Examining Predictors of Health Information Technology Usage among Early Career Physicians

BY

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THESIS

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This thesis is dedicated to my mother, father, Mark and Brian, without whose love and support I could never have aimed so high.

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LIST OF ABBREVIATIONS

AHRQ	Agency for Healthcare Research and Quality
CPOE	Computerized Physician Order Entry
ECP	Early Career Physicians
EMR	Electronic Medical Record
FC	Facilitating Conditions
GHU	General Health Information Technology Usage
HIE	Health Information Exchange
HIT	Health Information Technology
ICT	Information and Communication Technology
MAPP	Mobile Application
MMIT	Medication Management Information Technology
NA	Not Available or Applicable
PHR	Personal Health Record
SEM	Structural Equation Modeling
SM	Secure Messaging
TAM	Technology Acceptance Model
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology

SUMMARY

The use of Health Information Technology (HIT) is becoming more prevalent in medical care provision throughout the United States and research suggests that the utilization of HIT tools by physicians provide advantages to the patient by improving efficiency, care provision, and ultimately clinical outcomes. As healthcare organizations introduce voluntary new tools in clinical practice settings, understanding the underlying predictors of physician usage remains an important area of research, as high frequency usage is key to technology implementation success.

We conducted a study on predictors of HIT use among Early Career Physicians (ECP), defined as medical residents and fellows, using a cross-sectional written survey. The goals of the study were to explore the provider perspective by identifying items of importance to HIT adoption (for outcome variables of general usage and specific tool type usage) and determine how usage varies by other variables such as facilitating conditions and physician characteristics. The sample consisted of 246 physicians at an urban academic hospital in the Midwest region of the United States. All variables were self-reported measures, and dependent variables measured HIT frequency of use through ordinal scales. A general HIT usage composite variable was calculated, with high-frequency use defined as respondents who indicated above the median frequency for three out of four tool types. Factors associated with high use were examined by logistic regression.

Facilitating conditions, a multidimensional factor reflecting organizational support for usage of technology, was found to be positively associated with high general HIT usage and high specific tool usage for one of four tool types (mobile health applications); furthermore, the association of usage with facilitating conditions and physician characteristics varied by the general HIT and tool type dependent variable. Models examining relationships between high HIT use, facilitating conditions factor, and additional variables suggest particular topics, such as information and communication technology and data sharing, may be of higher importance to ECPs who are high users of technology and should be considered for inclusion in training and ongoing organizational support.

These findings, used in conjunction with user learning preferences, may provide information for healthcare organizations to target training and implementation of HIT tools to physician subpopulations as a means to promote greater acceptance and optimal use of technology. In addition, examining the provider perspective should be included in comprehensive assessments of HIT, and results of this study should be considered with other research when implementing HIT tools, in order to improve physician adoption of technology that has the potential to reduce medical errors and improve care coordination.

1. INTRODUCTION

1.1 The Definition and Evolution of Health Information Technology

Health Information Technology is a broad term that can be attributed to various tools (e.g., computers, devices, software, and information systems) that serve many purposes and have many participants, such as provider users, patient users, technology developers, and support staff; however, all tools involve technology that is applied in the context of health. To further define this term, one can categorize it by purpose. These include practice management software, clinical decision support systems, or data sharing and communication tools with other healthcare participants. In consideration to the numerous purposes and participants, the study of HIT is not confined to one academic field and may fall under a number of health-specific and informatics fields. In addition to the multitude of methodological approaches by discipline, it can be expected that this definition and research will evolve over time, as technology improves and overall HIT tool availability, networks, and use increase.

Users of HIT, as well as researchers, recognize the ambiguity surrounding the term. Hersh (2009) recognized the debate over the definition and developed a more unified, yet interdisciplinary, approach to understanding the study of HIT. His definition of HIT comprises of a strong overlap of Information and Communications Technology (ICT), which focuses on the technology itself with network and communication ability, and the fields of medical and health informatics, which focus on the study of acquisition, storage, and use of information in the health setting.

For the purposes of the current research, HIT is broadly defined as any information technology that is used in healthcare, specific to the following tool types that involve multiple participants for the purpose of clinical care and communication or sharing of data: Computerized Physician Order Entry (CPOE), Personal Health Records (PHR), Mobile Health Applications (MAPP), and Secure Messaging (SM).

1.2 **The Potential of Health Information Technology to Transform Healthcare**

Despite the ambiguity of the term, HIT is promoted as a means to improve efficiency, quality of care, and care coordination by the Committees on Energy and Commerce, Ways and Means, and Science and Technology (2009), and receives federal funding through the Health Information Technology for Ecomonic and Clinical Health Act. These goals for HIT are believed to be accomplished when “providers use them to their full potential. . . .”—in other words, when data is able to be free-flowing, secure, and private, and also when tools are easier to use with enhanced capabilities (Blumenthal, 2010, 382). Furthermore, it is believed that HIT adoption has the potential to integrate and support patient-centered models of care that promote patient safety, clinical effectiveness, and practice efficiency (Bitton et al., 2012).

Personal health records are specific HIT tools that have various uses and are characterized by varying degrees of integration. After roundtable discussions by Kaiser Permanente Institution, the American Medical Informatics Association, and the Agency for Healthcare Research and Quality (AHRQ), Detmer et al. (2008, 1) summarized the potential of PHRs as follows:

> only the integrated model has true transformative potential to strengthen consumers' ability to manage their own health care. Integrated PHRs improve the quality, completeness, depth, and accessibility of health information provided by patients; enable facile communication between patients and providers; provide access to health knowledge for patients; ensure portability of medical records and other personal health information; and incorporate auto-population of content.

Information and communications technology also has the potential to improve health service provision, although this may be limited by tool capabilities. Health Information Exchanges (HIE), a subcategory of HIT, is recognized by Williams et al. (2012, 527) for its goal to allow "for information to follow patients to support patient care." Therefore, overcoming barriers and understanding usage of these tools will be important steps to realizing HIT tools' full potential to transform healthcare.

1.3 **Research in Health Information Technology**

In recent years, research on the impact of HIT has increased, and results indicate that care provision quality improvement is possible with availability and use of specific tools (Poon et al., 2010), although there remain areas for enhancement around coordinated care (Bates and Bitton, 2010; O'Malley, 2011). Results from independent studies report advantages of Medication Management Information Technology (MMIT), although reviews have been less definitive in their conclusions (McKibbon et al., 2012; Mueller et al., 2012). McKibbon et al. (2012, 27–28) suggest that the relatively large amount of studies on electronic medication ordering show promise, and that "consistent with other reviews of MMIT, most studies measured changes in process and the majority of these showed benefit"—their review assessed the primary end points of 87 trials, in which 69 used process indicators and 23 used clinical outcomes. Although MMIT showed significant improvement in prescribing behaviors, findings remained unclear if patient outcomes improved. More research correlating provider usage process indicators and clinical outcomes is needed to assess how outcome improvement can be widely achieved. Thus, there are ambiguous findings of HIT's impact on clinical outcomes, even among high-quality reviews on highly used tools that are often studied, such as MMIT, in which gaps exist in methods, reporting, and indicators (McKibbon et al., 2011).

A review of MMIT clinical decision support tools that examined technology's impact on adverse drug events also concluded ambiguous findings and suggests the need for further research (Fischer et al., 2010). Focusing on the broad use of HIT, rather than a specific tool, a review by Chaudry et al. (2006) concluded that HIT reduces paper dependency to cut costs, leads to more accurate and timely surveillance and monitoring, and can improve outcomes through a 54%–61% reduction in utilization of care and a substantial reduction in medical errors. Overall, HIT has been shown to afford advantages to the patient and healthcare organization in individual studies and reviews. However, there remain questions in assessing the overall effect of clinical outcomes in reviews, as outcome indicators vary considerably, and may be confounded by HIT use.

1.4 **Research Methodologies**

Standardized research remains not only an obstacle for reviews of HIT, but also for comparison of particular tools that are implemented in specific contexts, as each healthcare organization is unique and tools may be customized. Comparisons may be limited by varying approaches to outcomes that include: economics, patient outcomes, physician usage, and qualitative interviews (McKibbon et al., 2011). Reliance on the use of popular methods such as the randomized controlled trial has also been called into question for evaluating HIT, because incorporating context-specific usage that is dependent upon social and organization factors add to the difficulty of translating research results to practice settings (Kaplan, 2001). While enabling adaptation to unique aspects for specific health organizations, using varying measures limits comparability of findings.

