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In this issue:

4. **Examining Cloud Data Security Vulnerabilities During Usage**
Daniel Amoah, Microsoft Corporation
Samuel Sambasivam, Woodbury University

17. **Cybersecurity Maturity Model Certification Initial Impact on the Defense Industrial Base**
Hala Strohmier, University of North Carolina Wilmington
Geoff Stoker, University of North Carolina Wilmington
Manoj Vanajakumari, University of North Carolina Wilmington
Ulku Clark, University of North Carolina Wilmington
Jeff Cummings, University of North Carolina Wilmington
Minoo Modaresnezhad, University of North Carolina Wilmington

30. **The COVID-19 Pandemic's Impact on Information Technology Employment, Salaries, and Career Opportunities**
Patricia Sendall, Merrimack College
Alan Peslak, Penn State University
Wendy Ceccucci, Quinnipiac University
D. Scott Hunsinger, Appalachian State University

39. **A Comparison of Internationalization and Localization Solutions for Web and Mobile Applications**
Peng Wang, Pinterest, Inc.
Hee Jung Sion Yoon, City University of Seattle
Sam Chung, City University of Seattle

47. **GIS for Democracy: Toward A Solution Against Gerrymandering**
Peter Y. Wu, Robert Morris University
Diane A. Igoche, Robert Morris University

54. **Determinants of Health Professionals' Intention to Adopt Electronic Health Record Systems**
Jie Du, Grand Valley State University
Jenna Sturgill, Grand Valley State University

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Journal of Information Systems Applied Research

Determinants of Health Professionals' Intention to Adopt Electronic Health Record Systems

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Abstract

The purpose of this study is to understand health professionals' perception and intention towards Electronic Health Record (EHR) systems and how those intentions play a vital role in improving the adoption of EHR systems. We proposed a research model based on the unified theory of acceptance and use of technology and health belief model to investigate the impact of specific factors on health professionals' intentions of using EHR systems. The results showed that trust is a significant influencing factor to the adoption and acceptance of EHR systems by health professionals. This study then recommended that further investigation into the barriers and drivers of EHR adoption should be done. By identifying and understanding the determinants of adopting EHRs, interventions and education can be designed to improve the adoption of EHRs.

Keywords: Electronic health record, health care, adoption, trust, and survey.

1. INTRODUCTION

Due to the increasing cost of health care, rise of chronic disease, and a projected 10% less amount of healthcare workers by 2025, Electronic Health Record (EHR) systems are becoming increasingly popular (Tavares & Oliveira, 2018). EHR is a repository of patient data in a digital form that includes data such as medical history, medication and allergies, immunization status, laboratory test results, radiology images, vital signs, personal statistics, and billing information, all stored and exchanged securely (Gunter & Terry, 2005). The combination of an EHR system and a patient portal, increases a patient's ability to carry out self-management activities, making the use of the health care system more effective and sustainable as the job market declines (Tavares & Oliveira, 2018). Although the adoption rate for EHRs has been increased in recent years, many challenges and barriers still exist. To improve the adoption of EHRs, understanding the factors that impact the adoption of EHRs is the first step.

The purpose of this study is to understand health professional's perception and intention towards EHRs and how those intentions play a vital role in improving the adoption and implementation of EHRs. Our research question is: What factors are the determinants for the health professionals to adopt and use EHRs? We proposed a research model by combining the unified theory of acceptance and use of technology (UTAUT2) and health belief model (HBM) to investigate the barriers and drivers for EHR adoption. An electronic questionnaire was developed to gather insight from health information management (HIM) professionals, who manage EHRs throughout the hospital setting and college students majoring in HIM who are privileged to EHR access. The results show that trust plays a significant role in EHR adoption. By identifying and understanding the determinants of adopting EHRs, interventions and education can be designed to improve the adoption of EHRs.

The remainder of this paper is organized as follows. Section 2 provides a literature review of studies that investigated factors that impact EHR adoption. Section 3 introduces our research model and hypotheses. The methodology including survey development and data collection is presented in Section 4 and the results are presented in Section 5. Discussions on the results and implications are presented in Section 6. Section 7 concludes the paper.

