopt means that they will use it more while another will interpret it as using it less (i.e. more efficiently). Regardless, EE, PE, and SI each had effect sizes much smaller than those of mandates, penalties, and enforcements. In summary, an institutional theory model is better at explaining EHR engagement than a traditional UTAUT model.

6. Conclusion

After the results of our qualitative and quantitative studies, we determined institutional theory to describe EHR engagement more accurately. Our next step is to test this model with thousands of healthcare practitioners to gain a better understanding. For example, the effects of the covariates training and trust leave us with some unanswered questions that should be addressed in future research. The coefficients training ($\beta = 0.101$) and trust ($\beta = 0.077$) both indicate that higher levels of trust in the EHR vendor and the clinician's organization lead to more time spent using the EHR. Does this mean that the clinician is using the EHR less efficiently? Likely not. It may mean that the clinician is using more of the optional EHR features. Therefore, future research should measure engagement separately for mandated versus optional features to better understand the effects of these important covariates.

7. References

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