One attempt to develop a parsimonious and complete model for evaluating the impact of HIT on patient safety and quality outcomes is the Triangle Model. This model incorporates socio-behavioral aspects and uses four main components: technology, organization, provider, and patient, and three main processes or activities: provider-technology, organization-technology, and organization-provider (Ancker et al., 2012). The advantage of this model is that it incorporates technology tools, usage, and facilitation of tools, in addition to recognizing organizational and social factors. The current study focuses on a specific piece of this model—the provider perspective, and examines the relationship of provider usage of technology with organizational support. While the current research is not designed as a comprehensive assessment, it addresses the need for research to highlight items of importance related to ECP HIT use.

1.5 Potential Confounders of Usage on Research Results and Generalizability Limitations

Health Information Technology is a complex issue to research, as variation exists not only in research methods, but also in tool types, availability, capability, and usage of these tools. General and specific HIT tool use differs between healthcare organizations, and between and within medical specialties (Schnipper et al., 2009; Pallin et al., 2010). In a national survey, Audet et al. (2004) reported that American subspecialists were significantly more likely to use patient reminders and communicate with other providers via email than primary care physicians (respectively 24% versus 14%, and 30% versus 22%). Variation also exists within specialty, as a survey of 61 Massachusetts emergency departments reported that although 41% captured current visit information electronically, a lower percent used specific tools—15% used medication ordering and 11% used medication error checking (Pallin et al., 2010).

Research also indicates that patient outcomes may vary at different hospital sites with the same tool availability. In a randomized controlled trial conducted at two academic hospitals, use of the same medication reconciliation tool led to different patient benefits, as only one site achieved a statistically significant improvement in the outcome end point related to potential adverse drug events. The researchers theorized that staff, level of integration, and organization-wide sensitization may have impacted results (Schnipper et al., 2009). This particular study illustrates the multifaceted nature of HIT implementation and use, as well as the potential impact of usage, not only availability, on patient outcomes.

A major impediment to generalizability of HIT study results may arise from the type of healthcare organization that serves as a site for research. Most high-quality studies of HIT emerge from leading healthcare and academic institutions that are predominantly larger entities and presumed to have more resources for HIT adoption. In a sample of 1,837 physicians in a cross-sectional survey in the United States, 69% of salaried physicians used an Electronic Medical Record (EMR), versus 51% of non-salaried physicians, and 87% of physicians employed at larger health entities (entities with more than 50 physicians) had electronic access to test results, versus 36% of solo physicians (Audet et al., 2004). This effect may lead to results that are not generalizable to other practice sizes that may have varying resources. For instance, large urban hospital systems are likely to have different infrastructure, training, support services, and even product availability than practice sites of solo practitioners.

Trends among hospital HIT acquisition also vary with market availability of products, as one study identified differences in EMR vendor activity between hospital sizes and between geographic area within the United States (Vest et al., 2012, 229), and the researchers discovered that "the pace of EHR market changes was statistically different ($p<0.01$) across the categories of hospital size," with more product availability for smaller and medium-sized hospitals and no significant change among large hospitals (defined as hospitals with more than 250 beds).

Issues into the disparity in product availability, compatibility of complimentary specific tools, and adoption require more examination, and this, in addition to disparities among availability and use between hospitals, and between and within specialties within organizations, support the need for more organization-specific case studies, as well as comparison between organizations.

1.6 **Participants in Health Information Technology and Coordinating Care**

While tool capabilities are key issues for HIT implementation success, the ability of users to utilize the tools to their full potential is also a critical factor. Participants in HIT are not limited to only physicians and patients, but extend to a variety of health professionals including: nurses, pharmacists, public health officers, managers, community workers, and social workers. One example is an HIE that uses real-time health information from hospital staff to inform public health officials of cases for potential outbreak investigation. Another example is telemedicine, which allows physicians to manage patient care from a distance.

However, using HIT for improving coordinated care through patient-medical homes, a team-based care model led by one physician, remains a mostly unmet potential use (O'Malley, 2011). One obstacle in assessing this is the lack of standardization in defining “coordinated care” as an outcome variable when evaluating HIT. Sponsored by the AHRQ, the task of consolidating a working definition for coordinated care was undertaken by a meta-review of more than 40 definitions of the topic found in peer-reviewed journals. In this review, coordinated care is described by McDonald et al. (2007) as encompassing the following elements: (1) numerous participants (including the patient) are typically involved in care coordination; (2) in order to carry out these activities in a coordinated way, each participant needs adequate knowledge about their own and others' roles and available resources; (3) integration of care activities has the goal of facilitating appropriate delivery of health care services; (4) coordination is necessary when participants are dependent upon each other to carry out disparate activities in patient care; and (5) in order to manage all required patient care activities, participants rely on exchange of information. Care coordination is thus characterized foremost by the participation of multiple persons. Secondly, it focuses on appropriate care delivery, increased communication of roles, and sharing and integration of information from disparate activities. These elements of care coordination have the potential and need to be strengthened through the implementation of HIT tools.

1.7 **The Provider Perspective**

Much HIT research is currently focusing on how organizations can maximize the potential of HIT to reduce adverse drug events, medical errors, and enhance care utilization. Individual health care provider usage of HIT tools will impact these outcomes (Ancker et al., 2012), and attitudes and psychosocial factors are related antecedents to frequency of use (Venkatesh et al., 2003). There is also need for further development research into understanding the multifaceted nature of facilitating conditions (Garcia-Smith and Effken, 2013) and physician usage of HIT tools in a dynamic healthcare environment.

1.8 Usage and the Early Career Physician Perspective

Factors related to ECP high usage of HIT remains an important, yet under-researched area that will have long-term impact as providers age through the system. Considering the disparity of HIT use by individual physician characteristics and practice setting, this survey will focus on exploring key provider factors of importance for HIT associated with care provision.

Uncovering the ECP perspective may be important to organizations, and results of exploratory research about factors associated with high usage among this subpopulation may be translated into actionable change. This research seeks to identify factors associated with high usage of technology that may be used to inform targeted interventions including trainings and support services. Used in conjunction with user learning preferences, a strategy for targeted implementation to ECP who are high users may be more effective to promote specific tool usage, thus leading to general high usage, improved patient care, decreased medical errors, and ultimately improved patient outcomes.

2. CONCEPTUAL FRAMEWORK AND RELATED LITERATURE

2.1 The Technology Acceptance Model

The Technology Acceptance Model (TAM) (Davis et al., 1989) describes the special case of technology adoption in the workplace. It emerged from the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975) that considers the complex relationship between beliefs, attitudes, intention, and behavior, and allows for the inclusion of the Theory of Planned Behavior, an extension of TRA to include the relationship of voluntariness and use (Simon and Paper, 2007). The TAM's most current iteration is the Unified Theory for Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and includes a factor for Facilitating Conditions (FC) and omits an explicit construct on attitudes. The results of UTAUT were reported in a 2003 review of eight competing acceptance models. The theory has been popularized in a variety of research fields on the basis of strong psychometric techniques and psychological theory of the attitude-behavior relationship, inclusion of sociological and environmental factors, and potential for organizations to use the results—as understanding technology acceptance factors can be used to inform targeted training (Venkatesh et al., 2003). In the 1990s, as technology gained popularity in healthcare, the TAM was successfully adapted by researchers in health informatics to examine tools such as telemedicine (Sheng et al., 1998) and continues to be used for tools such as EMR (Tavakoli et al., 2013). Aspects of the theory are also incorporated into Ancker's Triangle Model for HIT evaluation (Ancker et al., 2012). The evolution of the theory led to numerous iterations of the underlying theory, model, and variables that now form a diverse body of research with strengths and weaknesses.

A primary advantage of the UTAUT model framework is that it has undergone reliability and validity testing in multiple countries, industries, and workplace settings. Origins for this psychometric behavior model can be found in sociological TRA and the Theory of Planned Behavior. The theory was adapted to examine the relationship between attitudes and behavior, as well as the influence of other contributing context-specific variables that can be applied to a flexible theoretical framework (described as antecedent or external variables).

Another strength of the TAM, besides the validation of the constructs over time in the health care setting, is the strong inter-item correlation between items for its latent constructs for performance expectancy, effort expectancy, facilitating conditions, and subjective norm subscales. Although these constructs have undergone many adaptations and contributing factors have been edited to suit the needs of specific research, the model components have continued to be popular in current HIT research (Sheng et al., 1998; Garcia-Smith and Effken, 2013; Tavakoli et al., 2013).

However, there are also disadvantages to UTAUT. Behavior is complex, and may be influenced by specific tool, user type, voluntariness, and workplace setting; these context-specific factors reduce reliability of adopting prior results to new research. The model itself may also be limited in translating the theory and more distal attitudes into actionable facilitation of usage behavior for specific tools. In addition, the model risks oversimplifying human behavior in statistical analysis. This may lead to an identification problem that may result from various sources, such as overly similar question items to describe the same construct, or inclusion of concepts that are overly similar, and complex covariances (Hayduk, 1987).