2. LITERATURE REVIEW

The Technology Acceptance Model (TAM) (Davis, 1989), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003), and extensions of these models have been used to determine users' acceptance or adoption of technology in various scopes. In this section, these models and their extensions applied to the health care field were first reviewed. Works that added a factor associated with privacy risk or trust to variations of these models were reviewed next. How our study extends the literature is presented at the end.

Technology Acceptance Model

Vitari and Ologeanu-Taddei (2018) used variables of TAM, perceived ease of use (PEOU) and perceived usefulness (PU) to measure the intention of different occupational groups in the same hospital setting, to use the EHR system. PEOU is defined as "the degree to which a person believes that using a particular system would be free from effort" (p. 1); PU is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (p. 1). Vitari and Ologeanu-Taddei (2018) sought to clarify the possible differences, in intention to use an EHR and its antecedents, existing between the different staff categories. They administered a survey to measure the medical staff's perceptions of EHR, using questions derived from a review of previous studies: PU, PEOU, misfit, data security, anxiety, self-efficacy, and trust. Each variable was measured using one question and each question was answered using a seven-point Likert scale, with one indicating "strongly disagree" and seven indicating "strongly agree." They found that secretaries' and assistants' perception of the ease of use of EHR does not influence their intention to use it nor could they be influenced by self-efficacy in the development of their perception of the ease of use of EHR. This finding can be explained because secretaries and assistants are required to follow more stringent rules and procedures for their work, including working with EHR, with less professional autonomy than healthcare professionals.

Another study that utilized TAM was (Beglaryan, Petrosyan, & Bunker, 2017) study on hospital-based physicians' perspective on EHR. The main objective of their work was to understand the barriers of implementation from the point of view of end users; identify major determinants of physicians' technology acceptance; and develop a deeper understanding of the various factors impacting implementation through development of an enhanced TAM. TAM and its numerous extensions are often criticized by researchers for its incomplete scope. In particular it is argued that these models ignore: a) group and social processes related to IT implementation; b) technology's organizational and social consequences. TAM models are said to leave a gap between an individual's reactions towards technology and their intentions of using technology. Specifically, TAM does not account for the motivations of acting and for how different reasons for acting interact together to emerge as intentions. Beglaryan et al. (2017) explored the implementation barriers from the perspective of end users, with a particular emphasis on the acceptance and post-acceptance stages of the implementation. All items were measured using a five-point Likert-scale, ranging from "strongly agree" to "strongly disagree." Their results suggested that the major barriers of EHR acceptance among physicians include group level clinical concerns, impact on job performance, required effort to utilize the system, personal characteristic of innovativeness, interference with patient-provider relationships, and resistance to change. However, perceived ease of use did not cast a significant direct effect on behavioral intention, which is aligned with previous studies reporting that a PEOU-behavioral intention (BI) link is often found as the weakest correlation in the core TAM. They also found that the main direct determinant of behavioral intention is projected collective usefulness (PCU), and that PU transmits its effect to behavioral intention through PCU. A limitation of this model was there might be discrepancies between intentions and actual behavior as pointed out by several other studies.

The Unified Theory of Acceptance and Use of Technology

The UTAUT model has played a critical role in evaluating technology intention and EHR acceptance. Alazzam et al. (2016) used UTAUT2 (Venkatesh, Thong, & Xu, 2012), an extension of UTAUT to explore the antecedent factors of medical staff intentions to use an EHR system by conducting a review of studies that use the UTAUT2 model and involve trust in stored data. The aim of their study was to compare and combine results from different studies using the UTAUT2 model, in the hopes of identifying patterns among the studied results. They anticipated habit will directly affect the intention of medical staff to use EHRs. Thus, a high level of intention to use is likely to increase employee adoption of EHRs. To detect a set of determinants of acceptance of EHRs by medical staff, Alazzam et al. (2016) created a research model based on UTAUT2 but added new constructs to measure the trust medical staff have in stored data. Alazzam et al. (2016) termed the added set of constructs "e-health extension to UTAUT2."

