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Predicting Tablet Computer Use: An Extended Technology Acceptance Model

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An Extended Technology Acceptance Model

by

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Abstract

While information technology has rapidly changed work in the United States in the past 50 years, some businesses and industries have been slow to adopt new technologies. Healthcare is one industry that has lagged behind in information technology investment for a variety of reasons. Recent federal initiatives to encourage IT adoption in the healthcare industry provide an ideal context to study factors that influence technology acceptance. Data from 261 practicing pediatricians were collected to evaluate an extended Technology Acceptance Model. Results indicated that individual (i.e., perceived usefulness, perceived ease of use), organizational (i.e., subjective norm), and device (i.e., compatibility, reliability) characteristics collectively influence pediatricians' intention to adopt tablet computers in their medical practice. Theoretical and practical implications are discussed. Future research should examine additional variables that influence information technology adoption in organizations.

Chapter 1: Introduction

Given the widespread use of information technology (IT) to accomplish work tasks, it is easy to overlook how work was done before IT was universally available in organizations. Without email, teleconferencing, and web conferencing, communication and collaboration among employees required many redundant phone calls between pairs of employees and expensive travel for face-to-face meetings. Today, technology enables employees to rapidly communicate and collaborate with individuals in other work units, states, and countries. In order to find a key piece of information, an employee had to go to the local library to search the card catalog, locate the book, and flip through the pages to find the critical piece of information. Today, the internet provides instantaneous access to massive quantities of information, in an easily searchable form. Complex calculations and forecast models that are easily run today would be nearly impossible 50 years ago with just paper and pencil. Ultimately, all of these IT innovations have improved work processes by reducing the amount of time, money, and effort individuals and organizations spent to accomplish tasks.

Initially, the cost of such technologies enabled only large corporations to benefit from IT related efficiencies; however, breakthroughs in microprocessors, computers, and industry standards enabled individuals and organizations of all sizes to reap the benefits of IT (Friedman, 2007; Howard, 1995). In the field of industrial-organizational psychology, IT is transforming areas like selection and training. For example, Mead, Olson-Buchanan, and Drasgow (2013) discuss how advances in technology enable selection managers to automate application screening and test scoring. Also, organizations may rely on Internet testing for initial assessments to reduce costs and gain access to a larger applicant pool (Sackett & Lievens, 2008). Finally, advances in measurement theory (e.g., Item Response Theory) are allowing firms to administer adaptive tests, which shorten testing time, increase test security, and allow test administrators to examine individual items for bias. Likewise, technology-delivered training is steadily increasing in popularity; in 2009, 36.5% of training hours were available as technology-based courses (American Society for Training & Development, 2010). Online training makes materials accessible at any time, so content is able to be reused at little or no cost to the organization. This represents a major shift from traditional instructor-led, real time training which requires many more support personnel. Also, technology enables training specialists to design high-fidelity simulators for physicians, military personnel, and air traffic controllers. Collectively, these examples highlight the rapid progression of organizational IT adoption in the late 20th and early 21st century. This dynamic environment provides opportunities for industrial-organizational psychologists to research how technology influences individuals and organizations (Coovert & Thomson, 2013; Kantrowitz & Dawson, 2012).

While IT innovation has rapidly changed work in the United States in the past fifty years, some businesses and industries have been slow to adopt new technologies. The purpose of the current study is to improve our understanding of factors that influence information technology adoption. Healthcare is one industry that has lagged behind in IT investment due to individual, technological, and organizational factors (DePhillips III, 2007). Given recent initiatives to encourage IT adoption (e.g., electronic medical records), it provides an ideal context to study this question.

The Technology Acceptance Model (TAM; Davis, 1986) is a parsimonious theory of information technology adoption in organizations. It proposes that individual reactions toward a piece of technology influence intentions to use the technology, which ultimately influence actual use. Researchers have expanded the model by including contextually relevant variables to better understand the factors that influence IT adoption. The current research model under investigation extends the TAM by including variables from industrial-organizational psychology (i.e., job satisfaction), social psychology (i.e., social norms), and human factors (i.e., device reliability and compatibility) to understand pediatricians' intention to adopt tablet computers. Tablet computers are an excellent way to examine the current research question because they are a relatively new technology and have the potential to help physicians carry out their work duties by providing them access to critical information at the point of care, communicate with patients and other physicians, and organize patient information (e.g., electronic health records). Ultimately, the results of this study contribute to our theoretical understanding of variables that influence IT adoption and inform practice by identifying ways to improve IT adoption rates.

Organizational Information Technology Investment

Rapid technological innovation is changing the United States workforce in the 21st century (Rand Corporation, 2004). Initially, information technology was only available for large corporations. However, advancements in hardware and software enabled the spread of the personal computer to companies of all sizes. More recently, organizations have found novel and inexpensive ways to use information technology to improve business processes. While the surge in new technology is transforming the way we work, there is large variability across different industries in terms of financial investment. The healthcare industry is one data and knowledge intensive industry that has fallen behind in IT adoption rates. Preliminary reasons for the lack of IT adoption in the industry are discussed.

There has been a rapid increase in the prevalence of information technology (IT), defined as the use hardware and software to store, analyze, access, and distribute information, in organizations (Davis, 1995). This is underscored by the fact that investment in IT equipment and software by private U.S. firms increased by more than 300% from 1995 to 2010 (Bureau of Economic Analysis, 2010). Most IT spending has come from data intensive industries like financial services, manufacturing, and communications to effectively manage and utilize the massive amount of digital information available to organizations (Gartner, 2010).

Initial accounts of the increased availability of IT highlighted breakthroughs in microprocessors and computer memory, which made personal computers (PC) cheaper, faster, and smaller for organizations (Howard, 1995). Next, the Windows-enabled PC allowed non-programmers to easily create digital content. By the mid-1990s, the software industry's agreement on standards for exchanging email (SMTP), documents (HTML, XML, and SOAP) and Web pages (HTTP and TCP/IP) enabled people share information between departments and organizations that used different hardware and software platforms. Finally, the massive investment in fiber-optic cables in the late 1990s permitted the newly created user-content to be rapidly shared with customers and coworkers around the world (Friedman, 2007). These advancements changed the role of the computer from a computational tool for scientists and engineers at universities and large corporations to an information creation and delivery system affordable for even small companies and individuals throughout the world (Friedman, 2007; Van der Spiegel, 1995).

Discussions on the implications of new information technologies at work highlight productivity and efficiency gains from increased communication and collaboration among employees within (e.g., flattening hierarchical structure) and between organizations (e.g., outsourcing non-core competencies) (Coovert, 1995; Davis, 1995). For example, a multinational corporation can assemble a virtual team of high performing individuals from the headquarters and regional offices and use a video conferencing system to hold meetings and share presentations (e.g., Cisco TelePresence) or collaborate on digital documents (e.g., GoToMeeting). These technologies reduce travel costs while speeding up the time it takes to schedule a meeting. Manning, Massini, and Lewin (2008) report that small, medium, and large firms are offshoring nearly any function that can be digitized, such as IT, product development (i.e., research & development, product design), and administrative functions (e.g., accounting, human resources), to reduce labor costs and gain access to qualified personnel. This collaboration between organizations located in different countries is possible because of the aforementioned IT breakthroughs. While adopting new technologies is common for most industries, other sectors like healthcare have lagged behind in IT adoption.

A Gartner (2010) report found that the healthcare industry has spent approximately 50% less than other industries on IT investment, despite the fact that medical knowledge doubles every five years (IBM, n.d.). This is unexpected considering the fact that national healthcare expenditures are 17.6% of gross domestic product (GDP) and are projected to increase to 19.8% by 2020 (Centers for Medicare & Medicaid Services, 2009). Given the escalating costs and the massive growth in clinical knowledge, observers note the potential of health information technology (HIT), defined as technologies which allow healthcare providers to "collect, store, retrieve, and transfer information electronically," to help professionals operate more efficiently and make fewer errors (MedPac, 2004, p. 5).

Recently, the federal government has encouraged the adoption of HIT such as electronic medical records (EMR) and secure electronic health information exchanges (The Office the National Coordinator for Health Information Technology, 2011). Healthcare experts note the potential of EMR to control costs, reduce medical errors, and improve patient outcomes by providing complete patient history information (e.g., clinical history, medications, tests) to all medical facilities involved with the patient (MedPac, 2004). In addition, popular press articles are heralding tablet computers (e.g., Apple iPad, Samsung Galaxy Tab) as promising devices to be used in conjunction with new HIT software (e.g., Berger, 2010). Tablet computers combine the best features of earlier mobile technologies used by healthcare providers, with the computing power, high resolution screen, and ease of data entry of the computer on wheels (COW) and the portability, customizability, and wireless connectivity of the personal digital assistant (PDA) (Ducey, Grichanik, Coovert, Coovert, & Nelson, 2011).

Despite the potential benefits of HIT, previous research has noted the high failure rate of widespread adoption initiatives in the healthcare industry (DePhillips III, 2007).

Implementing HIT interventions present a number of challenges and barriers due to organizational (e.g., cost, managerial support, and changes in workflow), individual (e.g., individual acceptance, ease of use, and loss of control), and device (e.g., design, compatibility with tasks, and flexibility) characteristics. Given the promise of health information technology to improve quality of care, it is critical that we identify factors that predict IT adoption to aid in the planning of successful IT interventions.

In sum, information technology advancements in the last 35 years have had a large impact on the way people work. However, research has found that healthcare has fallen behind other industries in terms of technological innovation. The lack of technological investment and the recent influx of new IT solutions in healthcare provide an excellent context to study factors related to IT adoption. While some healthcare industry observers have provided their expert opinions on issues related to adoption, other researchers have relied upon a well-supported theoretical framework to better understand factors that predict technology use in organizations.

Theoretical Background

The Technology Acceptance Model is the most widely used IT adoption model (Davis, 1986). The original TAM provides a parsimonious account of technology adoption based on the Theory of Reasoned Action (TRA; Fishbein & Ajzen, 1975). The Technology Acceptance Model and its successor TAM-2 (Venkatesh & Davis, 2000) posit individual (e.g., ease of use, usefulness) and organizational (e.g., social norms, facilitating conditions) antecedents to predict behavioral intention to use (i.e., acceptance) and/or actual use of a new technology in an organization.

Theory of Reasoned Action. TAM uses Fishbein and Ajzen's (1975) Theory of Reasoned Action as a foundation to understand use. The TRA is a general social psychology theory that has been successfully used to predict a variety of behaviors, such as voting (Ajzen, Timko, & White, 1982), eating at fast-food restaurants (Brinberg & Durand, 1983), and condom use (Sutton, McVey, & Glanz, 1999). It proposes that an individual's behavior is determined by one's intention to perform a behavior, which is jointly determined by one's attitude toward the behavior and the subjective norm about the specific behavior (see Figure 1).