Weaknesses of the TAM have been considered and evaluated through subsequent research studies after the formation of the model. Particular uses of specific HIT tools and general use were incorporated into the current research survey tool, as well as the added FC factor and other construct variables. Specific usage of many tools reflects general usage, which may be important to encourage high usage of newly introduced and voluntary tools designed to improve patient care. In order to address some of the weaknesses and adapt the theory to the current context, additional variables on specific uses were added that reflect experiences of early career physicians as they further their training in the health setting.

2.2 Adaptation of the Technology Acceptance Model

For the scope of the current research project, reflecting general usage, focus was placed on the a priori factor of FC, with inclusion of individual variables representing performance expectancy, effort expectancy, and subjective norm.

2.2.1 Facilitating Conditions and Other Unified Theory of Acceptance and Use of Technology Variables

Use of EMR has been found to be associated with FC and underlying attitudes, such as "difficulties with technology, complementary changes and support, electronic data exchange, financial incentives, and physicians' attitudes" (Miller and Sim, 2004, 119), however, these findings had the greatest effect among smaller practices. To address some of these difficulties, the FC factor was comprised of statements of importance regarding: resource availability, knowledge, support services, and compatibility of tools.

This construct examines the importance of organization-level aspects and may be used for potential recommendations to remove barriers from higher levels of usage during implementation. In UTAUT, the FC construct is defined “as the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system” (Venkatesh et al., 2003, 453). Venkatesh’s review found FC to be strongly associated with usage of tools as a predictor for both intended and actual use, as well as suitable in contexts with varying degrees of voluntariness. The effect was stronger among older users, who may place greater importance on support services.

Facilitating Conditions also involves the compatibility or integration of systems leading to usability issues, a primary concern related to usage differences and possible impact on potential adverse drug events (Schnipper et al., 2009).

The other primary TAM variables and domains included: effort expectancy reflecting ease of use, performance expectancy reflecting perceived usefulness, and subjective norm reflecting influence from other people. Additional variables outside of TAM were included in the current research for their potential effect modification of the association between the FC factor and usage. These may be considered vital as they may add to the completeness of the model describing the data; however they may lead to difficulty in establishing reliable estimates of the primary TAM constructs.

2.2.2 Other Variables Related to Technology Acceptance

Variables related to usage vary by the type of research, tool, and population. A study of PHR among the elderly cited computer literacy as the primary patient-centered barrier to use (Lober et al., 2006). Physician attitude, although not prior experience, training, or satisfaction, was determined to be a statistically significant predictor of CPOE usage among primary care physicians (Schectman et al., 2005). This indicates a need to further explore variables that reflect barriers and attitudes, through methods such as compiling perceived importance of topics related to HIT.

Variables regarding provider-side barriers were considered in the study design, including: computer literacy, general communication, incorporating technology into routine care, research into HIT's impact on clinical workflow, support from administration, awareness to legal and regulatory issues, feeling a greater sense of security and privacy, and using evidence-based tools.

There is also the need to further uncover importance for particular uses of specific features of HIT tools, as "availability and use of specific EHR features by primary care physicians was associated with higher performance on certain quality measures." (Poon et al., 2010, 203). The current research includes statement items on particular uses of tool types for data sharing and ICT between providers, and data sharing and ICT between physician and patient.

2.2.3 **Physician Characteristics**

The physician characteristics added to the current study serve as external variables and include: years of experience, age, gender, and care type.

Adapted from UTAUT, external variables of age, experience, and gender were included to assess potential confounding or interaction. An additional variable, care type, was included to examine differences between specialties, defined as self-identified primary care physicians or subspecialists/other. Experience, gender, training, and age characteristics have been shown in prior research to be predictors of usage for workers across industries (Venkatesh, 2003), although little is known about the effect of these characteristics among ECP and between care types. The inclusion of these characteristics is supported by Ancker et al. (2012, 63), who state that: "some provider attributes such as specialty, typing skills, EHR training and experience, and age may influence how much they use the technology."

Experience has been consistently discovered to be a highly significant modifier that influences the effect of effort expectancy and subjective norm on behavioral intention. The effect is understood to be stronger among older workers and with workers with less experience. The effect of the experience and age influence on the relationship between facilitating conditions and actual usage is somewhat different, with a stronger effect among older workers with more experience (Venkatesh et al., 2003). The TAM suggests that younger workers may be high users of technology. A study on user satisfaction found that younger age groups were more familiar with a CPOE tool, and user familiarity and training of a CPOE tool was positively related to satisfaction, and familiarity was positively related to frequency of use (Ghahramani, 2009). However, Ghahramani (2009) did not find significant effects of specialty, prior use, or gender on user satisfaction.

2.2.4 **Intended and Actual Usage**

The direct effect of future or intended use of technology was testable within the current research, based on prior results of a strong statistical association between behavioral intention and actual behavior. In a meta-analysis, Sheppard et al. (1988) concluded that among 87 studies, the correlation was approximately 0.53 between behavioral intent to use and actual use. Under the UTAUT model and review by Venkatesh et al. (2003), the direct effect of intention and actual use was again examined and determined that intention to use is a significant predictor of usage.

2.2.5 **Dependent Variables**

The current research considers a more generalized view of high and low frequency of HIT use, as well as tool-specific use. Question items from a survey tool developed for this research project were framed with consideration to the overarching theme of tools used for care provision that encompass aspects of coordinated care, as described by AHRQ. The specific tools selected represent care coordination and improving quality of care; CPOE for prescription ordering and communicating between providers (e.g., pharmacist and physician), PHR for patient health information management and data sharing between patients and physicians, SM for communication among health practitioners and between practitioner and patient, as well as potential sharing of information or communication via health-specific mobile applications.

3. METHODS

Analysis was conducted on cross-sectional data collected from January through April 2013 by an anonymous survey distributed to ECP (defined as residents and fellows) at one urban academic hospital system in the Midwest region of the United States. This study was not designed as a formal evaluation of any particular tool, but exploratory research into predictors of general usage on FC and items of importance, among a subpopulation of physicians. There was no baseline for usage frequency for the selected tools or general usage, nor on self-identified physician care type. The maximal target sample size was estimated to be 350 based on feasibility and resource availability.

Subjects were recruited from a convenience sample of resident physicians and fellows, based on departmental consent to participate and availability of resources ($5 gift cards were distributed as non-contingent incentives). The ECP were identified through department staff or at department conferences. The researchers were not able to identify respondents from the completed and returned surveys. The materials, contained in a non-descript envelope, included the survey instrument, introductory cover letter, and incentive. The Institutional Review Board at the University of Illinois at Chicago approved the study and survey instrument.

3.1 Survey Instrument

The survey tool for the research study consisted of questions developed in consultation with senior researchers and physicians, including experts in epidemiology, HIT, survey methodology, and practicing medical professionals. The tool collected information on subject demographics and characteristics, knowledge, learning style, technology usage, and 36 statement items with a 7-point response scale of importance. A scale with 7 points was used in other similar studies using TAM (Davis, 1989; Simon and Paper, 2007), although these responses ranged from strongly disagree to strongly agree. The current tool's response scale for items of importance ranged from 1–7, with 1="not important at all" and 7="extremely important." This was an unforced scale that included the middle value of 4 as "neutral/ no opinion either way."

Items of importance were generated from UTAUT, sources available for reproduction by the AHRQ HIT Compendium, and review of the literature. Prior survey questions used specifically for testing the TAM model and its associated theories were included—these related to constructs for FC (q25, q30, q31, and q35), performance expectancy (q1 and q14), effort expectancy (q18 and 36), and subjective norm (q16 and q29). Question text is available in Appendix A. Additional survey items were chosen based on reviewing prior research published in medical and peer-reviewed journals. Items were chosen for their relevance to HIT adoption in medical care provision, as well as potential relationship with HIT use for clinical care. These included topics of specific tool and general HIT use, overcoming provider-side barriers, ICT and data sharing between providers, ICT and data sharing between providers and patients, and coordinated care aspects.

For the dependent variable items, the statement was phrased in a consistent manner to assess frequency of use. The response scale categories were defined as follows: 5="Everyday," 4="A few days per week," 3="About once a week," 2="Less than once a week," 1="Don't use," 0="Not available or applicable" (NA).

Most items were closed-ended questions and designed to be unforced, and some questions were open-ended to allow for additional information gathering. Open-ended questions included self-described practice setting, other EMR brands that were not listed, and other items of importance that were not listed.

3.1.1 **Physician Characteristics**

Age was analyzed as a continuous variable and gender was binary. Experience was assessed in years by the question: “How many years of experience do you have working with any Electronic Medical Record?” with a response range from “less than 1” to “4+.” The current study included an additional variable for care type based on a question about the respondents’ practice setting. Response categories for this question were: primary care, subspecialist, or other.