The Health Belief Model

The health belief model was created in 1950s and is a psychological model that attempts to explain health preventative behaviors (Rosenstock, 1974). This model suggests that an individual's behavior is determined by threat perception and evaluation of the behaviors to resolve the threat. The threat perception depends on vulnerability and severity, and evaluation of the threat is determined as perceived benefits minus perceived barriers. Three other variables included in HBM are self-efficacy, cues to action, and general health orientation (Rosenstock, Strecher, & Becker, 1988).

Ng et al. (2009) used the health belief model to study user's computer security behaviors. To understand how security awareness programs influence a user's attitude and behavior to be more security-conscious, Ng et al. (2009) examined the influences for a user to use computer security at their organization. By identifying the determinants of computer security behavior, interventions can be constructed to change the user's behavior. In the perspective of the HBM (Rosenstock, 1974; Rosenstock et al., 1988), an individual's behavior is determined by the threat perception and what it takes to resolve the threat. Ng et al. (2009) found that perceived susceptibility, perceived benefits, and self-efficacy were all impactful determinants of a user's computer security practices. Self-efficacy was important because computer users must be confident and able to perform the necessary mitigation measures and it was the most strongly related to intention and behavior. Perceived barriers, cues to action, general security orientation, and perceived severity were all found to not have statistical significance.

Ng et al. (2009) extended the health belief model to a new area of research to help determine how to change user's behaviors. This can be applied to not just computer security behaviors but also EHR behaviors. Sher et al. (2017) used the health belief model to examine perspectives of HIM professionals on privacy effectiveness in EHRs. Their study administered a cross-sectional survey to determine HIM professional's intention to protect EHR privacy. Survey items were measured on a seven-point Likert-scale ranging from "strongly disagree" to "strongly agree," with multiple questions for each construct. The results found that perceived susceptibility and perceived severity were weak predictors of preventative behavior, which is opposite of what the HBM argues. However, the constructs perceived benefits, perceived barriers, self-efficacy, and cues to action were found to be significant predictors of intention to protect EHR privacy, as the HBM proclaims. Sher et al. (2017) also emphasized the importance of organizations to communicate the benefits certain practices have on the use of EHRs.

The Combinations of Theories

Tavares and Oliveira (2018) used an integrated model approach to understand the factors that drive electronic health record adoption. They used the combination of UTAUT2, the health belief model (HBM), and the diffusion of innovation theory (DOI) for their research model. HBM constructs, perceived health risk, and self-perception, were used to replace UTAUT2 construct hedonic motivation to better predict motivation to use. Data was collected using a mobile phone survey resulting in the constructs compatibility, performance expectancy, and habit playing significant roles on the dependent variable intention to recommend. The combination of the three theories were found to be a successful model because they each had constructs with statistically significant impact on explaining the adoption of EHRs. Performance expectancy, due to its effect on behavioral intention, suggested that individuals care about the results and advantages that EHRs can bring to manage health more effectively. However, the social influence hypothesis was not supported. Based on their results, and the high impact of performance expectancy, Tavares, and Oliveira (2018) emphasized the importance of communicating the advantages that EHRs provide to users.

Trust in User's Acceptance
Researchers had added a factor associated with privacy risk or trust to variations of TAM-based models (Jang & Lee, 2018; Palos-Sanchez, Hernandez-Mogollon, & Campon-Cerro, 2017) and the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Yun, Han, & C. Lee, 2013; Zhou, 2013) to examine the usage intention for location-based service. In the field of health care, trust has also been added into UTAUT2 (Alazzam et al., 2016) and TAM (Vitari & Ologeanu-Taddei, 2018) to explore users' acceptance or adoption of EHRs.

Previous literature has supported that the combination of UTAUT2 and HBM is a successful model (Tavares & Oliveira, 2018) to understand the factors that drive EHR adoption. However, the role of trust and privacy in a combination of UTAUT2 and HBM has received little attention in research to date. This study proposes a research model that (1) combines UTAUT2 and HBM, and (2) incorporates trust and privacy as factors that impact users' adoption of EHRs.