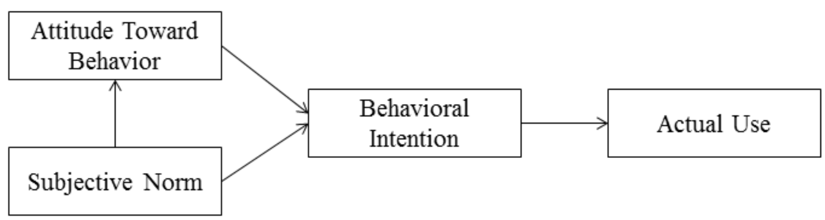


Figure 1. Theory of Reasoned Action (Fishbein & Ajzen, 1975)

Fishbein and Ajzen (1975) define attitude toward behavior as an individual's evaluative affect about performing the target behavior. One's attitude toward the behavior is determined by the perceived outcomes (e.g., the perceived consequences, effort required, and cost) of performing the specific behavior multiplied by the evaluation of those consequences. Subjective norm is "the person's perception that most people who are important to him think he should or should not perform the behavior in question" (1975, p. 302). Subjective norm focuses on the influence of other people in the surrounding environment on the individual's intention to perform a behavior. This construct is determined by the "perceived expectations of specific referent individuals or groups and by the person's motivation to comply with those expectations" (Fishbein &

Ajzen, 1975, p. 302). Collectively these two constructs impact behavioral intention, defined as an individual's "subjective probability that he will perform some behavior", such that when one's attitude toward the behavior is more positive and the social norms about performing the behavior are stronger, the person forms a stronger behavioral intention to engage in the behavior (1975, p. 288). Ultimately, a stronger behavioral intention leads to a higher probability of carrying out the specific behavior (i.e., actual use). For technology adoption, the Theory of Reasoned Action postulates that IT adoption is influenced by one's behavioral intention to use the piece of technology, which is jointly determined by the individual's attitude toward the technology and the norms regarding the piece of technology in the individual's environment (e.g., coworker and supervisor beliefs).

While TRA provides a general framework to understand voluntary behaviors, it does not specify the specific beliefs that will be important in a context like IT adoption. Fishbein & Ajzen (1975) recommend for researchers to first identify the relevant beliefs by using free response interviews with representative participants in the population. The researchers recommend identification of 5 to 9 beliefs, determined by the most frequently reported responses of the interviewees. In practice, the TRA is costly and time consuming because it is necessary to contextualize it for every behavior in question. Furthermore, there is the potential to introduce considerable sampling error and not identify some of the most important beliefs by looking at a small subset of the population.

Technology Acceptance Model. Davis (1986) took a more comprehensive approach to identify the critical beliefs related to technology adoption in organizations. He systematically reviewed the information technology, human factors, and psychometrics literature related to technology adoption in organizations. Based on this literature review, he identified two common beliefs that influence IT adoption: perceived usefulness (PU) and perceived ease of use (PEOU). These two beliefs are influenced by external variables such as design features of the IT system and organizational training. The relative weights of the two beliefs are determined by multiple regression and combine to determine one's attitude toward using the system, defined as an individual's evaluative affect about using the system. In turn, attitude toward using the system and PU directly influence one's behavioral intention to use the system, defined as an individual's subjective probability that he or she will use the IT system. Finally, behavioral intention impacts system use, defined as "an individual's actual direct usage of the given system in the context of his or her job" (Davis, 1986, p. 25). In addition to the direct path from PEOU to attitude, the model proposes that perceived ease of use is an antecedent of perceived usefulness (see Figure 2). The rationale for each link in the model is discussed below.

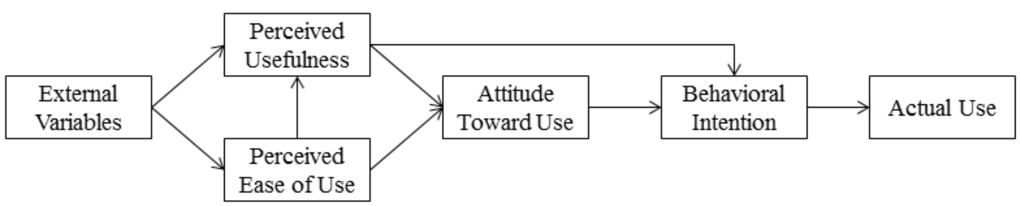


Figure 2. Technology Acceptance Model (Davis, 1986)

The Technology Acceptance Model provides a concise way to model the impact of external variables on one's beliefs, attitudes, and intentions. External variables can be anything that is outside of the individual. For example, an external variable like training provided by the organization may positively influence an individual's perceived ease of use of a new piece of technology because the training session helped the new user setup and navigate the new device. As another example, external features like the quality or number of options of one software program compared to a functionally similar program may influence perceived usefulness because if one statistical software provides more options for analysis or graphs, it may be rated higher on PU compared to another, equally easy to use, program.

Next, perceived usefulness is defined as “the degree to which a person believes that using a particular system would enhance his or her job performance” (Davis, 1989, p. 320). It is a cognitive evaluation of how adopting a new piece of technology will influence one’s job performance. PU influences one’s attitude toward using a new piece of technology because people form positive attitudes toward new technology that they believe will positively affect their job performance. In addition, perceived usefulness directly impacts behavioral intention to use the technology because people form intentions to use a device that they believe will increase their job performance, regardless of their personal feelings (i.e., PEOU) toward the technology, because people are motivated to obtain performance-contingent rewards (e.g., promotions, raises).

Perceived ease of use refers to “the degree to which a person believes that using a particular system would be free of effort” (Davis, 1989, p. 320). It is proposed to influence one’s attitude toward using the new technology. In the model, Davis et al. (1989) propose mechanisms by which PEOU influences both attitude and PU. First, a system that is easier to use impacts the user’s sense of self-efficacy (Bandura, 1982) to carry out the steps required to operate the system. A person with high self-efficacy regarding the new device has a strong belief in his or her ability to use the device. This ultimately results in a more positive attitude toward the technology. Second, when a system is perceived as easy to use, it impacts a person's performance (i.e., PU) because the new technology enables the person to accomplish the task with less effort, allowing the saved effort to be used for other work related tasks.

Based on the TRA, the Technology Acceptance Model posits a link from attitude to behavioral intention and behavioral intention to actual use. This causal chain of constructs implies that a more positive (negative) attitude toward the system creates a stronger (weaker) behavioral intention toward using the system. In addition, when an employee believes that an IT system will positively impact his or her work performance (PU), they form a stronger behavioral intention to use the device. Ultimately, a stronger (weaker) behavioral intention to use the technology tends to result in more (less) actual technological use.

TAM expands on the Theory of Reasoned Action by proposing specific individual beliefs (PU and PEOU) that impact one's attitude toward an IT system. The identification of PU and PEOU from a comprehensive literature search results in a more parsimonious set of beliefs over Fishbein and Ajzen's (1975) recommendation of using interviews to elicit between 5 and 9 beliefs. Furthermore, the two key beliefs in TAM provide greater generalizability across different contexts and technologies compared to separate belief elicitation interviews for each unique context and/or technology with the TRA model.

The specification of individual beliefs enables one to examine the relative importance of individual beliefs (by comparing beta weights) on one's attitude rather than multiplying each belief by its appropriate evaluation and additively combining the products into a general attitudinal construct as in the Theory of Reasoned Action

(Fishbein & Ajzen, 1975). Further, by examining beliefs separately, it is possible to trace the impact of external variables on each belief. This is practically important because it enables people to manipulate external variables to improve beliefs (PU and PEOU) and ultimately actual use. In addition, TAM posits a causal link between PEOU and PU; in comparison, the Theory of Planned Behavior does not specify any relationships between beliefs. Finally, the original conceptualization of TAM excluded the subjective norm construct proposed in the Theory of Reasoned Action. However, this construct was later included in a revised model, the Technology Acceptance Model-2 (TAM2; Venkatesh & Davis, 2000).

Technology Acceptance Model-2. TAM2 builds on TAM by modeling the determinants of perceived usefulness. The expanded model includes subjective norm as a causal antecedent of perceived usefulness and as a predictor of intention to use a technology system. In addition to subjective norm, TAM2 posits two other social forces (voluntariness and image) that influence perceived usefulness and behavioral intention. Moreover, TAM2 proposes four cognitive instrumental processes (job relevance, output quality, result demonstrability, and perceived ease of use), that influence perceived usefulness. Finally, TAM2 excludes attitude toward use as an antecedent of behavioral intention (Venkatesh & Davis, 2000). The theoretical rationale for each variable and all of the linkages is discussed below. See Figure 3 for the model.

For the social processes, subjective norm is defined as “the person’s perception that most people who are important to him think he should or should not perform the behavior in question" (Fishbein & Ajzen, 1975, p. 302). Venkatesh & Davis (2000) include a link between subjective norm and behavioral intention because they reason that people may elect to perform a behavior even when they do not have positive feelings toward the behavior if important referent people believe they should perform the behavior (i.e., compliance with a mandatory policy). The researchers theorize a relationship between subjective norm and perceived usefulness because of internalization (Kelman, 1958). Internalization refers to when an individual believes important people in the organization want him or her to use the system and he or she incorporates (internalizes) the important person's belief into his or her belief structure. For example, if a person thinks that a supervisor believes a technology is useful, the employee may start to believe it is useful as well. Therefore, subjective norm is positively related to perceived usefulness.

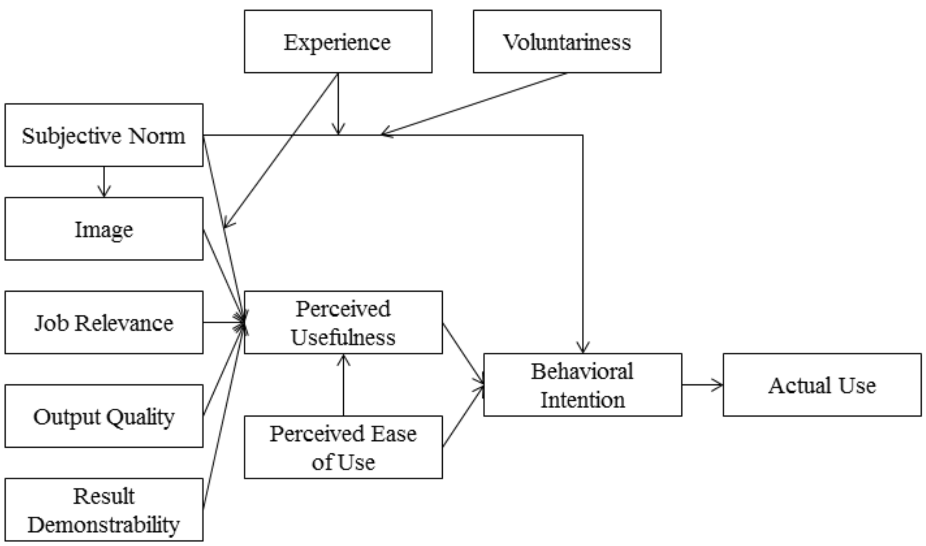


Figure 3. Technology Acceptance Model-2 (Venkatesh & Davis, 2000)

Second, voluntariness is defined as the extent to which people believe an adoption decision is non-mandatory. Voluntariness is proposed to be a moderator of the relationship between subjective norm and behavioral intention based on previous research by Hartwick and Barki (1994) who found that when a system was mandatory, there was a significant relationship between subjective norm and behavioral intention compared to when a system was voluntary. That is, when use was required, individual's intentions to adopt a system were more heavily determined by important others like supervisors who expected employees to use a new technology. Conversely, when adoption was voluntary, behavioral intention to adoption a new technology was more strongly determined by one's attitudes like PEOU and PU compared to subjective norms.