3.1.2 **Facilitating Conditions**

Facilitating conditions consisted of four variables: “Having increased resources to assist me in using EMR components to its full potential,” “Increasing my knowledge of EMR components,” “Having a specific person readily available to assist me with system difficulties,” and “Using HIT tools that are fully compatible to my EMR system”; these items had a response scale of 1–7, indicating self-perceived level of importance.

For subsequent regression analysis, a z-score based on the sum of FC factor indicators was used. This was done to increase interpretability of models by using z-score for factors and maintaining the original response scale for individual covariates. The z-score has a mean of 0 and a variance equal to 1; meaning that a one-unit increase in z-score indicates one standard deviation above the mean and a one-unit decrease indicates one standard deviation below the mean. Other individual variable covariates are interpreted as one-unit changes in importance.

3.1.3 **General Health Information Technology Usage Variable**

The dependent variable used in logistic regression modeling, known as General HIT Usage (GHU), was a dichotomous indicator calculated from a multistep process using a normative approach. This general composite variable was developed by first calculating the median responses for each HIT tool (the decision to omit intended use is discussed in the following section). The second step was to create a sum for each respondent based on the median score of the four actual usage questions.

3.2 Tool Development and Validation

The survey tool was pre-tested with five medical students (not included in the inclusion criteria of the study population) to verify overall clarity of instructions, comprehension of wording, face validity of selected content, terminology used within the tool, feasibility, and acceptability for participation. The results of this pre-test led to refined instructions, the inclusion of a HIT terminology glossary, and estimated time duration needed for survey completion.

3.3 Analysis Plan

Analyses were conducted to uncover the provider perspective. The first analysis was a compilation of the most important variables among the entire sample. The second was a factor analysis to examine FC. Factor analysis for FC was conducted using tests for pairwise correlations with the number of factors determined by a threshold for eigenvalues greater than 1, and Cronbach's alpha measured factor reliability. A standardized score coefficient was calculated and included in regression models.

Thirdly, we conducted regression models to assess the relationship between facilitating conditions and HIT usage, adjusted by physician characteristics. The dependent variable for this logistic regression modeling was for specific tools and the composite variable. This composite used frequency usage information from CPOE, PHR, SM, and MAPP variables and was calculated based on the distribution of responses, creating a unique normative-based variable to the observed data. Sensitivity analysis by tool type was conducted with chi-square tests of independence.

The fourth analysis used the composite variable as the dependent variable, in which items of importance were selected from bivariate regression results that indicated items of statistical significance ($p<0.10$) to general usage. These covariates were added to FC and improved model fit was determined by the chi square likelihood ratio test of reduced and complete models. Analyses were conducted using Stata 13.

4. RESULTS

4.1 Sample Characteristics

Ten out of 15 contacted medical departments participated and 350 of 852 total residents and fellows were reached. Of 350 ECP reached, 246 completed and submitted the survey, resulting in a response rate of 70%. In the invited resident population, the average age was 30 years with a 1:1 ratio of males to females. Within the survey sample, the average respondent was 30 years of age and consisted of 59% females. The gender difference between the sample and population was statistically significant ($t=-2.58$, $p=0.01$).

The respondents also had means of: 2.3 years of post-graduate training, 3.3 years of experience with EMR, and experience with 2.1 EMR brands. Eighty-eight percent of respondents used apps on smartphones or tablets every day for personal use. Fifty-five percent of respondents self-identified their practice setting as subspecialist or other, and 45% self-identified their practice setting as primary care physicians. The respondents had a mean value of 2.2 for an overall HIT knowledge index indicating “good” (calculated as the average of respondents’ average score for knowledge of CPOE, PHR, clinical decision support, Health Insurance Portability and Accountability Act (HIPAA), and HIE; the response scale for knowledge items ranged from 0=“poor” to 4=“excellent”).

4.2 Overall Items of Importance Related to Improving Patient Care

Among the entire sample, medians were calculated to identify the most important items related to improving patient care. Results are reported in Table I and question item text is available in Appendix A. The measurement scale ranged from 1–7, with statistical medians greater than or equal to 6 indicating the items of high importance.

TABLE I

MOST IMPORTANT ITEMS AMONG ALL EARLY CAREER PHYSICIANS, INDICATED BY MEDIAN>=6

Statement	% >=6
Q1	90%
Q2	81%
Q4	55%
Q10	61%
Q11	63%
Q12	77%
Q13	68%
Q14	70%
Q16	51%
Q18	70%
Q19	80%
Q20	55%
Q21	83%
Q22	93%
Q23	54%
Q24	68%
Q25	65%
Q27	53%
Q28	72%
Q29	66%
Q30	53%
Q31	69%
Q35	74%
Q36	76%

4.3 **Facilitating Conditions Analysis**

Factor analysis was conducted on one latent construct identified by UTAUT to confirm that the four a priori predicted factor indicators had a sufficient structure to warrant the creation of one factor. A correlation matrix was produced (reported in Table II) and Cronbach's alpha was calculated to assess reliability of the factor.

TABLE II

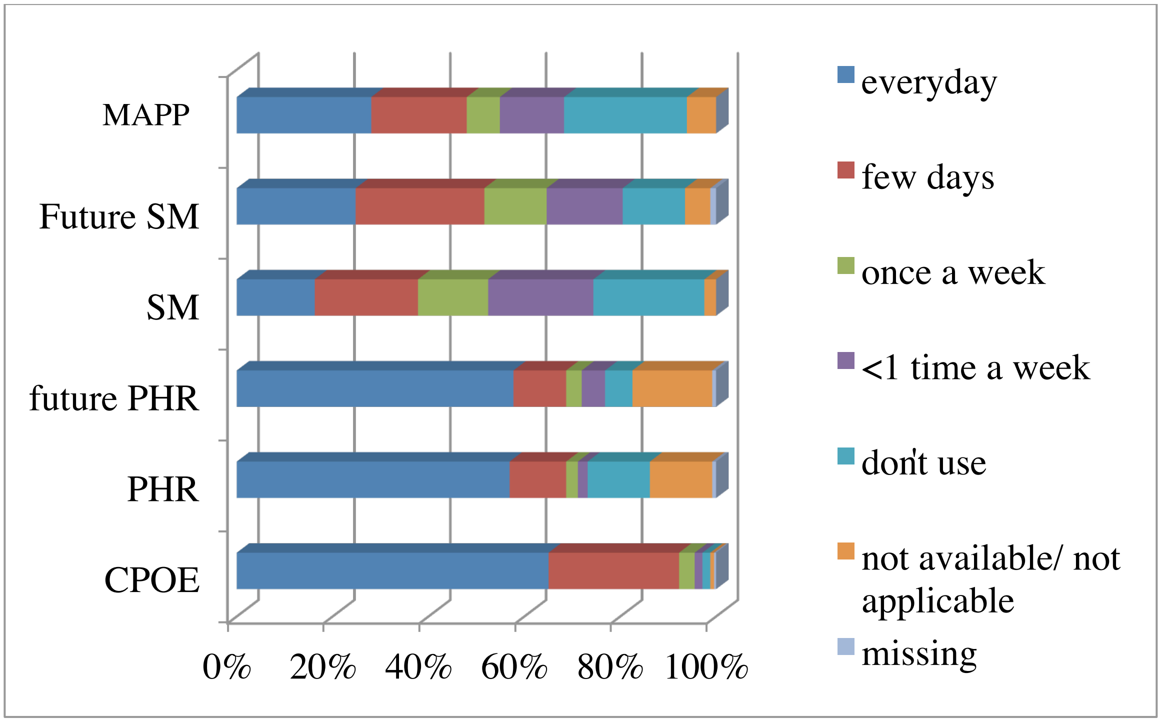
CORRELATION MATRIX FOR FACILITATING CONDITIONS FACTOR INDICATORS

	q25	**q30**	**q31**	**q35**
q25: Resources	1			
q30: Knowledge of components	0.50	1		
q31: Specific support person	0.48	0.44	1	
q35: Compatibility	0.32	0.43	0.39	1

All pairwise correlations between indicators were significant at the $p<0.05$ level, and factor analysis resulted in eigenvalue=1.73 (greater than the standard 1.0 threshold for a significant factor), and Cronbach's alpha=0.75 (greater than 0.7 standard threshold for strong correlation). These results validated the formation of the FC factor, which was then transformed into a sum score and standardized coefficient for subsequent regression analysis.

4.4 <u>General Health Information Technology Usage Composite Variable Analysis</u>

The percent frequency distribution of usage variables for the entire sample is reported in Figure 1, and sensitivity analysis for the dependent variable responses are reported in Section 4.4.2.



Notes: MAPP=Mobile Health Application, SM=Secure Messaging, PHR=Personal Health Record, and CPOE=Computerized Physician Order Entry

Figure 1. Percent response distribution by individual usage variable.