3. RESEARCH MODEL

Our research model is built upon the UTAUT2 (Venkatesh et al., 2012) and the HBM (Rosenstock, 1974; Rosenstock et al., 1988). There are seven constructs in our research model (see Fig. 1). The six independent variables are perceived benefits (BEN) (HealthIT.gov, 2019), perceived barriers (BAR) (Ng et al., 2009; Stanford_Medicine, 2018), privacy (PRI) (Sher et al., 2017), social influence (INF) (Tavares & Oliveira, 2018), self-efficacy (EFF) (Ng et al., 2009; Sher et al., 2017), and trust (TRU) (Alazzam et al., 2016). The one dependent variable in the research model is the subjects' self-reported attitude toward EHR adoption (BEH) (Tavares & Oliveira, 2018). The six hypotheses are posited:

H1 – Perceived benefits (BEN) of using EHRs are positively related to EHR adoption intention.
H2 – Perceived barriers (BAR) to using EHRs are negatively related to EHR adoption intention.
H3 – Privacy issues (PRI) of using EHRs are negatively related to EHR adoption intention.
H4 – Social influence (INF) to using EHRs are positively related to EHR adoption intention.
H5 – Self-efficacy (EFF) to using EHRs are positively related to EHR adoption intention.
H6 – Trust (TRU) to EHRs is positively related to EHR adoption intention.

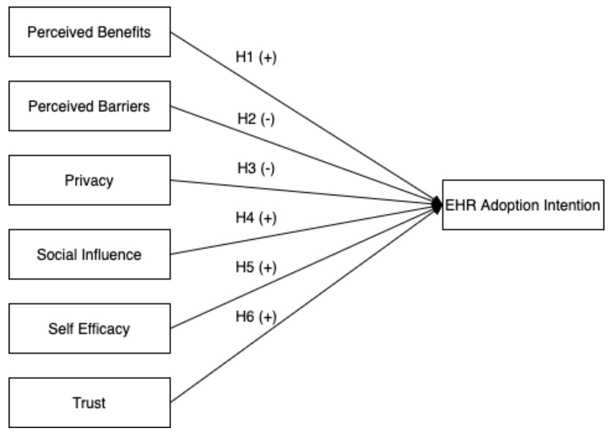

Fig. 1 Research Model

4. METHODOLOGY

Survey Development
An electronic survey was implemented to test the hypotheses. The survey questions were derived from (Alazzam et al., 2016; HealthIT.gov, 2019; Ng et al., 2009; Sher et al., 2017; Stanford_Medicine, 2018; Tavares & Oliveira, 2018). The survey questions are categorized into eight groups based on the constructs of our research model: demographics, perceived benefits, perceived barriers, privacy, social influence, self-efficacy, trust, and EHR adoption intentions. All items except the demographic items are scaled on a seven-point Likert scale: Strongly Disagree = 1, Somewhat Disagree = 2, Disagree = 3, Neutral = 4, Agree = 5, Somewhat Agree = 6, and Strongly Agree = 7.

Survey participants were health information management professionals. The survey was administered using the Qualtrics online survey platform. The survey consisted of seven demographic questions and 33 EHR questions with a target completion time of less than 15 minutes. All of study participants were informed about the research purpose, confidentiality protection, and the anonymity of the information collected, and each signed a consent form before participating.

Data Processing

A total of 51 responses were received, over a three-week period. After removing the 11 records of missing values, the data collection yielded 40 usable survey response sets. The table below summarizes the demographics of the sample.