In addition, TAM2 proposes system experience as a moderator of the link between subjective norm with perceived usefulness and behavioral intention. Venkatesh and Davis (2000) reason that the relationship between subjective norm and behavioral intention/perceived usefulness will be weaker over time. It is believed that people must rely on other people's opinions (i.e., subjective norms) when they form initial beliefs or intentions toward a system. But, once the person has more experience with using the system and has identified the strengths and weaknesses of the system, the influence of the referent individual's opinion decreases.

The final social process, image, is defined as the extent to which a person believes the technology enhances one's status in the organization. Image is theorized to be positively influenced by social norms (link from subjective norm to image) because if important organizational members believe in a system, then system use will enhance one's status in the organization. The term for this type of social influence is referred to as identification (Kelman, 1958). In addition, image will directly influence perceived usefulness. It is proposed that if a person believes system use will elevate his or her status in the organization, it will enable one to increase productivity since the person has more power and influence to accomplish tasks – thus improving perceived usefulness.

TAM2 proposes four cognitive instrumental processes: job relevance, output quality, result demonstrability, and perceived ease of use as determinants of perceived usefulness. Venkatesh & Davis's (2000) overarching rationale for the cognitive processes is based on theoretical work of action theory (Fishbein & Ajzen, 1975), expectancy theory (Vroom, 1964), and behavioral decision theory (Beach & Mitchell, 1996). The common view among the three theories is that people decide to perform certain behaviors based on "a mental representation linking instrumental behaviors to higher-level goals" (Venkatesh & Davis, 2000, p. 191). That is, people perform specific behaviors based on an understanding that they will lead to desirable results.

First, job relevance is defined as an individual's perception of how applicable the technology is to one's job. It is one's evaluation of how well a new system supports critical work-related tasks. Essentially, it is one's perception of the compatibility between work demands and technological abilities. Job relevance is proposed to positively impact perceived usefulness because when a system supports many key job tasks, then the individual is likely to believe that his or her performance will increase.

Second, output quality is defined as one's perceptions of how well a system performs the tasks it was designed to accomplish. Output quality is distinct from job relevance because given a comparison between two systems that are equally job relevant, an individual will choose the system with the higher output quality. For example, if two systems perform the same statistical analyses but one software program has a less complex output, then that system will have a higher output quality. Therefore, output quality is proposed to have a positive impact on perceived usefulness.

Third, result demonstrability is defined as how easily a user can directly attribute performance increases to system use. The authors argue for this link based on the job characteristics model (Hackman & Oldham, 1976), which proposes knowledge of actual results as a critical psychological state for work motivation. Results demonstrability is conceptually similar to this psychological state in that if people are able to easily observe the impact of technology use, then they will perceive the system to be more useful. Thus, TAM2 proposes a positive relationship between result demonstrability and perceived usefulness.

Finally, TAM2 keeps the same conceptualization of perceived ease of use and the other constructs (PU, behavioral intention, and actual use) from TAM (Davis, 1986). In the original model, a system that has higher PEOU will positively impact behavioral intention and PU. Finally, compared to the moderators proposed between the social process subjective norm and behavioral intention/perceived usefulness, the cognitive instrumental processes are believed to predict perceived usefulness over time regardless of variables like experience and voluntariness.

In summary, TAM (Davis, 1986) and TAM2 (Venkatesh & Davis, 2000) provide contextual models to predict technology adoption in organizations based on individual, cognitive, and organizational variables. TAM and TAM2 use the Theory of Reasoned Action, from social psychology, as a foundation (Fishbein & Ajzen, 1975). TAM2 extends the basic TAM framework of PU and PEOU by proposing three social forces (subjective norm, voluntariness, and image) and four cognitive instrumental processes (job relevance, output quality, result demonstrability, and PEOU) which influence perceived usefulness and behavioral intention. In addition, TAM2 postulates two moderators: experience and voluntariness. Numerous studies have empirically examined the propositions of these two models with generally favorable results.

Tests of the IT Adoption Models

Extensive research has been done on the Technology Acceptance Model. The parsimonious framework has been successfully applied to predict adoption of a variety of technologies in many different contexts. While researched less extensively, the majority of the links in TAM2 have been confirmed by research. In sum, both contextualized models of IT adoption have abundant empirical support.

TAM. Initially, Davis et al. (1989) found that the TAM explained more variance in behavioral intention to use a piece of technology for work tasks compared to the TRA. Specifically, TAM explained 47% and 51% of behavioral intention at time 1 and 2, respectively, compared to 32% and 26% at time 1 and 2 for TRA. These results demonstrate that a model contextualized specifically for IT adoption in organizations (i.e., TAM) outperforms the general social psychology model predicting behaviors (i.e., TRA), on which it was based.

Since this initial support of TAM over TRA, TAM has been used to predict technology adoption with professional, student, and general user samples. In professional settings, researchers have found strong support for the model. For example, Agarwal and Prasad (1999) found that all the key paths in TAM were supported when predicting computer adoption in a large organization. Similarly, Amoako-Gyampah and Salam (2004) used TAM to successfully predict use of an enterprise response planning system in a large organization. In addition, Wixom and Todd (2005) replicated the significant paths among all of the key constructs when examining acceptance of inventory software in a sample of employees from a variety of industries (e.g., consumer goods, financial services, and government). Gong, Xu, and Yu (2004) examined teachers' adoption of web-based learning applications. The researchers found support for all of TAM's hypotheses. In addition, Igbaria, Zinatelli, Cragg, and Cavaye (1997) validated the Technology Acceptance Model in small firms to predict computer adoption. Collectively, these results demonstrate the versatility of TAM to predict technology adoption in many different organizational settings. In these studies, TAM accounted for between 25% (Igbaria et al., 1999) and 59% (Wixom & Todd, 2005) of the variance in behavioral intention.

In addition, researchers have used student and general samples to investigate technology adoption. Davis, Bagozzi, and Warshaw (1989) examined word processing software adoption use among MBA students. Taylor and Todd (1995) applied TAM to examine business school students' use of a computer resource center. In both studies, the researchers found support for all of the proposed linkages in TAM. Moreover, researchers have applied the Technology Acceptance Model to general users' adoption of IT. Gefen (2003) used TAM to predict users' intention to engage in online shopping. Lederer, Maupin, Sena, and Zhuang (2000) examined users' acceptance of the World Wide Web. In both studies, strong support was found for TAM to predict IT intention/usage. Among the studies using student and general user samples, TAM explained between 15% (Lederer et al., 2000) and 61% (Gefen, 2003) of the variance in behavioral intention to use a piece of technology.

Research on TAM has reached the point where studies using different samples (e.g., student, professional, and general user) and technologies (e.g., email, telecommunications, internet, and hardware) have been aggregated to produce meta-analytic path coefficients. The effect size of the path coefficients collapsed across context (i.e., samples) and technology demonstrate the widespread success of the model. The PEOU-behavioral intention ($\beta = 0.19$, 95% CI = 0.15-0.22), PU-behavioral intention ($\beta = 0.51$, 95% CI = 0.46-0.55), and PEOU-PU ($\beta = 0.48$, 95% CI = 0.42-0.54) paths in the model are strongly supported by research (King & He, 2006). All of the proposed paths in the model are statistically significant (i.e., the confidence interval does not include 0.00). Other meta-analyses (Ma & Liu, 2004; Schepers & Wetzels, 2007) of TAM have obtained very similar point estimates for the relationships. It is worth nothing that the results suggest that PU is a stronger predictor of behavioral intention compared to PEOU and that the relationship between PEOU and attitude is primarily through PU.

In addition to these overall path coefficients, King and He (2006) examined differences in the relationships by users (student, professional, and general users) and technology (job-office applications, general, and internet). First, there were differences among the users for the PEOU-BI relationship such that there was a larger effect size for general users compared to professionals. Second, there were some differences among the technologies. The PEOU-BI relationship was weaker for job-office applications compared to internet technologies. Also, the PU-BI relationship was stronger for job-office applications compared to internet technologies.

In summary, TAM has been validated in diverse samples including organizational, student, and general user samples. In addition, TAM has demonstrated its versatility to predict adoption of many different pieces of information technology. Meta analytic estimates demonstrate the importance of PU and PEOU to predict IT adoption. But, results suggest that PU is more important compared to PEOU when predicting behavioral intention to adopt a piece of technology. Finally, there are minor differences among the path coefficients when comparing different samples and technologies.

TAM2. Since TAM2 was proposed more recently, fewer studies have investigated the model. When Venkatesh and Davis (2000) introduced TAM2, they also empirically tested it with four separate samples of employees from a (n) manufacturing, financial services, accounting, and international investment firm. Across all studies, they found support for the three social forces (subjective norm, voluntariness, and image) and four cognitive instrumental processes (job relevance, output quality, result demonstrability, and perceived ease of use) as predictors of PU. Moreover, there was support for voluntariness as a moderator of the subjective norm-behavioral intention relationship, such that when use was voluntary, the relationship between subjective norm and behavioral intention was not significant. Finally, the hypothesized moderator of experience was supported such that relationship between subjective norm and behavioral intention/perceived usefulness was not significant once people had more experience (measurement point 3) with the system.

In another professional setting, Chismar and Wiley-Patton (2003) used TAM2 to predict adoption of internet based health applications among physicians. The researchers found support for the influence of job relevance and output quality on PU. However, subjective norm, image, and result demonstrability did not significantly impact their hypothesized outcomes. In addition, PEOU was not related to PU or intention. Further, Yu, Li, and Gagnon (2009) examined health information technology adoption among medical staff with a modified TAM2. They found that image predicted PEOU and subjective norm predicted PU and PEOU. Also, all TAM hypotheses were supported. However, Yu et al. (2009) did not examine the impact of output quality, result demonstrability, or job relevance on PU, as proposed in the original model.

Using undergraduate and graduate students, Chan and Lu (2004) examined adoption of internet banking. First, all paths from the original TAM were supported except the PEOU-BI relationship. Next, the results generally supported the hypothesized links of TAM2 (i.e., subjective norm-PU and image-PU). However, the relationship between results demonstrability and PU was not supported. One weakness is that the researchers did not test the complete TAM2 model because they did not examine experience or voluntariness as moderators. Also, output quality was excluded from the model.

While fewer studies have empirically tested TAM2, a meta-analysis of TAM by Schepers & Wetzels (2007) included subjective norm as a predictor of attitude/behavioral intention because numerous studies added it to the basic TAM model. The meta-analytic path coefficients for subjective norm-attitude toward use ($\beta = 0.08$, $p < .01$) and subjective norm-behavioral intention ($\beta = 0.16$, $p < .01$) support its inclusion in TAM2. However, Schepers & Wetzels (2007) did not examine the moderating effect of voluntariness or experience. In summary, there is evidence for most of the hypothesized relationships in TAM2. However, with the exception of Venkatesh and Davis (2000), few studies have tested the full TAM2 model.

TAM and TAM2 in Healthcare. Relevant to the current research question, the healthcare industry has applied TAM and TAM2 to predict medical professionals' adoption of various health information technologies with generally consistent results. One question that remains unanswered is if the TAM is equally appropriate for different industries (e.g., education, government, and healthcare) since it was developed primarily for private sector corporations. TAM meta-analyses (e.g., King & He, 2006; Ma & Liu, 2004; Schepers & Wetzels, 2007) combine all professional samples into one group, assuming that they are homogenous. However, the researchers provided no empirical justification for the appropriateness of this assumption. Given differences in employee characteristics, job demands, and culture between medicine and private sector corporations, it is necessary to review research on the TAM in the healthcare industry.