The median frequency of use for each tool type were: PHR=5 (everyday), CPOE=5 (everyday), SM=3 (about once a week) and MAPP=4 (a few days per week). If the respondent scored equal to or above the median on three of four tool types, the respondent was classified as having high GHU. The GHU variable included 196 observations—comprised of 90 high users (46%) and 106 low users (54%). Of the 246 subjects, GHU could not be assessed for 50 (20%) subjects due to missing or NA responses.

4.4.1 Correlation between Intent and Actual Reported Usage

Among respondents who answered all dependent variable questions as possible users, the pairwise Pearson's R statistic=0.88 for the correlation between current and future use of PHR, and the pairwise Pearson's R statistic=0.79 for the correlation between current and future use of secure messaging. Correlations between all individual dependent variables are reported in Table III.

TABLE III

CORRELATION MATRIX FOR ALL DEPENDENT VARIABLES

	CPOE	PHR	FUTURE PHR	FUTURE SM	MAPP	SM
CPOE	1					
PHR	0.17	1				
p-value	0.03					
FUTURE PHR	0.17	0.85	1			
p-value	0.02	<0.0001				
FUTURE SM	0.18	0.04	0.15	1		
p-value	0.02	0.62	0.04			
MAPP	0.12	0.06	0.11	0.39	1	
p-value	0.12	0.45	0.16	<0.0001		
SM	0.14	0.03	0.08	0.76	0.35	1
p-value	0.06	0.74	0.29	<0.0001	<0.0001	

Results indicated that intended use and current use for tool types of PHR and SM were highly correlated, above the threshold of 0.7, with statistical significance determined at the $p<0.05$ level. This supports the UTAUT conclusion that intended usage has a statistically significant direct relationship with actual usage (Venkatesh et al., 2003;

Schectman et al., 2005). In order to reduce duplicity of tools in the GHU variable, the intended use dependent variables were omitted from the composite variable and from regression analysis.

4.4.2 **Dependent Variable Sensitivity Analysis**

Fewer than three responses were missing on any one of the four actual usage questions, and these respondents were dropped from the analytic sample. Respondents responding with NA were also dropped from regression analysis. For sensitivity analysis, respondents who answered NA were compared to respondents who answered categories 1–5 using a chi-square test, in order to assess potential response bias in category responses for individual variables that were used to create the composite dependent variable GHU.

TABLE IV

CHI-SQUARE RESULTS FOR PHYSICIAN CHARACTERISTICS AND USAGE, BY TOOL TYPE

	Care type, 1 degree of freedom chi-square value (p-value)	Age, 18 degrees of freedom	Years of training, 6 degrees of freedom	Gender, 1 degree of freedom
CPOE	2.5057 (0.1134)	8.7126 (0.9660)	1.6305 (0.9504)	0.0664 (0.7967)
PHR	0.0081 (0.9282)	9.0898 (0.9576)	3.7866(0.7055)	1.456 (0.2276)
SM	1.2199(0.2694)	12.2981 (0.8315)	12.6464 (0.0490)[a]	1.66 (0.1976)
MAPP	0.1299 (0.7185)	15.7183 (0.6122)	10.1864 (0.1170)	0.3922 (0.5312)

[a] indicates significance at $p<0.05$

These results, by tool, only identified one statistically significant chi-square value, concluding that the respondents who responded NA versus categories 1–5 were similar. This result indicated that the omission of NA respondents from the GHU regression analytic sample would not lead to significantly biased results.

4.4.3 **Regression Analysis**

Next, we examined the effect of use regressed on FC for each tool type as well as the general HIT use composite variable. This was conducted to identify which tool type was associated with facilitating conditions, without adjusting for physician characteristics. We first conducted bivariate analysis and subsequent multivariate logistic regression to examine the association of use with FC and physician characteristics. Results are reported in Tables V and VI.

TABLE V

RESULTS FOR USE REGRESSED ON FACILITATING CONDITIONS[a]

	FC OR (95%CI)
PHR	1.32 (0.98, 1.79)
CPOE	1.09 (0.81, 1.47)
SM	1.27 (0.95, 1.69)
MAPP	1.39 (1.04, 1.87)
GHU	1.36 (1.01, 1.82)

[a]n=191

Regression results for FC on usage by tool type and general HIT usage, shown in Table V, indicate that higher FC was associated with both higher MAPP and higher general HIT use, significant at the $p<0.05$ level; therefore, an increase of 1 standard deviation for FC is associated with an approximate 1.4 greater odds for being classified as a high MAPP user versus a low MAPP user, and FC is associated with a similar increase in likelihood for being classified as a high general HIT user versus a low general HIT user.

TABLE VI

RESULTS OF USE ON FACILITATING CONDITIONS AND PHYSICIAN CHARACTERISTICS[a]

	FC OR (95%CI)	*AGE (95%CI)*	*EMR_EXP (95%CI)*	*CARE TYPE (95%CI)*	*GENDER (95%CI)*
Model 1: PHR	1.34 (0.96, 1.88)	0.88[b] (0.80, 0.97)	1.20 (0.86, 1.67)	1.08 (0.54, 2,16)	1.25 (0.66, 2.35)
Model 2: CPOE	1.07 (0.77, 1.49)	0.97 (0.90, 1.05)	1.31 (0.94, 1.81)	1.06 (0.53, 2.12)	1.21 (0.65, 2.28)
Model 3: SM	1.08 (0.79, 1.48)	1.03 (0.94, 1.13)	1.04 (0.76, 1.44)	2.17[b] (1.13, 4.19)	1.41 (0.77, 2.58)
Model 4: MAPP	1.41[b] (1.02, 1.95)	0.97 (0.89, 1.07)	0.71 (0.51, 1.00)	0.93 (0.48, 1.80)	1.75 (0.95, 3.23)
Model 5: GHU	1.27 (0.92, 1.75)	0.94 (0.85, 1.03)	1.01 (0.74, 1.40)	1.40 (0.73, 2.70)	1.81 (0.98, 3.34)

[a] n=187
[b] indicates statistical significance at $p<0.05$. Referents: Care type=primary care, Gender=male.

The results of Table VI suggest that predictors of FC and physician characteristics vary slightly by tool type. For each additional year in age, the odds of being classified as a high PHR user versus a low PHR user declined by 12%, controlling for all other covariates. For CPOE, neither FC nor physician characteristics were considered significant predictors of high or low use. For SM, self-identified primary care physicians were 2.17 times more likely to be classified as a high user versus a low user, controlling for all other covariates. For MAPP, for each increase in standard deviation of FC, respondents were 1.41 times more likely to be classified as a high user versus low user, controlling for all other variables.

When comparing bivariate and multivariate results of FC, physician characteristics were found to impact the magnitude of the effect of FC on use in two models; specialty impacted the FC coefficient for SM, and specialty and gender impacted the FC coefficient for GHU. However, for the remaining tool types, results of Table VI were largely similar to the findings of Table V, indicating the additional covariates did not significantly alter the relationship of usage on FC.

4.5 Model of General Health Information Technology Usage with Items of Importance

The aim of this model selection was to examine the relationship of GHU on FC and additional items of importance regarding care provision.

The steps to building the GHU model began with the FC factor score and then individual items related to UTAUT constructs were added. Bivariate logistic regression was conducted for GHU and each item of importance, and items with a $p<0.10$ significance threshold were kept for multivariate regression, which identified 19 significant items out of 32 that were directly related to high general HIT usage (four items were not considered because they were FC factor indicators). Results of the bivariate logistic regression are reported in Appendix B.

Model comparison was next conducted with GHU on FC and 19 significant items, using results of the likelihood ratio chi-square test and decision rule of alpha<0.05 with 1 degree of freedom for each additional individual variable tested with the FC covariate. This provided the statistical rule to identify better model fit for the complete versus reduced model, among the observed data. The results of this analysis showed the effects of both FC and other covariates in relation to usage.

Improved model fit for GHU on FC and the additional 19 items resulted in nine separate models that led to statistically significant improvement of model fit from the FC-only model. Results of the FC factor and 19 additional items are reported in Appendix C. Further specification was ended at this point, due to risk of overly specifying the model. The FC coefficient significance was reduced to insignificance in each model, indicating that the additional items' coefficient was a significant predictor of being classified as high GHU, regardless of FC. In Table VII, nine models were created, each model including the FC score and a different, yet significant, variable related to GHU. The variable number indicates which variable was included in the model in addition to FC; question item text is available in Appendix A.