Demographic	Category	Percentage
Age	Under 20 years old	0
	20-29 years old	12.5
	30-39 years old	25
	40-49 years old	30
	50-59 years old	20
	60 years or older	12.5
Gender	Male	30
	Female	70
Education	High school	5
	Some college	12.5
	Career training	7.5
	2-year degree	5
	4-year degree	45
	Master degree	17.5
	Professional degree	2.5
	Doctorate	5
Average experience		5.6 years

Table 1. Demographics of Participants

Data Analysis Steps

We conducted a two-step analysis to examine the effects of the key constructs on the EHR adoption intention dependent variable. First, an exploratory factor analysis (EFA) was done to extract the factors (latent variables) to validate our model constructs. Second, a multiple regression analysis was conducted using the SPSS calculated factor scores. The dependent variable was regressed on the six IVs to determine the main effects.

5. RESULTS

Construct Validity and Reliability

We conducted the factor analysis (using primary axis analysis) on the data set to extract the factors that influence HIM professionals' attitude toward EHR adoption. We use 0.5 as the recommended threshold (Hair, Anderson, Tatham, & Black, 1998). Five rounds were run before we arrived at a set of factors loading at 0.5 or above (BAR5 was removed in Round 4 due to unexpected loading on the TRU construct). Eight items (EFF2, EFF3, BAR7, BAR3, PRI2, BAR6, BAR10, and BAR5) having a factor loading lower than 0.5 were removed from further consideration.

The results of EFA resulted in eight factors being extracted from the data: TRU, BEN, INF, BAR_1, BEH, PRI, BAR_2, and EFF. Note that the BAR resulted in the splitting of the original BAR construct into two factors: BAR_1 and BAR_2. This unexpected result will be addressed in the discussions section later in this paper.

Cronbach Alpha coefficient was used to test the reliability of the items. The acceptable value of Cronbach Alpha should be at least 0.70 (Nunnally & Bernstein, 1994). However, for exploratory studies, a minimum Cronbach Alpha value of 0.5 is allowable (Hinton, McMurray, & Brownlow, 2004). Table 2 summarizes the factor loadings and Cronbach Alpha values for each item. The factor loadings for all items are greater than 0.5 and the Cronbach Alpha values for all factors are greater than 0.7 except BAR_2 with a .546. The Cronbach Alpha in BAR_2 is weak but allowable given the low number of questions (two questions) in that construct. Therefore, the factors loadings and the Cronbach Alpha coefficients show construct validity and reliability, allowing us to proceed with our regression analysis and hypothesis testing.

Construct	Item	Factor loadings	Cronbach Alpha
TRU			0.938
	TRU1	.575	
	TRU2	.800	
	TRU3	1.055	
	TRU4	.886	
	TRU5	.618	
	TRU6	.710	
	TRU7	.962	
	TRU8	.744	
BEN			0.885
	BEN1	.819	
	BEN2	.989	
	BEN3	.863	
	BEN4	.526	
INF			0.883
	INF1	.673	
	INF2	.950	
	INF3	1.011	
BAR_1			0.845
	BAR1	.781	
	BAR2	.879	
	BAR4	.831	
BEH			0.927
	BEH1	.828	
	BEH2	1.050	
	BEH3	.763	
PRI			0.844
	PRI1	.858	
	PRI3	.745	
	PRI4	.829	
BAR_2			0.546
	BAR8	.567	
	BAR9	.741	
EFF	EFF1	.739	

Table 2. Factor Loadings and Cronbach Alpha

Hypothesis Testing
To test the hypotheses, a multiple regression analysis was conducted using SPSS. The latent variable, trust has a significant coefficient as expected ($p = 0.008$). Thus, H6 was supported. Other variables were not significant. Therefore H1 - H5 were not supported.

Variables	Coefficient
TRU	.451**
BEN	.204
INF	.186
BAR_1	-.041
PRI	-.071
BAR_2	.208
EFF	.096
R^2	.450
Adjusted R^2	.330

Table 3: Regression Results

6. DISCUSSION

Discussion of Results
The results of this study show that trust is a significant determinant of the attitude toward adoption of EHR. Health care professionals who trust EHR systems have a more positive attitude toward adoption of EHR. Our findings indicate that perceived benefits, perceived barriers, social influence, privacy, and self-efficacy are not significant. Self-efficacy has been reported as a significant determinant in EHR adoption (Sher et al., 2017). However, in our study, only one question about self-efficacy was used in our data analysis, which might not be adequate to measure the respondents' self-efficacy. Social influence was not found as a significant determinant to EHR adoption in the previous literature (Tavares & Oliveira, 2018). Since all of our survey respondents have an average of five years in the health care field and 70% of them have a 4-year degree or a higher degree, they might not find many barriers in using EHR systems. Given the survey respondents' experience of using EHR, they might not likely be influenced by the other people regarding adopting an EHR system.