Recently, a review by Holden and Karsh (2010) examined the individual links of TAM and found support for it as a theory of health information technology acceptance. The impact of perceived usefulness on behavioral intention was supported in all 16 studies and perceived usefulness on attitude was significant in all three studies. Also, the impact of PEOU on PU was significant in 10 of 12 studies. There was strong support for the attitude-behavioral intention (5/6) and behavioral intention-use (2/3) relationships. However, the impact of perceived ease of use on attitude was significant in 1 of 2 studies and perceived ease of use on behavioral intention in 7 of 13 studies. Holden and Karsh (2010) offer some possible explanations for the inconsistent relationship between PEOU and behavioral intention/attitude. It is plausible that participants did not have enough experience with the technology, that sample characteristics like intelligence resulted in many of the non-significant results, or the availability of support staff influenced this relationship. It is worth noting that the authors did not conduct a meta-analysis to estimate path coefficients because the studies examined different samples of medical professionals (e.g., physicians, nurses, occupational therapists, and pharmacists) from different countries (e.g., UK, US, Taiwan, Hong Kong, Canada, and Finland) and numerous technologies (e.g., telemedicine technologies, electronic medical records, PDAs, and computerized provider order entry).

An exhaustive literature review of applications of TAM in the healthcare industry identified 20 articles. Table 1 provides the reference, a description of the full model the researchers used, the technology examined, sample characteristics, and the amount of variance in the most distal outcome measured (e.g., if attitude toward use and BI were measured, then BI is reported; if BI and actual use were measured, actual use is reported).

In sum, the available evidence suggests that TAM is appropriate in healthcare settings (Coovert, Nelson, & Coovert, 2011). Specifically, perceived usefulness consistently predicted healthcare professionals' adoption and use of health information technology. Also, perceived ease of use correlated with perceived usefulness in most studies. However, there are inconsistent results between PEOU and IT acceptance possibly due to differences in intelligence, competence, adaptability to new technologies, and the nature of the work between physicians and the general workforce (Holden & Karsh, 2010). Relevant to the present investigation, many researchers extended TAM by including unique variables to better understand health information technology adoption.

Table 1

Examining IT Adoption in the Healthcare Industry with TAM or TAM2

Reference	**Model**	**Technology**	**Sample**	**Variance Explained**
Barker et al. (2003)	TAM	Spoken dialogue system	Physicians (N = 10)	-
Bhattacherjee & Hikmet (2007)	Extended TAM with perceived compatibility predicting PU, related knowledge predicting PEOU, and resistance to change (predicted by perceived threat).	Computerized order entry	Physicians (N = 129)	55%
Chau & Hu (2001, 2002); Hu et al. (1999)	Extended TAM with subjective norms and perceived behavioral control predicting BI. Compatibility predicting PU and PEOU.	Telemedicine	Physicians (N = 408)	40-44%
Chen et al. (2008)	Extended TAM with external variables (user characteristics, internet access, and organization factors) predicting PU and PEOU.	Web-based learning	Public health nurses (N = 202)	45%
Chismar & Wiley-Patton (2003)	TAM2	Internet and Internet-based health applications	Physicians (N = 89)	59%
Han et al. (2005)	Extended TAM with perceived compatibility predicting use.	Mobile medical information system	Physicians (N = 242)	70%
Handy, Hunter, & Whiddett (2001)	Extended TAM with individual and organizational characteristics predicting acceptance and system characteristics influencing PEOU and PU.	Electronic medical records	Physicians and midwives (N = 167)	-
Horan et al. (2004)	Extended TAM with perceived readiness (predicted by organizational readiness and technical readiness) and perceived compatibility predicting BI.	Online disability evaluation system	Physicians (N = 141)	44%
Liang, Xue, & Byrd (2003)	Extended TAM with compatibility and job relevance predicting PU, support predicting PEOU, and personal innovativeness predicting PEOU and usage.	Personal digital assistant	Healthcare professionals (N = 173)	62%
Liu & Ma (2006)	Extended TAM with perceived system performance predicting PU and PEOU.	Electronic medical records	Medical Professionals (N = 77)	54%

Table 1

Examining IT Adoption in the Healthcare Industry with TAM or TAM2 (continued)

Reference	**Model**	**Technology**	**Sample**	**Variance Explained**
Melas et al. (2011)	Extended TAM with IT feature demands predicting PU and IT knowledge predicting PEOU.	Clinical information systems	Medical staff (N = 604, Physicians = 534)	83%
Paré, et al. (2006)	Extended TAM with psychological ownership predicting PU and PEOU.	Computerized order entry	Physicians (N = 91)	55%
Rawstorne et al. (2000)	TAM	Patient care information system	Nurses (N = 61)	29-30%
Tung, Chang, & Chou (2008)	Extended TAM with perceived financial cost, compatibility, and trust predicting BI.	Electronic logistics information system	Nurses (N = 252)	70%
Van Schaik, Bettany-Saltikov, & Warren (2002)	TAM	Portable system for postural assessment	Physiotherapists (N = 49)	39%
Vishwanath, Brodsky, & Shaha (2009)	Extended TAM with individual characteristics (age, specialty, and job position), attitudes toward health information technology, and cluster ownership predicting PU and PEOU.	Personal digital assistant	Physicians (N = 215)	55%
Wu et al. (2008)	Extended TAM with subjective norm and trust predicting BI; management support predicting PU, PEOU, and subjective norm.	Adverse event reporting system	Medical professionals (N = 290)	-
Wu, Wang, & Lin (2007)	Extended TAM with compatibility, mobile healthcare system self-efficacy, and technical support and training predicting PU and PEOU.	Mobile healthcare systems	Physicians, nurses, and medical technicians (N = 137)	70%
Yu, Li, & Gagnon (2009)	Combined TAM & TAM2 model with image and job role predicting PU, subjective norm predicting PU and PEOU, and computer level predicting PEOU.	Health information technology applications	Staff members from long-term care facilities (N = 134)	34%
Zhang, Cocosila, & Archer (2010)	TAM2	Mobile information technology	Homecare nurses (N = 84)	38%

Extended Technology Acceptance Models

In addition to testing theoretically based extensions of TAM like TAM2, researchers have proposed other contextually relevant constructs to improve the explanatory power of the Technology Acceptance Model. The extended TAM variables can be grouped into three broad categories: individual, device, and organizational characteristics. Individual characteristics include in4dividual differences in affect, perceptions, and knowledge about the piece of technology. For example, personal innovativeness, IT knowledge, and attitude toward health information technology are individual differences between potential users. Device characteristics include constructs related to the device such as perceived compatibility, IT feature demands, and perceived system performance. Finally, organizational characteristics include things outside of the device and individual. For example, management support, training, and subjective norms. Variables from all three categories have been used to predict PU, PEOU, BI, and attitude toward use in the healthcare industry.

Many of the studies reviewed in Table 1 extended the Technology Acceptance Model by including contextually relevant variables from one or two categories (e.g., individual and device characteristics). For example, Melas, Zampetakis, Dimopoulou, and Moustakis (2011) examined physician adoption of communication and information technology. Uniquely, the researchers assessed antecedents of PEOU and PU. First, they examined physicians’ self-report IT knowledge as a predictor of PEOU. Second, they examined IT feature demands (physician's preference for IT features such as rapid image display and systems which provide accurate treatment recommendations) as a predictor of PU. Using structural equation modeling (SEM), Melas et al. (2011) found that IT knowledge positively predicted PEOU and IT feature demands negatively predicted PU. Previous research suggests that adding variables to TAM may improve our understand of technology adoption. For a complete list of variables included in the extended TAM models in healthcare, see Table 2 for the definition, hypotheses, reference(s), and results for each variable.

As can be seen in Table 2, adding variables to TAM has considerable promise to better understand HIT acceptance. Some of the most popular variables include perceived compatibility, social norms, and user characteristics. Relevant to the current study, Holden and Karsh (2010) call for more research using the "added variables approach" in TAM to better understand the factors that predict healthcare IT adoption and use (p. 167). However, few studies have collectively examined the impact of individual, device, and organizational characteristics on health information technology adoption.

Research Models

Based on the evidence supporting the Technology Acceptance Model and the success of including additional variables to better understand factors related to adoption, I used the research model shown in Figure 4a in the current study. In addition to the research model, Figures 4b and 4c show alternative plausible models with minor modifications to determine which model has the best fit. The research models integrate components from the Theory of Reasoned Action (Fishbein & Ajzen, 1975), Technology Acceptance Model (Davis, 1986), and Technology Acceptance Model-2 (Venkatesh & Davis, 2000) to examine tablet computer acceptance and use among pediatricians (Coovert et al., 2011). Before discussing the rationale for all the links, it is worth noting the unique contributions of the models to the technology adoption literature.

Table 2

Variables Added to the Technology Acceptance Model

External Variable	**Definition**	**Predictor of:**	**Reference(s)**	**Results for New Variable**
Attitude toward Health Information Technology	Individual's affective orientations toward the use of technology in healthcare.	PU & PEOU	Vishwanath, Brodsky, & Shaha (2009)	Supported for PU (-) and PEOU (+)
Cluster Ownership	Prior ownership of related technologies.	PU & PEOU	Vishwanath, Brodsky, & Shaha (2009)	Supported for PEOU (-)
Image	Extent to which a person believes the technology enhances one's status in the organization.	PEOU & BI	Yu et al. (2009)	Supported for BI (-) and PEOU (+)
Internet access factors	Time spent online, computer equipment in the home and workplace, and internet access in the home and workplace.	PU & PEOU	Chen et al. (2008)	Supported (+) internet access in the workplace.
IT Feature Demands	Physician's preference for various IT features.	PU	Melas et al. (2011)	Supported (-)
IT Knowledge	Self-report knowledge of computers and IT.	PEOU	Melas et al. (2011); Yu et al. (2008)	Supported (+) for both studies
Management support	Individual's perception that managers create an open and encouraging climate for use.	PU, PEOU, & Subjective Norm	Wu et al. (2008)	All supported (+)
Mobile healthcare system self-efficacy	Individual's perceptions of his or her ability to use mobile healthcare systems to accomplish a healthcare task.	PU & PEOU	Wu et al. (2007)	Supported (+) for both outcomes
Organizational characteristics	Training and support, management support, consultation.	Attitude toward using	Handy, Hunter, & Whiddett (2001)	Only reported descriptive statistics.
Organizational factors	Type of health center and work load.	PU & PEOU	Chen et al. (2008)	Not supported
Perceived Behavioral Control	Perception of the availability of internal and external resources required to use IT equipment.	BI	Chau & Hu (2001, 2002); Yi et al. (2006)	Supported (+)

Table 2

Variables Added to the Technology Acceptance Model (continued)