TABLE VII

RESULTS FOR GENERAL USE REGRESSED ON
FACILITATING CONDITIONS AND ADDITIONAL VARIABLES

Model #	Facilitating Conditions			Additional Variable			
	OR	Lower 95% CI Bound	Upper 95% CI Bound	Variable #	OR	Lower 95% CI Bound	Upper 95% CI Bound
1	1.19	0.86	1.64	q11	1.30	1.00	1.68
2	1.20	0.88	1.65	q4	1.30	1.01	1.66
3	1.22	0.90	1.67	q6	1.27	1.02	1.59
4	1.13	0.79	1.60	q20	1.35	0.99	1.84
5	1.19	0.86	1.64	q3	1.29	1.01	1.63
6	1.17	0.85	1.61	q17	1.27	1.04	1.54
7	1.22	0.89	1.66	q7	1.52	1.15	2.01
8	1.05	0.74	1.49	q27	1.45	1.10	1.91
9	1.06	0.76	1.49	q32	1.48	1.15	1.90

The results from Table VII indicate a negative confounding effect of the introduced additional variable on the effect of use on FC. The results for models eight and nine produced the greatest confounding effect upon FC, which may indicate that feeling a greater sense of security and privacy for electronically transmitted health information and responding to patient questions about treatment electronically may be important to incorporate into basic training, rather than ongoing support, among ECP who are high GHU.

Specific tool usage indicated to be significantly more important for high GHU than low GHU, controlling for facilitating conditions, were identified in this analysis. These included uses between practitioners, such as: “using SM to communicate with in-network health practitioners,” “sharing EMR health information electronically with other practitioners,” and “using secure messaging to communicate time sensitive information with colleagues.” Specific tool usage between ECP and patients include: “using a PHR to communicate with patients,” “sharing EMR health information electronically with patients,” “receiving requests electronically to schedule appointments,” and “responding to patient questions about their treatment electronically.”

Overall, the results suggest GHU on FC is significantly related to the following topics: ICT and data sharing among physicians, ICT and data sharing between physicians and patients, incorporating HIT into routine care, using HIT tools that have automatic alerts that are computer generated, and feeling a greater sense of security and privacy for electronically transmitted health information.

5. DISCUSSION

This study aimed to: identify HIT-related items of importance to ECP related to improving patient care provision, develop a general HIT use variable, examine significant covariates for high HIT use, examine changes the relationship of usage with facilitating conditions with additional variables, and identify items of specific importance for future training and support services to ECP.

5.1 **Implications**

5.1.1. **Items of Importance**

Overall items of most importance may be useful to organizational choices for tool implementation and targeted training material content. In Table I, these are listed with the overall percent of respondents who reported at or above a median of six. Trainings may also be increasingly effective when customized to the preferred learning styles of ECP. Responses from the current research show the most frequent response for preferred learning style method is talking to a knowledgeable coworker—62 of 246 respondents indicated that this was their learning preference.

The responses of learning preferences may also provide insight into opportunities to establish a team-based approach to providing support to all physicians' use of voluntary tools. Coworkers who are high general HIT users may be identified by organizations, and may serve as team leaders for providing support to other physicians' learning of new HIT tools. Organizations should consider using a decentralized method for continuous support through identifying early adopters. Organizations also should consider that items indicated as significant in Appendix B are items of greater importance to high GHU versus low GHU, and items of significance in Appendix C may indicate items that are important in basic training, regardless of organizational support.

5.1.2 **Facilitating Conditions**

The FC factor was found to be a significant predictor for high usage of MAPP and GHU. The significance of the MAPP model may reflect the high voluntariness of using this tool, and the particular importance organizational support may have for promoting its use. The significance for the composite variable indicates, regardless of voluntariness of tool usage and adjusting for possible physician characteristics, for each standard deviation increase in greater importance on facilitating factors, respondents are 1.27 times more likely to be classified as high general users. However, further research is needed to assess the temporal association of usage on FC over time. This research was cross-sectional and did not test whether or not FC promoted more frequent use longitudinally.

Contrary to the results of the theory posited by Venkatesh et al. (2003), the effect of age did not significantly confound the relationship of FC, although age was a significant independent covariate for PHR usage. In addition, variables reflecting other UTAUT constructs, although indicated as important to the entire sample, were not significantly associated with high versus low GHU in regression analysis. Primary care physicians are more likely to be high users of SM than subspecialist or others, which may indicate a significant difference of specialty for specific tool types. Results also suggest a trend that females are greater general users of HIT and specific users of MAPP, although this effect was not statistically significant in the multivariate analysis. These findings suggest potential impact of physician characteristics on specific tool usage.

Facilitating conditions as a construct was supported by the current results, and was found to be a predictor of use that is of increasing importance for voluntary tools, as well as HIT in general, although not significantly modified by physician characteristics among ECP.

5.2 **Limitations**

For this study, setting statistical thresholds of significance for regression model has strengths and weaknesses. While the likelihood ratio chi-square test determines the best fit model for the observed data, selection from numerous variables with the same response scale may lead to an identification error and be vulnerable to collinearity concerns, as this may lead model selection to erroneously omit variables with valuable information.

Research into human behavior has been limited with empirical approaches such as standard regression procedures that have difficulty explaining complex relationships with multidimensional variables, complex covariances, and indirect effects. A priori hypothesis testing has also proven to be difficult in its application to technology acceptance and usage among under-researched subpopulations, and may have limited comparison with other research findings.

Despite the limitations, there is potential to uncover a model with measurement and structural models by the use of Structural Equation Modeling (SEM). This technique uses more information from the data to explain complex relationships, which may be more suited to the study topic and UTAUT (Hankins et al., 2000). This study, however, was not an explicit study of these theories and did not use SEM, and only extracted a more recently added construct of FC. While SEM may provide more information than a regression model, regression models can be used to identify significant differences between high and low users.

In addition, sample size was not high enough to support detailed analysis with numerous predictors, as model result significance levels would be limited by low category counts. Low counts can reduce stability in the regression coefficient estimates.

5.3 **Measurement and Response Bias**

The goal of this research was to uncover the general attitudes and usage of a select physician subgroup of ECP, as usage may vary by physician characteristics. The survey questions of usage did not capture differences based on particular organizational availability of tools, as ECP may practice at various organizations.

A comprehensive list of all items of importance relevant to the ECP perspective on HIT is limited by the survey questions. Findings of this study thus are limited to its closed-ended list of items of importance (listed in Appendix A); this list is by no means exhaustive and based on predetermined potential items, although it does highlight certain topics that are of high importance to ECP.

Actual usage was determined in the survey tool as a self-reported measurement, and may have been a less-sensitive measure of usage than information system logs. Future research should consider a direct measure of actual usage through information system logs, which may collect a variety of data from counting clicks, messages sent, number and time duration of sign ins, and account activations.

While the resident and fellow population was 50% female, the survey respondents were 59% female, suggesting a potential response bias, as females may have been more likely to complete and return the questionnaire than males. This difference may also be the result of sub-specialist departments that were less likely to participate and may have had more males, which may have skewed the ratio of males to females.

5.4 **Future Research**

Future research should consider using objective measurements of usage frequency. In addition, patient outcomes could also be used as an endpoint, as prior research results remain ambiguous regarding the impact of HIT on clinical outcomes.

Studies may consider including more tools into the general HIT usage variable, which would provide greater sensitivity to the GHU composite variable. General and specific usage are important topics to research, as usage may be context-specific.

In addition, a more comprehensive measurement for usage and structural model, such as the Triangle Model, may be important to comprehensive evaluation. This may incorporate results of the current study to identify future curriculum or trainings and topics for evaluation, which were identified by ECP as important. Comprehensive assessments of HIT implementation should examine not only the provider perspective, but examine the dynamic relationship over time, pre- and post-implementation with specific facilitating conditions. Prospective studies can be designed to examine the impact of facilitating conditions on usage change as implementation unfolds.