During the EFA, we found that one perceived barrier question (BAR5) was loaded in the construct of trust. BAR5 says physicians use other means as work arounds for EHR, which indicates certain barriers of using EHRs. In reality, physicians might choose using other means as work arounds for EHR due to personal preference, time limit, or other considerations. Also, BAR5 seems more concrete and observable than the other more abstract BAR questions. This might explain why BAR5 was not loaded in the construct of perceived barriers. Some trust questions seem observable too. For instance, TRU3 (EHRs provides verification of user identity) is concrete and observable. This may help explain why BAR5 was loaded as trust.

The EFA analysis also resulted in the splitting of the perceived barrier factor (BAR) into two separate factors (BAR_1 and BAR_2). A simple look at the questions gives insight into why this may have been necessary (Table 4). The first three items (BAR1, BAR2, and BAR4) all highlight the physician role and look at the perceived barriers from the physician's perspective. These three questions were loaded as BAR_1 (barriers perceived by physicians). The other two items (BAR8 and BAR9) emphasize the barriers as time consuming or considerable investment of effort other than time. These two questions were loaded as BAR_2 (barriers perceived by general health care professionals). Given these differences, it seems at least logical that the perceived barriers factor needs to be split. The question as to how people perceive the barriers of using EHR is one that should be explored in the future.

Item	Question
BAR1	Using an EHR has increased the total number of hours physicians work on a daily basis.
BAR2	Using an EHR detracts from physicians' professional satisfaction.
BAR4	EHRs contribute greatly to physician burnout.
BAR8	Using an EHR is time-consuming.
BAR9	Using an EHR would require considerable investment of effort other than time.

Table 4. Questions of Perceived Barriers

Implications for Research and Practice
There are at least two implications of these findings for the research community. First, trust is a significant determinant to adoption of EHR. The results suggest that the more trust the users have on the EHR systems, the more likely they will adopt EHR. The trust can be built in the forms of EHR capturing, storing, and transferring patient medical records properly. Ensuring that adequate security mechanisms are put in place is an effective way to build trust in health care professionals when considering adopting EHRs. Second, we found that trust is the only significant determinant to adoption of EHR. The limited number of significant factors in the model could be an indicator that better models are needed.

Implications for practice focus around informing health care professionals about the security mechanisms implemented in EHRs so that they can trust the system and be more willing to adopt it. References and tutorials that explain how the patient medical data will be handled in the EHR will help the adoption of EHR. One of the best indicators for adoption of EHR is the decision maker's trust of the technology.

Limitations
There are two limitations that must be acknowledged regarding this research. One limitation of the research is that this was a small sample size. Future research could replicate this study using a larger sample size. Another limitation is that some questions of self-efficacy and perceived barriers were removed due to low factor loadings. This might indicate that future work is required to explore these concepts. For example, the perceived barriers could be measured based on the role of a health care professional in a health care setting. Self-efficacy was measured using one question in our study. There may be other self-efficacy questions, which might be significant in motivating a health care professional to adopt EHRs.

7. CONCLUSIONS

To better understand health care professionals' intention to adopt EHR systems, a survey was developed based on the unified theory of acceptance and use of technology model and the health belief model. The survey of seven demographics questions and 33 EHR questions, expecting to take less than 15 minutes, was administered, to 51 health information management professionals. After removing 11 records with missing values, 40 were considered in the results. The results showed that trust is a significant determinant of the attitude toward adoption of EHR. Perceived benefits, perceived barriers, social influence, privacy, and self-efficacy did not have significant impacts on the health care professionals' attitudes towards EHR. Questions on perceived barriers and self-efficacy should both be explored more extensively in the future. With the continued rise in use of EHR systems in the hospitals, this study hopes to help EHR developers and policy makers to better understand the motives and perspectives that will affect the successfulness of a health care professional to adopt an EHR system.