External Variable	Definition	Predictor of:	Reference(s)	Results for New Variable
Perceived Compatibility	Perception that IT equipment is compatible with work processes.	PU & BI	Bhattacherjee & Hikmet (2007); Chau & Hu (2001); Han et al. (2005); Horan et al. (2004), Liang et al. (2003), Tung, Chang, & Chou (2008), Wu et al. (2007)	Supported (+) in all studies
Perceived Financial Cost	Person's perception that using an IT system will cost money.	BI	Tung, Chang, & Chou (2008)	Supported (-)
Perceived Organizational/Technical Readiness	An individual's perception of the organization's level of preparation and resources to support an IT system.	BI	Horan et al. (2004)	
Perceived System Acceptability	Perception of information management issues related to access, information security, and uses of the information.	Attitude toward using	Handy, Hunter, & Whiddett (2001)	Only reported descriptive statistics
Perceived System Performance	An individual's perceptions that a piece of technology is reliable and responsive for normal use.	PU, PEOU, & BI	Liu & Ma (2006)	Supported (+) for PEOU and BI
Personal Innovativeness in IT	Willingness of an individual to try out any new IT	Result demonstrability, Image, & PEOU	Yi et al. (2006), Liang et al. (2003)	Supported (+) for result demonstrability & PEOU
Psychological Ownership	An individual's feelings of ownership toward a piece of IT.	PU & PEOU	Paré, et al. (2006)	Supported (+) for both outcomes
Related Knowledge	Familiarity and knowledge of relevant IT equipment.	PEOU	Bhattacherjee & Hikmet (2007)	Supported (+)
Resistance to Change	User's tendency to oppose change.	BI	Bhattacherjee & Hikmet (2007)	Supported (-)

Table 2

Variables Added to the Technology Acceptance Model (continued)

External Variable	Definition	Predictor of:	Reference(s)	Results for New Variable
Subjective Norms	Perception that person feels important people want him to use equipment.	BI	Chau & Hu (2001, 2002); Wu et al. (2008); Yi et al. (2006)	Chau & Hu (2001, 2002): Not supported. Wu et al. (2008) & Yi et al. (2006): Supported (+)
Subjective Norms	Perception that person feels important people want him to use equipment.	PU & PEOU	Yu et al. (2009)	Both supported (+)
Technical support and training	Technical support and amount of training provided by individuals with relevant IT knowledge.	PU & PEOU	Liang et al. (2003), Wu et al. (2007)	Only supported (+) for Liang et al. (2003)
Trust	An individual's confidence in the quality, reliability, and security of the device.	BI	Tung, Chang, & Chou (2008); Wu et al. (2008)	Tung et al. (2008): Supported (+); Wu et al. (2008): Not supported
User characteristics	Chen et al. (2008): age, education, job tenure, job position, computer competence, and previous technology experience. Vishwanath, Brodsky, & Shaha (2009): age, job position, specialty. Yu et al. (2009): Job role	PU & PEOU	Chen et al. (2008); Vishwanath, Brodsky, & Shaha (2009); Yu et al. (2009)	Chen et al. only computer competence predicted (+) PU. Vishwanath et al. (2009): age predicted (-) PU and job position predicted (+) PEOU. Yu et al. (2009): job role (+) predicted PU.
User characteristics	Age, gender, prior computer experience.	Attitude toward using	Handy, Hunter, & Whiddett (2001)	Only reported descriptive statistics

This is the first study to use TAM to predict tablet computer usage by physicians. It is important to demonstrate that the model applies equally well to a new piece of technology. That is, the meta-analytic path coefficients from previous research (shown in the figure) are similar when predicting acceptance of tablet computers (Schepers &

Wetzels, 2007). Second, the research models examines individual (PU and PEOU), device (compatibility and reliability) and organizational variables (subjective norm) as antecedents of adoption. This is unique because few studies have considered the joint effects of the different categories of variables. Finally, the research model extends the Technology Acceptance Model by exploring the impact of IT use on job satisfaction. The definition for each construct and the rationale for all links are discussed below.

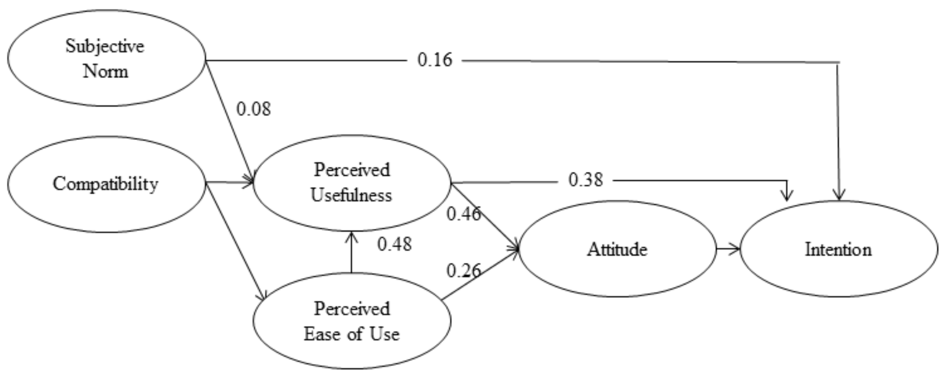


Figure 4a. Extended Technology Acceptance Model to Predict Behavioral Intention

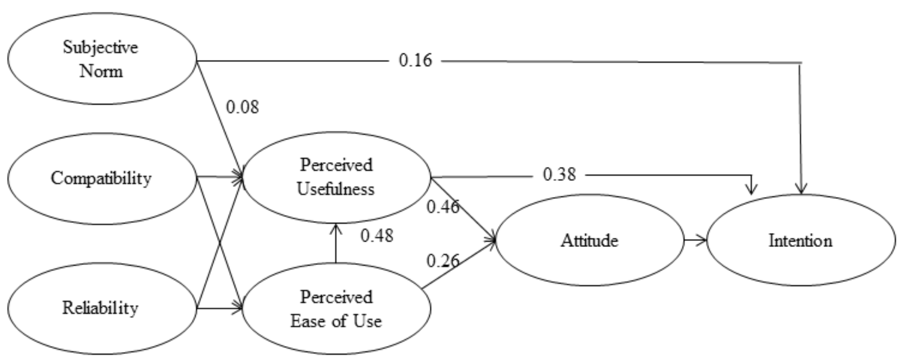


Figure 4b. Extended Technology Acceptance Model including Reliability to Predict Behavioral Intention

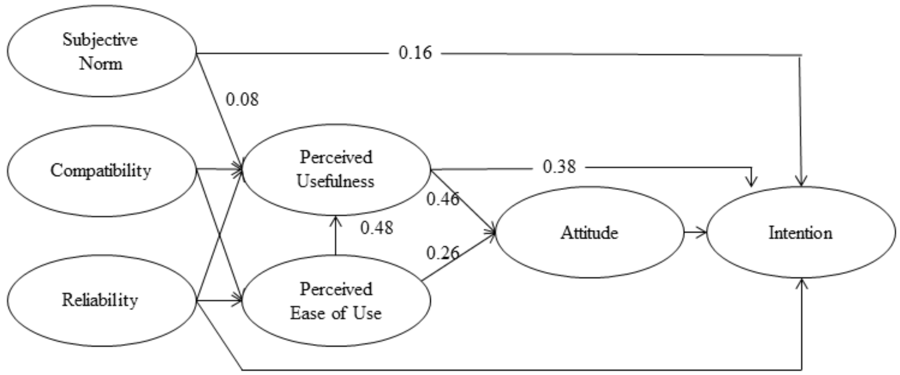


Figure 4c. Extended Technology Acceptance Model including Reliability with a Direct Path to Behavioral Intention

Research Model 4a. The rationale for each link in Model 4a draws on the aforementioned theoretical and empirical work.

Subjective Norm. Fishbein and Ajzen (1975) define subjective norm as "the person's perception that most people who are important to him think he should or should not perform the behavior in question" (p. 302). Subjective norm is related to behavioral intention because people may elect to perform a behavior even if they do not have positive feelings toward the behavior if important referent people believe they should perform the behavior (i.e., compliance with a mandatory policy) (Venkatesh & Davis, 2000).

Hypothesis 1a: Subjective norm is positively related to behavioral intention.

Venkatesh and Davis (2000) theorize a relationship between subjective norm and perceived usefulness because of internalization (Kelman, 1958). Internalization refers to when an individual believes important people in the organization want him or her to use the system and he or she incorporates (internalizes) the important person's belief into his or her belief structure.

Hypothesis 1b: Subjective norm is positively related to perceived usefulness.

Compatibility. Compatibility is defined as an individual's perception of how relevant the technology is to one's job (Venkatesh & Davis, 2000). It is one's evaluation of how well a new system supports critical work-related tasks. For healthcare, higher congruence between a physician's work style and the tasks supported by the IT equipment results in greater perceived usefulness. Therefore, compatibility is proposed to positively impact perceived usefulness because a device that helps a physician with work functions will lead the individual to believe that usage enhances job performance.

Hypothesis 2a: Compatibility is positively related to perceived usefulness.

Moreover, compatibility is hypothesized to influence perceived ease of use because a system that is more compatible with work tasks is more likely to be recognized as easy to use. Conversely, a system that requires a physician to change the way he or she works is likely to be perceived as less easy to use.

Hypothesis 2b: Compatibility is positively related to perceived ease of use.

Perceived Usefulness. According to Davis (1989) perceived usefulness (PU) is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (p. 320). In TAM, PU is proposed to influence attitude toward use because a person forms a positive attitude toward a new technology that is believed to positively impact his or her job performance.

Hypothesis 3a: Perceived usefulness is positively related to attitude toward use.

Also, PU influences BI because when an individual believes a system improves work performance, they form a stronger behavioral intention to use the IT system. The reasoning for both links comes from the Technology Acceptance Model (Davis, 1986).

Hypothesis 3b: Perceived usefulness is positively related to behavioral intention.

Perceived Ease of Use. Perceived ease of use (PEOU) refers to "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320). PEOU is proposed to positively impact attitude and PU for the reasons outlined by Davis et al. (1989). Namely, PEOU is related to attitude because a device that is easier to use results in higher self-efficacy toward the device. A person with higher self-efficacy regarding the new device has a strong belief in his or her ability to use the device. This ultimately results in a more positive attitude toward the technology.

Hypothesis 4a: Perceived ease of use is positively related to attitude toward use.

Also, when a system is perceived as easy to use, it impacts a person's performance (i.e., PU) because the new technology enables the person to accomplish the task with less effort, allowing the saved effort to be used for other work related tasks.

Hypothesis 4b: Perceived ease of use is positively related to perceived usefulness.

Attitude toward Tablet Use. Attitude toward tablet usage takes its definition from the Theory of Reasoned Action. Fishbein and Ajzen (1975) define attitude toward the behavior as an individual's evaluative affect about performing the target behavior. According to TRA, attitude toward use is hypothesized to positively impact behavioral intention to use the device because a more positive attitude toward the system creates a stronger behavioral intention to use the system (Fishbein & Ajzen, 1975).

Hypothesis 5: Attitude toward use is positively related to behavioral intention.

Research Model 4b. Research model 4b includes all of the hypotheses of model 4a plus the construct of reliability.

Reliability. Reliability refers to a person's perception of a system's reliability and responsiveness during normal operations. PEOU and PU reflect an individual's affective and cognitive appraisal of how easy a system is to use and how much it influences job performance. Reliability is proposed to positively affect PEOU and PU because individuals are more likely to be satisfied with a system that is believed to perform better (Liu & Ma, 2006). Given this reasoning:

Hypothesis 6a: Reliability is positively related to perceived usefulness.