APPENDICES

APPENDIX A

TABLE VIII

STATEMENTS OF IMPORTANCE REGARDING IMPROVING THE ABILITY OF EARLY CAREER PHYSICIANS TO PROVIDE CARE TO PATIENTS

#	STATEMENT
1	Using Health information technology (HIT) tools that allow me to accomplish tasks quicker than by using paper
2	Using the Electronic Medical Record (EMR) to order prescriptions
3	Using a Personal Health Record (PHR) to communicat with patients
4	Using secure messaging to communicate with in-network health practitioners
5	Using secure messaging to communicate with out-of-network health practitioners
6	Sharing EMR health information electronically with patients
7	Sharing EMR health information electronically with other practitioners
8	Increasing my computer literacy
9	Increasing my patients' computer literacy
10	Using a PHR to improve my knowledge of my patients' other care activities
11	Using secure messaging to communicate time sensitive information with colleagues
12	Increasing clear communication to other health care providers
13	Incorporating Health Information Technology (HIT) into my routine care provision
14	Using HIT to improve my job performance
15	Increased ongoing research for HIT changes that impact clinical workflow
16	Support from administration to incorporate HIT tools in my care
17	Receiving requests electronically to schedule appointments
18	Using the Computerized Physician Order Entry system for checking contraindications
19	Using HIT tools that are easy to use

APPENDIX A (continued)

TABLE VIII (continued)

20	Using HIT tools that have automatic alerts that are computer generated
21	Being able to refill medication electronically
22	Being able to order lab or diagnostic tests electronically
23	Receiving patient reports of changes to their symptoms electronically
24	Viewing patient-generated reports of clinical values (e.g., blood pressure)
25	Having increased resources to assist me in using EMR components to its full potential
26	Increasing my awareness of legal and regulatory issues regarding HIT tools
27	Feeling a greater sense of security and privacy for electronically transmitted health information
28	Sending referrals or follow-ups electronically
29	Using HIT tools that are used by the majority of my colleagues
30	Increasing my knowledge of EMR components
31	Having a specific person readily available to to assist me with system difficulties
32	Responding to patient questions about their treatment electronically
33	Trying HIT tools that have demonstrated success in peer-reviewed literature
34	Receiving requests electronically from patients for assistance with insurance, such as wri letter on my patients' behalf
35	Using HIT tools that are fully compatible to my EMR system
36	Using HIT tools that are intuitive to learn

APPENDIX B

TABLE IX

RESULTS OF GENERAL HEALTH INFORMATION TECHNOLOGY USAGE REGRESSED ON ITEMS OF IMPORTANCE

	b	p	95% CI lower bound	95% CI upper bound
q1	0.0200897	0.9110371	-0.3323212	0.3725005
q2	0.2697414	0.0620464	-0.0135885	0.5530713
q3	0.296634	0.0074384	0.0794174	0.5138505
q4	0.2961434	0.0128788	0.0627674	0.5295193
q5	0.1643642	0.0954987	-0.0288768	0.3576051
q6	0.2694996	0.0111732	0.0613164	0.4776827
q7	0.4013725	0.0026796	0.1393466	0.6633984
q8	0.0932657	0.2330046	-0.0600037	0.2465351
q9	0.1170225	0.1717439	-0.0508073	0.2848523
q10	0.212953	0.0515371	-0.0014201	0.4273261
q11	0.2797368	0.017517	0.0489498	0.5105237
q12	0.2393685	0.0729386	-0.0222586	0.5009955
q13	0.2878885	0.0278527	0.0313355	0.5444416
q14	0.1712251	0.1726455	-0.074857	0.4173072
q15	0.229306	0.0460071	0.0040641	0.4545479
q16	0.0294797	0.7965617	-0.1946448	0.2536042
q17	0.2465581	0.0060645	0.0704658	0.4226503
q18	0.2421636	0.089013	-0.0369287	0.5212559
q19	0.2267154	0.1461089	-0.0790158	0.5324466
q20	0.3381313	0.0096255	0.0821542	0.5941084
q21	0.339175	0.0163604	0.0622767	0.6160733
q22	-0.1142596	0.5615048	-0.499967	0.2714478
q23	0.1454929	0.1396857	-0.0475796	0.3385654
q24	0.1630203	0.138473	-0.0526487	0.3786892
q25	0.2697176	0.0483955	0.0019014	0.5375339
q26	0.1632144	0.1269916	-0.0464048	0.3728337
q27	0.3715343	0.0017596	0.1387412	0.6043273
q28	0.2651447	0.0395293	0.0127083	0.5175812
q29	0.1450515	0.2237242	-0.0886128	0.3787158
q30	0.2042437	0.0796229	-0.0241294	0.4326169
q31	0.0946169	0.4812377	-0.1686832	0.357917
q32	0.4132525	0.0002773	0.1904666	0.6360384
q33	0.2591273	0.0194769	0.0417385	0.4765161
q34	0.3032797	0.0016593	0.114292	0.4922675
q35	0.196046	0.2059807	-0.1077767	0.4998687
q36	0.2510255	0.1140467	-0.0603157	0.5623666

APPENDIX C

TABLE X

RESULTS FOR GENERAL HEALTH INFORMATION TECHNOLOGY USAGE REGRESSED ON FACILITATING CONDITIONS AND ADDITIONAL VARIABLES

	Model 1					**Model 2**					**Model 3**				
	model stats	*b*	*p*	*min95*	*max95*	*model stats*	*b*	*p*	*min95*	*max95*	*model stats*	*b*	*p*	*min95*	*max95*
constant		-0.1832899	0.212461	-0.4714147	0.1048348		-0.7608998	0.1665115	-1.838844	0.3170444		-1.409491	0.1819927	-3.479369	0.660387
z_fc		.3056228*	0.0420437	0.0109922	0.6002533		0.2396735	0.1296446	-0.0702902	0.5496372		0.1937996	0.2740253	-0.1534545	0.5410537
q5							0.1153791	0.267321	-0.0884868	0.319245					
q18												0.2051631	0.2360186	-0.134173	0.5444992
chi square	4.258469					5.193475					5.722663				
chi square p-value	0.0390551					0.0745163					0.0571925				

	Model 4					**Model 5**					**Model 6**				
	model stats	b	p	min95	max95	model stats	b	p	min95	max95	model stats	b	p	min95	max95
constant		-1.473136	0.1175592	-3.317933	0.3716608		-1.887081	0.0724771	-3.946315	0.1721539		-1.135744	0.1035422	-2.503145	0.2316572
z_fc		0.2041616	0.2219414	-0.1234586	0.5317818		0.1755307	0.2904577	-0.1499144	0.5009759		0.223281	0.1654564	-0.0922474	0.5388094
q12		0.2133013	0.1636427	-0.0868319	0.5134345										
q2							0.2749778	0.0981734	-0.050911	0.6008666					
q10												0.1682218	0.1605973	-0.0667698	0.4032134
chi square	6.289328					6.708839					6.274166				
chi square p-value	0.0430814					0.0349296					0.0434092				

	Model 7					**Model 8**					**Model 9**				
	model stats	b	p	min95	max95	model stats	b	p	min95	max95	model stats	b	p	min95	max95
constant		-1.022408	0.1419248	-2.386836	0.3420204		-1.387209	0.1228399	-3.149325	0.3749074		-1.489175	0.1129637	-3.330631	0.3522811
z_fc		0.2025793	0.2377459	-0.1337198	0.5388785		0.2067829	0.2310184	-0.1315936	0.5451594		0.1620174	0.3686977	-0.1912397	0.5152745
q15		0.1628473	0.2163644	-0.0953318	0.4210263										
q28							0.203929	0.1687223	-0.0864782	0.4943362					
q13												0.2223653	0.1578191	-0.0861976	0.5309283
chi square	5.802926					6.666022					6.312471				
chi square p-value	0.0549428					0.0356855					0.0425858				

	Model 10					**Model 11**					**Model 12**				
	model stats	b	p	min95	max95	model stats	b	p	min95	max95	model stats	b	p	min95	max95
constant		-1.289573	0.0701467	-2.685249	0.1061031		-1.669679	0.0292272	-3.17055	-0.1688088		-1.625844	0.0214976	-3.011844	-0.2398432
z_fc		0.1645828	0.347267	-0.1786187	0.5077842		0.1707995	0.3016594	-0.1533043	0.4949032		0.1842722	0.2503685	-0.1299349	0.4984794
q33		0.2056973	0.1106479	-0.0470216	0.4584161										
q11							0.2615816	0.0463822	0.0041938	0.5189695					
q4												0.2607892	0.0385643	0.0137204	0.507858
chi square	6.895825					8.486764					8.374214				
chi square p-value	0.031812					0.0143589					0.0151902				

	Model 13					**Model 14**					**Model 15**				
	model stats	b	p	min95	max95	model stats	b	p	min95	max95	model stats	b	p	min95	max95
constant		-1.331856	0.0176606	-2.432053	-0.2316596		-1.906566	0.0361021	-3.689581	-0.1235502		-1.428771	0.0218881	-2.650398	-0.2071446
z_fc		0.2024152	0.2047953	-0.1104588	0.5152892		0.1198269	0.5031043	-0.2309074	0.4705611		0.1706842	0.3022605	-0.1536038	0.4949722
q6		0.240799	0.0329338	0.0195229	0.4620751										
q20							0.302364	0.0540201	-0.0052241	0.6099521					
q3												0.2522841	0.0372981	0.014843	0.4897252
chi square	8.961183					8.224512					8.743621				
chi square p-value	0.0113267					0.0163708					0.0126284				

	Model 16					**Model 17**					**Model 18**				
	model stats	b	p	min95	max95	model stats	b	p	min95	max95	model stats	b	p	min95	max95
constant		-1.324753	0.0085241	-2.311788	-0.3377186		-2.639747	0.0021549	-4.326118	-0.9533752		-2.237797	0.0050935	-3.803632	-0.671962
z_fc		0.1564036	0.3413295	-0.165753	0.4785602		0.1968676	0.2138002	-0.1135077	0.5072429		0.0505636	0.7770897	-0.2994825	0.4006097
q17		0.2359506	0.0164581	0.0431484	0.4287529										
q7							0.418882	0.0034107	0.138495	0.699269					
q27												0.3719943	0.0083262	0.0956696	0.648319
chi square	10.33519					13.8055					11.69063				
chi square p-value	0.0056983					0.001005					0.0028934				

	Model 19				
	model stats	b	p	min95	max95
constant		-2.168951	0.0011805	-3.479575	-0.8583267
z_fc		0.060629	0.726355	-0.2789083	0.4001664
q32		0.3918317	0.0020734	0.1424491	0.6412144
chi square	14.6509				
chi square p-value	0.0006586				

CITED LITERATURE

Ancker, S. A., Kern, L. M., Abramson, E., and Kaushal, R. (2012). The Triangle Model for evaluating the effect of health information technology on healthcare quality and safety. *J Am Med Inform Assoc,* (19), 61–65. doi:10.1136/amiajnl-2011-000385.