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Appendix - Survey Questions

The survey questions are categorized into eight groups based on the constructs of our research model: demographics, perceived benefits, perceived barriers, privacy, social influence, self-efficacy, trust, and behavior intentions.

All items except the demographic items are scaled on a seven-point Likert scale: Strongly Disagree = 1, Somewhat Disagree = 2, Disagree = 3, Neutral = 4, Agree = 5, Somewhat Agree = 6, and Strongly Agree = 7.

Demographics (DEM):
DEM1: Age verification - I verify that I am at least 18 years old (yes/no)
DEM2: What is your age? (<20, 20-29, 30-39 , 40-49, 50-59, 60+)
DEM3: What is your gender? (Female, male)
DEM4: What is your highest level of education? (Less than high school diploma, high school or equivalent, some college, career training, 2-year degree, 4-year degree, master's degree, doctorate degree, professional degree)
DEM5: What is your title in your current position?
DEM6: How many years of experience do you have in your field? (0, <1 year, 1-2 years, 3-4 years, 5+ years)
DEM7: Do you have experience with Electronic Health Record (EHR)? (yes/no)

Perceived benefits (BEN):
BEN1: Using an EHR improves the quality of health care I provide to my patients.
BEN2: Using an EHR improves the communications between my patients and me.
BEN3: Using an EHR fosters my patient engagement in their care.
BEN4: Using an EHR reduces medical errors for my patients.

Perceived barriers (BAR):
BAR1: Using an EHR has increased the total number of hours physicians work on a daily basis.
BAR2: Using an EHR detracts from physicians’ professional satisfaction.
BAR3: Using an EHR detracts from physicians’ clinical effectiveness.
BAR4: EHRs contribute greatly to physician burnout.
BAR5: Physicians often use other means (paper notes, scanning, faxing, etc.) as work arounds for EHR.

BAR6: There are more challenges to using EHRs than benefits.
BAR7: Using an EHR is inconvenient.
BAR8: Using an EHR is time-consuming.
BAR9: Using an EHR would require considerable investment of effort other than time.
BAR10: Using an EHR would require changing work habits, which is difficult.

Privacy (PRI):
PRI1: The chance that EHR privacy may be breached is high.
PRI2: There is a strong probability that EHR privacy breaches may lead to privacy issues.
PRI3: The use of EHR is likely to cause privacy issues.
PRI4: I am concerned for the privacy of my patient's personal information during data transmission among different EHR’s.

Social influence (INF):
INF1: Most people who influence me think that electronic health records are helpful.
INF2: Most people who are important to me would use electronic health records.
INF3: Most people who are important to me believe that it is good to use electronic health records.

Self-efficacy (EFF):
EFF1: I am confident that I could complete a task using an EHR if I had seen someone else use it before trying it myself.
EFF2: I am confident that I could complete a task using an EHR if I could call someone for help if I got stuck.
EFF3: I am confident that I could complete a task using an EHR even if there was no one around to help me.

Trust (TRU):
TRU1: EHR are predictable and consistent regarding the usage of the information.
TRU2: EHR are honest with patients when it comes to using personal health information provided.
TRU3: EHRs provides verification of user identity.
TRU4: EHRs provide the actual identity of the user as claimed.
TRU5: EHRs provide authorization to access control of stored data according to the entity's privileges/rights of use.
TRU6: EHRs ensure the confidentiality of information accessibility.
TRU7: EHRs ensures that the data collected will be solely used for the intended purpose.
TRU8: EHRs ensures that stored data are protected from unauthorized manipulation/alteration.

Behavior intention (BEH):
BEH1: I intend to use EHRs.
BEN2: I intend to use EHRs in the next months.
BEN3: I plan to use EHRs frequently.