Hypothesis 6b: Reliability is positively related to perceived ease of use.

Research Model 4c. The final alternative model includes a direct link between reliability and behavioral intention. The rationale for including this direct link is that not only reliability impact behavioral indirectly through perceived ease of use and perceived usefulness but that it will influence participants' intention to use the device. Specifically, when a system is more reliable, individuals will form stronger behavioral intentions to use the system (Liu & Ma, 2006). Therefore:

Hypothesis 7: Reliability is positively related to behavioral intention.

Exploratory Analyses. In addition to the proposed models, I examined tablet computer use and the impact of use on job satisfaction. Given that tablet computers have recently been adopted in the field of medicine, these analyses are exploratory in nature because formal tests of these hypotheses (i.e., inclusion in the structural equation models) are not possible with small samples.

Individual and Team Tablet Use. Previous research suggests that physicians use tablet computers to accomplish individual and team-based tasks (e.g., Ducey et al., 2011). Individual tablet use is defined as "an individual's actual direct usage of the given system in the context of his or her job" to accomplish a work task (Davis, 1986, p. 25). For a physician, individual tablet usage could be using an application to calculate the appropriate drug dosage for a patient. Team tablet use is defined as an individual's collaborative usage of a given system to accomplish an interdependent task. A group of physicians sharing lab results and coordinating patient care among pediatricians, pathologists, and radiologists with tablet computers is an example of team tablet use (Ducey et al., 2011). I explored this reasoning to see if tablet computer use is best conceptualized as a single factor (i.e., tablet use) or two factors (i.e., individual and team tablet use). In addition, I examined the relationship between participants' behavioral intention to use a tablet computer and actual use. Given the aforementioned theoretical research, behavioral intention was expected to relate to use. Formally,

Hypothesis 8a: Behavioral intention is positively related to individual tablet use.

Hypothesis 8b: Behavioral intention is positively related to team tablet use.

Job Satisfaction. Finally, no studies have examined the impact of IT adoption on job attitudinal variables. One such variable is job satisfaction. Job satisfaction is defined as an employee's overall positive or negative assessment of his or her job (Spector, 1997). Given the lack of literature, I did not formally hypothesize a directional relationship between tablet computer use and job satisfaction.

Chapter 2: Method

Participants

Current residents or physicians in pediatrics or medical-pediatrics in the United States were recruited to participate in this study. The population of interest was pediatricians because the project was a follow up to previous research that examined tablet computer use among this population (Ducey et al., 2011). Also, the grant that funded this research addressed issues related to children's health. The sample excluded physician's assistants, nurses, and technicians because organizations are primarily providing physicians with tablet computers.

A Statistical Analysis Software (SAS) program was used to determine the sample size needed to test the most complex model (Figure 4a) (MacCallum, Browne, & Sugawara, 1996). For the model with 179 degrees of freedom, the minimum sample size for a test of close fit to achieve power of 0.80 is $N = 91$. However, MacCallum et al. (1996) note that while the minimum sample size might be enough for a test of overall fit, it "may not be necessarily adequate for obtaining precise parameter estimates" (p. 144). Therefore, other work has considered the ratio of number of indicators to the number of latent factors. The ratio in the current study was 3.43 ($\frac{24}{7} = 3.43$). Previous work recommends at least N = 100 for ratios of 3 and 4 and more than 200 to be safe (Marsh, Hau, Balla, & Grayson, 1998; Boomsma & Hoogland, 2001). Therefore, recommendations suggested that I needed at least a sample of 200 pediatricians.

Email addresses of pediatricians were obtained in two ways. First, a list of approximately 300 pediatricians' email addresses was obtained from Integrated Medical Data. The company is a fee-based service that maintains an email database which is updated monthly, permission passed quarterly, and CAN SPAM compliant. The email list provided contact information, gender, and specialty information for pediatricians in the United States. Second, I compiled a list of approximately 1,100 faculty and resident email addresses by searching the website for every medical school in the United States with a pediatrics department. Combined, the two sources resulted in a list of approximately 1,400 potential participants. Participants were recruited via email (see Appendix A for the recruitment email). Participation was encouraged by allowing research subjects to enter into a drawing to win one of 10 $10 Amazon.com gift cards.

Of the pediatricians contacted, 261 returned completed surveys, for a response rate of 18.64%. The sample was 65% female with an average age of 43.27 (*SD* = 11.08). Seventy-eight percent of participants were Caucasian, 9% were Asian/Pacific Islander, 5% were Black, 4% were Hispanic, and 3% responded Other. Additionally, 1% did not report their ethnicity. On average, attending physicians had been in practice for 14.75 years (*SD* = 22.94) in a variety of settings including academia (50%), university hospitals (17%), private practice (13%), or multiple locations (20%). Most pediatricians had been practicing medicine for more than five years (64%). A smaller group had been practicing for one to five years (22%). The remainder of the sample was still in training (i.e., residents) (11%) or failed to respond to this item (3%). The majority of physicians were general pediatricians (66%). The remainder of the sample worked in a variety of pediatric subspecialties such as critical care, neonatology, medical pediatrics, and hospitalist medicine.

Measures

When possible, survey items were adapted from previously developed scales with established psychometric properties (e.g., reliability and/or validity estimates). Unless noted, all items were measured using a 7-point Likert scale with the following response options: -3 = strongly disagree, -2 = moderately disagree, -1 = somewhat disagree, 0 = neutral (neither disagree nor agree), 1 = somewhat agree, 2 = moderately agree, 3 = strongly agree. For a complete list of items, refer to Appendix B - L.

Subjective Norm. Subjective norm was measured with three items adapted from Ajzen (1991). The items assessed pediatricians' perceptions of whether influential people think that they should use a tablet computer. Previous research has found that the scale has good reliability, factorial validity (factor loadings above .90), and discriminant validity (Venkatesh & Davis, 2000). The scale had adequate internal consistency in the sample ($\alpha = .77$).

Compatibility. Compatibility was measured with four items from Moore and Benbasat (1991). Items assessed pediatricians' perceptions of how relevant tablet computers are to their jobs. The scale has shown good reliability ($\alpha = .86$). Also, the scale shows strong factorial and discriminant validity with factor loadings above .58 on one factor and low loadings on other factors (e.g., PEOU, PU). The scale had good reliability in the sample ($\alpha = .89$).

Reliability. Reliability was measured with 3 items adapted from Liu and Ma (2006). The items assessed pediatricians' perception of a tablet computer's reliability and responsiveness during normal operations. Previous research has reported an acceptable Cronbach's alpha value of 0.77. The scale is unidimensional with factor loadings above .55 on the latent construct and low loadings on other factors. Moreover, all items have communalities above .71. In the current sample, the scale had strong reliability ($\alpha = .85$).

Perceived Usefulness. Perceived usefulness was measured with four items from Davis (1989). The items assessed pediatricians' perception that using a tablet computer would improve job performance. Previous research has found that the items have good reliability ($\alpha = .98$), are unidimensional, and have factor loadings above .88. Moreover, a factor analysis with an oblique rotation found strong evidence for a two-factor solution with perceived ease of use; indicating good discriminant validity with the second belief in the TAM. In the current sample, Cronbach's alpha was .97.

Perceived Ease of Use. Perceived ease of use was measured with four items from Davis (1989). The scale assessed pediatricians' belief that using a tablet computer would be free of effort. Previous research has found that the scale has good reliability ($\alpha = .94$), convergent validity, and factorial validity. A factor analysis with an oblique rotation found that PEOU was unidimensional and distinct from perceived usefulness. The items had good reliability in the current sample ($\alpha = .96$).

Attitude toward Use. Attitude toward use was measured using a 7-point sematic differential rating scale, according to recommendations by Ajzen & Fishbein (1980). The items assessed pediatricians' evaluative affect about using a tablet computer in their practice. It asked pediatricians to rate their tablet computer use in their medical practice along four bipolar adjectives (good-bad, wise-foolish, favorable-unfavorable, and positive-negative) with a seven point scale. The question stem and adjectives were adapted from Davis (1986). The scale demonstrated good reliability in the sample (α = .97).

Behavioral Intention. Behavioral intention was measured with two items adapted from Venkatesh and Davis (2000). The items assessed pediatricians' subjective probability of using a tablet computer. Previous research has found that the two item measure has good reliability (Cronbach's alpha values ranging from 0.82 – 0.97). In the current study, the scale had similar reliability (α = .96).

Individual Tablet Use. Individual tablet use was measured with three items based on prior work that identified common uses of tablet computers among pediatricians (Ducey et al., 2011). The questions asked how frequently a physician uses a tablet computer for patient (e.g., share lab results), educational (e.g., read journal articles), and professional (e.g., calculate drug dosage) functions with a 7-point Likert scale ranging from 1 (rarely) – 7 (16 or more times per week). While an objective measure of tablet computer use would be ideal, no tablet programs are currently available to track system usage. The scale had marginal reliability (α = .60). However, since these items are heterogeneous in content, it was expected that Cronbach's alpha would be low.

Team Tablet Use. Team use was measured with two items based on previous research (Ducey et al., 2011). The questions ask how frequently a physician uses a tablet computer to collaborate with other physicians on patient (e.g., discuss lab results with other patients) and educational (e.g., share podcasts, articles, or slideshow presentations related to medical research) functions with a 7-point Likert scale ranging from 1 (rarely) – 7 (16 or more times per week). The scale had good reliability ($\alpha = .80$).

Job Satisfaction. Job satisfaction was measured with the Abridged Job in General scale (AJIG; Russell et al., 2004). The AJIG is a shorter form of the Job in General scale (JIG; Ironson, Smith, Brannick, Gibson, & Paul, 1989), which is a general job satisfaction scale derived from the Job Descriptive Index (JDI; Smith, Kendall, & Hulin, 1969). The AJIG has participants describe how they feel about their job most of the time by responding to eight different words or phrases with yes, no, or a question mark. The AJIG has good reliability ($\alpha = .85$) and similar convergent and discriminant validity compared to the JIG. The scale had reasonable reliability in the current sample ($\alpha = .74$).

Demographic Survey. Demographic information regarding participants' age, gender, and ethnicity was collected at the end of the survey. Also, information on the number of years in practice, professional position, practice setting, and pediatric specialty was collected.

Procedure

Pediatricians were sent personalized emails inviting them to participate in the study. The email emphasized the inclusion criteria ("In order to be in the study, you don't need to use a tablet computer in your medical practice, but you must currently be a pediatric resident or pediatrician in the United States."). If eligible participants were interested, they accessed the survey via a hyperlink. The first page of the survey provided information about the study. After reading over the material, participants had to indicate that they agreed to participate in the study.

The survey began by asking participants an initial question about current tablet computer usage (“Do you currently use a tablet computer in your medical practice?”). Based on this response, survey items were phrased to reflect their current usage status. For example, the perceived usefulness item “Using a tablet computer improves my job performance” was used for individuals that currently used tablet computers, but the same item was presented as “Using a tablet computer would improve my job performance” for individuals who did not currently use a tablet computer. Also, if a participant did not currently use a tablet computer, then the items assessing self-reported individual and team usage were omitted and the most distal outcome assessed was behavioral intention. After completing the survey, participants filled out a demographic questionnaire and were provided instructions to enter the Amazon.com gift card raffle.