Audet, A. M., Doty, M. M., Peugh, J., Shamasdin, J., Zapert, K., and Schoenbaum, S. (2004). Information technologies: When will they make it into physicians' black bags? *Medscape General Medicine, 6* (4), PMCID: PMC1480565.

Bates, D. W., and Bitton, A. (2010). The future of health information technology in the patient-centered medical home. *Health Affairs, 29* (4), 614–21.

Bitton, A. Flier, L. A., and Jha, A. K. (2012). Health information technology in the era of care delivery reform: To what end? *Journal of the American Medical Association, 307* (24), 2593–4.

Blumenthal, D. (2010). Launching HITECH. *N Engl J Med, 362* (5), 382–5.

Chaudhry, B., Wang, J., Wu, S., Maglione, M., Mojica, W., Roth, E., Morton, S. C., and Shekelle, P. G. (2006). Systematic review: Impact of health information technology on quality, efficiency, and costs of medical care. *Ann Intern Med, 144* (10), 742–52.

Committees on Energy and Commerce, Ways and Means, and Science and Technology. (2009, 1 16). *Health Information Technology for Economic and Clinical Health Act or HITECH Act*. Retrieved 6 22, 2013, from Title IV—Health Information Technology for Economic and Clinical Health Act or HITECH Act: http://waysandmeans.house.gov/media/pdf/110/hit2.pdf

Davis, F. D., Bagozzi, R. P., and Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science, 35* (8), 982–1003.

Detmer, D., Bloomrosen, M., Raymond, B., and Tang, P. (2008). Integrated personal health records: Transformative tools for consumer-centric care. *BMC Medical Informatics and Decision Making, 8* (45), doi:10.1186/1472-6947-8-45.

Fischer, S. H., Tjia, J., and Field, T. S. (2010). Impact of health information technology interventions to improve medication laboratory monitoring for ambulatory patients: A systematic review. *J Am Med Inform Assoc, 17* (6), 631–6.

Fishbein, M., and Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Reading, MA: Addison-Wesley Pub. Co.

Garcia-Smith, D., and Effken, J. A. (2013). Development and initial evaluation of the clinical information systems success model (CISSM). *International Journal of Medical Informatics, 82* (6), 539–52.

Ghahramani, N., Lendel, I., Haque, R., and Sawruk, K. (2009). User satisfaction with computerized order entry system and its effect on workplace level of stress. *Journal of Medical Systems, 33* (3), 199–205.

Hankins, M., French, D., and Horne, R. (2000). Statistical guidelines for studies of the theory of reasoned action and the theory of planned behaviour. *Psychology and Health, 15*, 151–161.

Hayduk, L. (1987). *Structural Equation Modeling with LISREL*. Baltimore, Maryland: The Johns Hopkins University Press.

Hersh, W. (2009). A stimulus to define informatics and health information technology. *BMC Medical Informatics and Clinical Decision Making, 9* (24).

Kaplan, B. (2001). Evaluating informatics applications—some alternative approaches: Theory, social interactionism, and call for methodological pluralism. *Int J Med Inform, 64* (1), 39–56.

Lober, W. B., Zierler, B., Herbaugh, A., Shinstrom, S. E., Stolyar, A., Kim, E. H., and Kim, Y. (2006). Barriers to the use of a personal health record by an elderly population. *AMIA Annu Symp Proc* (514–518). American Medical Informatics Association.

McDonald, K. M., Sundaram, V., Bravata, D. M., Lewis, R., Lin, N., Kraft, S., McKinnon, M., Paguntalan, H., and Owens, D. K. (2007). *Closing the quality gap: A critical analysis of quality improvement strategies*. Rockville, MD: Agency for Healthcare Research and Quality.

McKibbon, K. A., Lokker, C., Handler, S. M., Dolovich, L. R., Holbrook, A. M., O'Reilly, D., Tamblyn, R., Hemens, B. J., Basu, R., Troyan, S., Roshanov, P. S., Archer, N. P., and Raina P. (2011). Enabling medication management through health information technology (Health IT). (R. M. Quality, Ed.) *Evidence Report/ Technology Assessment* (201).

McKibbon, K. A., Lokker, C., Handler, S. M., Dolovich, L. R., Holbrook, A. M., O'Reilly, D., Tamblyn, R., Hemens B. J., Basu, R., Troyan, S., and Roshanov P. S. (2012). The effectiveness of integrated health information technologies across the phases of medication management: A systematic review of randomized controlled trials. *J Am Med Inform Assoc, 19* (1), 22–30.

Miller, R. H., and Sim, I. (2004). Physicians' use of electronic medical records: Barriers and solutions. *Health Affairs, 23* (2), 116–26.

Mueller, S. K., Sponsler, K. C., Kripalani, S., and Schnipper, J. L. Hospital-based medication reconciliation practices: A systematic review. *Health Care Reform, 172* (14), 1057–1069.

O'Malley, A. S. (2011). Tapping the unmet potential of health information technology. *N Engl J Med, 364* (12), 1090–1.

Pallin, D. J., Sullivan, A. F., Auerbach, B. S., and Camargo, C. A. (2010). Adoption of information technology in Massachusetts emergency departments. *J Emerg Med, 39* (2), 240–4.

Poon, E. G., Wright, A., Simon, S. R., Jenter, C. A., Kaushal, R., Volk, L. A., Cleary, P. D., Singer, J. A., Tumolo, A. Z., and Bates, D. W. (2010). Relationship between use of electronic health record features and health care quality: Results of a statewide survey. *Medical Care, 48* (3), 203–9.

Schectman, J. M., Schorling, J. B., Nadkarni, M. M., and Voss, J. D. (2005). Determinants of physician use of an ambulatory prescription expert system. *Int J Med Inform, 74* (9), 711–7.

Sheppard, B. H., Hartwick, J., and Warshaw, P. R. (1988). The theory of reasoned action: A meta-analysis of past research with recommendations for modifications and future research. *Journal of Consumer Research, 88* (3), 325–43.

Schnipper, J. L., Hamann, C., Ndumele, C. D., Liang, C. L., Carty, M. G., Karson, A. S., Bhan, I., Coley, C. M., Poon, E., Turchin, A., Labonville, S. A., Diedrichsen, E. K., Lipsitz, S., Broverman, C. A., McCarthy, P., and Gandhi, T. K. (2009). Effect of an electronic medication reconciliation application and process redesign on potential adverse drug events: A cluster-randomized trial. *Arch Intern Med, 169* (8), 771–80.

Sheng, O. R., Hu, P. J., Chau, P. Y., Hjelm, N. M., Tam, K. Y., Wei, C. P., Tse, J. (1998). A survey of physicians' acceptance of telemedicine. *J Telemed Telecare, 4* (Suppl 1), 100–2.

Simon, S. J., and Paper, D. (2007). User acceptance of voice recognition technology: An empirical extension of the technology acceptance model. *Journal of Organization and End User Computing, 19* (1), 24–50.

Tavakoli, N., Jahanbakhsh, M., Shahin, A., Mokhtari, H., and Rafiei M. (2013). Electronic medical record in central polyclinic of isfahan oil industry: A case study based on technology acceptance model. *Acta Informatica Medica, 21* (1), 23–25.

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27* (3), 425–478.

Vest, J. R., Yoon, J., and Bossak, B. H. (2012). Changes to the electronic health records market in light of health information technology certification and meaningful use. *J Am Med Inform Assoc, 20* (2), 227–32.

Williams, C., Mostashari, F., Mertz, K., Hogin, E., Atwal, P. (2012). From the Office of the National Coordinator: The strategy for advancing the exchange of health information. *Health Affairs, 31* (3), 527–36.

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