Chapter 3: Results

Descriptive Statistics

Descriptive statistics (i.e., mean and standard deviation), scale reliabilities, and zero-order correlations for all variables are presented in Table 3. As previously mentioned, all scales, with the exception of attitude toward use and job satisfaction, were measured using a 7-point Likert scale with the following response options: -3 = strongly disagree, -2 = moderately disagree, -1 = somewhat disagree, 0 = neutral (neither disagree nor agree), 1 = somewhat agree, 2 = moderately agree, 3 = strongly agree. Therefore, the mean for each variable provides an indication of the average attitude for each variable such that scores closer to 0 indicate a more neutral attitude, positive values indicate a more favorable attitude, and negative values indicate a more unfavorable attitude. For example, the mean for subjective norm (M = -0.73) indicated that physicians in general felt that there was little pressure to use a tablet computer in their practice and the mean for perceived ease of use (M = 7.02) indicated that, on average, people perceived that it would be easy to learn to use a tablet computer. Reported scale reliabilities are coefficient alpha. All values are above .74 and indicate acceptable internal consistency reliability for each subscale.

Zero-order correlations provide preliminary support for many hypotheses. Relevant to the proposed structural equation models (see Figure 4a-4c), subjective norm was positively related to behavioral intention (r (259) = 0.34, $p < .01$) and perceived usefulness (r (259) = 0.32, $p < .01$). Compatibility was positively correlated with perceived usefulness (*r* (259) = 0.76, *p* < .01) and perceived ease of use (*r* (259) = 0.49, *p* < .01). Perceived usefulness was positively related to attitude toward use (*r* (259) = 0.80, *p* < .01) and behavioral intention (*r* (259) = 0.73). Perceived ease of use was positively related to attitude toward use (*r* (259) = 0.51, *p* < .01) and perceived usefulness (*r* (259) = 0.42, *p* < .01). Attitude toward use was positively related to behavioral intention, *r* (259) = 0.80, *p* < .01. Finally, reliability was positively related to perceived usefulness (*r* (259) = 0.61, *p* < .01), perceived ease of use (*r* (259) = 0.42, *p* < .01), and behavioral intention (*r* (259) = 0.73, *p* < .01). Prior to formally testing these hypotheses with structural equation modeling, I examined the data to ensure that they conformed to the assumptions of the statistical model.

Table 3
Correlations Among Observed Study Variables

Variable	*M*	SD	1	2	3	4	5	6	7	8
1. Subjective Norm	-0.73	3.82	(0.77)							
2. Compatibility	1.84	5.92	0.32**	(0.89)						
3. Reliability	3.64	3.36	0.19**	0.50**	(0.85)					
4. Perceived Usefulness	1.59	5.93	0.32**	0.76**	0.61**	(0.97)				
5. Perceived Ease of Use	7.02	5.06	0.05	0.49**	0.42**	0.42**	(0.96)			
6. Behavioral Intention	1.92	3.33	0.34**	0.72**	0.51**	0.73**	0.45**	(0.96)		
7. Attitude	5.23	5.44	0.27**	0.74**	0.58**	0.80**	0.51**	0.80**	(0.97)	
8. Job Satisfaction	7.13	1.41	-0.04	0.00	-0.05	-0.08	0.09	-0.05	-0.08	(0.74)

Note. *N* = 261. ***p* < .01 (2-tailed). Scale reliabilities displayed on diagonal.

Hypothesis Testing - Checking Assumptions

Maximum likelihood (ML) is a common way to obtain parameter estimates when conducting structural equation modeling because the method is scale free (i.e., a transformed variable can be converted back to the original scale) and scale invariant (i.e., estimates are not impacted by the scale of the observed variables). In addition, estimates are consistent, unbiased, and efficient when the data meet the assumption of multivariate normality (Kline, 2005). Therefore, it is critical to examine this assumption prior to testing the models.

Table 4 displays univariate skewness and kurtosis values for all items. These values can be subjected to a statistical test by dividing the value by the standard error, which is distributed as z. A p-value less than .05 indicates that the observed indicator exhibits excessive skew or kurtosis. As shown in the table, items for the perceived ease of use and attitude toward use scale were significantly negatively skewed. In addition, the same variables plus items for behavioral intention and compatibility had significant kurtosis. The items for job satisfaction were not tested because they were dichotomously scored (yes = 1, no or ? = 0). These results provide preliminary evidence that the data did not meet the assumption of normality. Additional evidence is provided by Mardia's (1970) test for multivariate skewness and kurtosis. Results indicated that the data had significant multivariate skewness, $b_{1,p} = 137.76$, $z = 34.72$, $p < .01$ and kurtosis, $b_{2,p} = 777.56$, $z = 16.63$, $p < .01$. In addition, the combined test of multivariate skewness and kurtosis was significant, $\chi^2 = 1482.03$, $p < .01$. Collectively, these statistical tests indicate that the data did not meet the assumption of multivariate normality.

Previous research has found that there are three major issues when using maximum likelihood estimation if the assumption of multivariate normality does not hold. First, standard error estimates tend to be negatively biased. As a result, the Type I error rate is inflated. Second, the overall chi-square value tends to be positively biased, which results in the rejection of true models. Finally, comparative fit indices tend to be underestimated with higher degrees of non-normality (Klein, 2005). Therefore, it is inappropriate to use maximum likelihood estimation.

Hypothesis Testing - Data Analysis Approach

Since the multivariate normality assumption did not hold in the sample, it was necessary to modify the data analysis approach. Two common ways to handle non-normal data are changing the estimation method or correcting statistics for the degree of non-normality. First, it is possible to change the estimation method to one that does not assume normality (e.g., asymptotic distribution free, weighted least squares). Simulation research suggests that weighted least squares and asymptotic distribution free estimation require sample sizes in the thousands to obtain accurate results with complex models (Curran, West, & Finch, 1996; Lei & Lomax, 2005). In addition, diagonally weighted least squares (a type of estimation in the family of weighted least squares), which works with smaller samples, does not produce asymptotically efficient parameter estimates (Jöreskog & Sörbom, 1996). Finally, the weighted least squares options are limiting because they do not offer all of the model fit indices that are available with maximum likelihood estimation (Kline, 2005). A second approach is to analyze the data with a method that assumes normality but use robust standard errors and an adjusted chi-square value that corrects for the degree of non-normality (e.g., Satorra & Bentler, 1994). Simulation research suggests that this approach works well across a variety of sample sizes and varying degrees of non-normality (Curran et al., 1996; Hu, Bentler, & Kano, 1992). Given the sample size of the current study (N = 261) and the limitations of diagonally weighted least squares, the available evidence suggests that the second approach is more appropriate to remedy the issue of non-normal data.

In order to implement SEM with robust standard errors and a corrected chi-square statistic, it was necessary to estimate an asymptotic variance-covariance matrix in addition to a raw variance-covariance matrix (Satorra & Bentler, 1994). Table 5 provides the intercorrelations among all indicator variables, which can be used to obtain the two matrices needed to replicate the analyses. In order to scale the latent factors, I used the marker variable strategy (i.e., setting the first item factor loading to 1.00 for each latent variable). All analyses were run using the software program LISREL 8.53 and the asymptotic variance-covariance matrix for the data was estimated with PRELIS in LISREL 8.53.

Hypothesis Testing - Model Evaluation Approach

Three models were fit to the data to determine which model provided the most plausible account of tablet computer adoption among pediatricians. Overall fit indices, individual path estimates, proportion of variance accounted for, and theory were considered when determining the most useful model. For overall fit indices, the chi-square test provides an indication of how well the model reproduces the covariance matrix. However, as previously mentioned, this statistic is inflated when data is not normal. Therefore, I used Satorra and Bentler's (1994) scaled chi-square, which corrects for the degree of non-normality. A non-significant chi square value indicates that sampling error is a plausible explanation for the observed discrepancy between the research and sample covariance matrices whereas a significant chi-square value indicates that it is not reasonable to argue that the hypothesized model is correct. However, the chi-square test is heavily influenced by sample size so it is necessary to examine additional fit indices when evaluating models.

Consistent with recommendations from Hu and Bentler (1999), the standardized root mean squared residual (SRMR), root mean square error of approximation (RMSEA), and Tucker-Lewis Index (TLI) were used to evaluate overall model fit. The SRMR quantifies the discrepancy between the sample and reproduced covariance matrix. The SRMR does a good job of identifying misspecified models. Smaller SRMR values indicate better fit and values less than .08 show adequate fit. The RMSEA provides an index of misspecification per degree of freedom. Based on simulations, Hu and Bentler (1999) suggest that a value less than .06 indicates good fit. Finally, the TLI provides an index of the discrepancy between the tested model and a null model. Values range between 0 and 1, with higher numbers indicating better fit and values greater than .95 indicating good fit.

In order to compare the three different models, I also used the chi-square difference test, expected cross validation index (ECVI), and Akaike Information Criterion (AIC). The chi-square difference test is useful for nested models (e.g., models 4b and 4c) to determine if relaxing or constraining one or more parameters results in significantly better fit. In order to use this test with the Satorra-Bentler scaled chi-square, it is necessary to calculate a correction factor, which is obtained by dividing a model's normal theory weighted least squares (NTWLS) chi-square by its Satorra-Bentler chi square (see Bryant & Satorra, 2012 for a detailed explanation). To compare non-nested models, I used the ECVI and AIC. The ECVI provides an indication of how well a model is likely to fit in another sample of equal size. It uses a single sample to approximate how well the model would cross-validate in a second sample, without actually collecting more data. Smaller values indicate better model-data fit. The AIC provides an indication of badness-of-fit such that smaller values indicate a better fitting model (Kline, 2005). Neither statistic is meaningful on its own (i.e., no recommended cut-off criteria), and values from one model must be compared with values from alternative models.

Table 4
Descriptive Statistics for Observed Variables

Variable	Mean	SD	Min	Max	Skewness	Skewness Z-Score	P-Value	Kurtosis	Kurtosis Z-Score	P-Value
1. SN1	-0.71	1.53	-3	3	0.15	0.97	0.33	-0.38	-1.47	0.14
2. SN2	-0.71	1.56	-3	3	0.17	1.11	0.27	-0.42	-1.66	0.10
3. SN3	0.69	1.52	-3	3	-0.09	-0.57	0.57	-0.33	-1.21	0.23
4. CO1	0.18	1.77	-3	3	-0.01	-0.07	0.95	-0.52	-2.26	0.02
5. CO2	0.64	1.66	-3	3	-0.11	-0.71	0.48	-0.48	-2.01	0.05*
6. CO3	0.77	1.72	-3	3	-0.12	-0.80	0.43	-0.58	-2.64	0.00**
7. CO4	0.26	1.71	-3	3	-0.02	-0.12	0.90	-0.51	-2.19	0.03*
8. RE1	1.31	1.32	-3	3	-0.20	-1.35	0.18	-0.41	-1.58	0.11
9. RE2	1.14	1.34	-3	3	-0.16	-1.04	0.30	-0.36	-1.35	0.18
10. RE3	1.19	1.15	-3	3	-0.11	-0.76	0.45	-0.26	-0.88	0.38
11. PU1	0.65	1.46	-3	3	-0.09	-0.58	0.56	-0.34	-1.27	0.20
12. PU2	0.28	1.55	-3	3	-0.02	-0.15	0.88	-0.36	-1.35	0.18
13. PU3	0.28	1.61	-3	3	-0.03	-0.18	0.86	-0.43	-1.72	0.09
14. PU4	0.38	1.61	-3	3	-0.04	-0.28	0.78	-0.46	-1.90	0.06
15. PEOU1	1.93	1.40	-3	3	-0.68	-4.20	0.00**	-0.54	-2.37	0.02*
16. PEOU2	1.54	1.32	-3	3	-0.31	-2.06	0.04*	-0.57	-2.56	0.01*
17. PEOU3	1.76	1.34	-3	3	-0.47	-3.01	0.00**	-0.60	-2.76	0.00*
18. PEOU4	1.78	1.31	-3	3	-0.47	-3.03	0.00**	-0.59	-2.69	0.01*
19. BI1	1.03	1.66	-3	3	-0.26	-1.72	0.09	-0.65	-3.09	0.01*
20. BI2	0.89	1.74	-3	3	-0.25	-1.64	0.10	-0.70	-3.52	0.00*
21. ATT1	1.37	1.42	-3	3	-0.33	-2.17	0.03*	-0.63	-2.98	0.00*
22. ATT2	1.19	1.39	-3	3	-0.19	-1.25	0.21	-0.56	-2.47	0.01*
23. ATT3	1.28	1.47	-3	3	-0.28	-1.88	0.06	-0.61	-2.84	0.01*
24. ATT4	1.39	1.40	-3	3	-0.32	-2.11	0.04*	-0.61	-2.85	0.01*
25. JOB1	0.98	0.15	0	1	-	-	-	-	-	-
26. JOB2	0.93	0.26	0	1	-	-	-	-	-	-
27. JOB3	0.87	0.33	0	1	-	-	-	-	-	-
28. JOB4	0.92	0.27	0	1	-	-	-	-	-	-
29. JOB5	0.88	0.33	0	1	-	-	-	-	-	-
30. JOB6	0.66	0.47	0	1	-	-	-	-	-	-
31. JOB7	0.93	0.26	0	1	-	-	-	-	-	-
32. JOB8	0.96	0.19	0	1	-	-	-	-	-	-

Note. N = 261. SN = Subjective Norm; CO = Compatibility; RE = Reliability;
PU = Perceived usefulness; PEOU = Perceived ease of use; BI = Behavioral intention;
ATT = Attitude; JOB = Job satisfaction. Job satisfaction items were scored
1 = yes or 0 = no or ?, so skew and kurtosis values are not reported.
* $p < .05$ (2-tailed). ** $p < .01$ (2-tailed).

Table 5
Intercorrelations Among Indicator Variables

Variable	*M*	*SD*	1	2	3	4	5	6
1. SN1	-0.71	1.53	-					
2. SN2	-0.71	1.56	.95**	-				
3. SN3	0.69	1.52	.31**	.30**	-			
4. CO1	0.18	1.77	.18**	.17**	.30**	-		
5. CO2	0.64	1.66	.19**	.20**	.14*	.56**	-	
6. CO3	0.77	1.72	.25**	.23**	.18**	.60**	.86**	-
7. CO4	0.26	1.71	.35**	.35**	.22**	.54**	.66**	.73**
8. RE1	1.31	1.32	0.102	0.096	.23**	.27**	.34**	.42**
9. RE2	1.14	1.34	0.11	0.111	.21**	.30**	.34**	.43**
10. RE3	1.19	1.15	0.10	0.09	.16**	.35**	.46**	.51**
11. PU1	0.65	1.46	.19**	.20**	.24**	.48**	.65**	.70**
12. PU2	0.28	1.55	.26**	.27**	.20**	.48**	.64**	.70**
13. PU3	0.28	1.61	.30**	.31**	.24**	.46**	.63**	.69**
14. PU4	0.38	1.61	.30**	.32**	.22**	.47**	.65**	.73**
15. PEOU1	1.93	1.40	-0.081	-0.088	0.106	.20**	.33**	.37**
16. PEOU2	1.54	1.32	0.041	0.053	.13*	.34**	.47**	.53**
17. PEOU3	1.76	1.34	-0.012	-0.015	.16**	.31**	.43**	.49**
18. PEOU4	1.78	1.31	0.019	0.009	.19**	.32**	.45**	.51**
19. BI1	1.03	1.66	.25**	.27**	.22**	.48**	.63**	.70**
20. BI2	0.89	1.74	.31**	.34**	.23**	.46**	.59**	.65**
21. ATT1	1.37	1.42	.18**	.22**	.19**	.43**	.66**	.71**
22. ATT2	1.19	1.39	.27**	.31**	.17**	.45**	.60**	.67**
23. ATT3	1.28	1.47	.24**	.27**	.15*	.46**	.65**	.72**
24. ATT4	1.39	1.40	.21**	.24**	.14*	.45**	.66**	.71**
25. JOB1	0.98	0.15	-0.01	0.00	0.07	0.10	0.09	0.04
26. JOB2	0.93	0.26	-0.07	-0.10	0.02	0.05	0.03	-0.01
27. JOB3	0.87	0.33	-0.03	-0.05	-0.01	-0.07	-0.06	-0.06
28. JOB4	0.92	0.27	-0.05	-0.05	0.11	0.10	-0.01	-0.02
29. JOB5	0.88	0.33	-0.06	-0.05	0.02	0.09	0.01	-0.02
30. JOB6	0.66	0.47	-0.03	-0.04	-0.04	0.05	-0.03	-0.03
31. JOB7	0.93	0.26	-0.09	-0.06	-0.01	0.03	-0.02	-0.08
32. JOB8	0.96	0.19	0.01	0.01	.18**	0.08	0.00	0.01

Note. * p < .05 (2-tailed). ** p < .01 (2-tailed).

Table 5

Intercorrelations Among Indicator Variables (continued)

7	8	9	10	11	12	13	14	15
-								
.33**	-							
.40**	.68**	-						
.44**	.62**	.69**	-					
.64**	.57**	.58**	.65**	-				
.68**	.50**	.48**	.57**	.86**	-			
.68**	.48**	.44**	.52**	.85**	.92**	-		
.71**	.47**	.44**	.52**	.83**	.89**	.92**	-	
.30**	.24**	.32**	.34**	.29**	.25**	.26**	.27**	-
.46**	.32**	.42**	.48**	.47**	.45**	.48**	.47**	.77**
.44**	.30**	.36**	.39**	.40**	.37**	.39**	.40**	.87**
.43**	.27**	.35**	.40**	.41**	.38**	.39**	.42**	.85**
.68**	.42**	.42**	.51**	.70**	.70**	.72**	.68**	.32**
.70**	.39**	.40**	.49**	.66**	.68**	.68**	.66**	.28**
.67**	.50**	.49**	.52**	.73**	.71**	.74**	.72**	.39**
.66**	.49**	.42**	.48**	.70**	.69**	.72**	.73**	.32**
.67**	.48**	.45**	.51**	.72**	.74**	.75**	.75**	.34**
.68**	.50**	.48**	.55**	.73**	.72**	.74**	.73**	.34**
0.08	-0.04	-0.08	0.00	0.09	0.08	0.12*	0.07	0.08
-0.03	0.01	0.02	0.01	-0.03	-0.03	-0.03	-0.05	0.16*
-0.04	-0.04	-0.05	-0.04	-0.08	-0.07	-0.09	-0.09	-0.03
0.01	0.08	0.05	-0.03	-0.01	0.01	0.00	-0.03	0.05
-0.01	-0.06	-0.01	-0.03	-0.03	0.00	-0.01	-0.03	0.08
-0.03	-0.1	-0.03	-0.07	-0.10	-0.10	-0.08	-0.11	-0.01
-0.02	-0.01	-0.09	-0.03	-0.06	-0.06	-0.04	-0.05	0.01
0.01	0.03	0.04	-0.05	-0.05	-0.04	-0.05	-0.04	-0.02

Table 5

Intercorrelations Among Indicator Variables (continued)

16	17	18	19	20	21	22	23	24
-								
.85**	-							
.83**	.93**	-						
.49**	.45**	.46**	-					
.47**	.42**	.41**	.92**	-				
.59**	.53**	.55**	.78**	.74**	-			
.50**	.42**	.43**	.72**	.70**	.83**	-		
.53**	.46**	.48**	.78**	.75**	.92**	.87**	-	
.56**	.49**	.52**	.78**	.74**	.92**	.85**	.94**	-
0.14*	.16**	.13*	0.11	0.08	0.11	0.10	0.08	0.08
0.18**	.17**	.16*	-0.01	-0.03	-0.03	-0.08	-0.05	-0.05
-0.01	-0.01	-0.01	-0.08	-0.08	-0.09	-0.11	-0.09	-0.09
0.12	.13*	0.09	-0.06	-0.07	-0.03	-0.03	-0.05	-0.04
0.03	0.08	0.06	-0.04	-0.04	-0.03	-0.08	-0.05	-0.09
-0.03	0.00	-0.02	-0.01	-0.03	-0.06	-0.08	-0.03	-0.05
0.04	0.05	0.01	-0.07	-0.07	-0.04	-0.08	-0.07	-0.08
0.10	0.05	0.06	-0.02	0.03	-0.03	-0.06	-0.04	-0.03

Table 5

Intercorrelations Among Indicator Variables (continued)

25	26	27	28	29	30	31	32
-							
.15*	-						
0.10	.20**	-					
.24**	.46**	.23**	-				
.25**	.26**	.39**	.32**	-			
.16**	.21**	.29**	.24**	.45**	-		
.35**	.21**	.29**	.24**	.48**	.30**	-	
.24**	.48**	.28**	.60**	.23**	0.11	.18**	-

Hypothesis Testing - Results

The results for research model 4a, research model 4b, and research model 4c are presented in Figure 5, Figure 6, and Figure 7, respectively. In addition, model fit statistics are displayed in Table 6. Results indicated that while the Satorra-Bentler Scaled chi-square test was statistically significant for all models, overall model fit indices were below the recommended cut-off criteria for all models with the exception of the SRMR for model 4a which was at the threshold but not less than .08 (Hu & Bentler, 1999). Collectively, the fit indices suggest that all of the models provided a good fit to the data. The output suggested no theoretically defensible modifications to improve model fit for any model.

Table 6
Model Comparison

Model	Satorra-Bentler Scaled $\chi2$	df	RMSEA (90% CI)	SRMR	TLI	ECVI (90% CI)	AIC	Satorra-Bentler Scaled $\Delta\chi2$*	Δdf	p
1 (Figure 4a)	277.39**	179	0.05 (0.04 - 0.06)	0.08	0.97	1.47 (1.31 - 1.66)	381.39	-	-	-
2 (Figure 4b)	376. 14**	238	0.05 (0.04 - 0.06)	0.07	0.96	1.92 (1.74 - 2.14)	500.14	-	-	-
3 (Figure 4c)	375.08**	237	0.05 (0.04 - 0.06)	0.07	0.96	1.93 (1.74 - 2.15)	501.08	1.06	1	0.70

Note. Model 1 was not nested in model 2, so it was not possible to conduct a $\chi2$ difference test.
** p < .01 (2-tailed). *Formula from Bryant & Satorra (2012).

Unstandardized estimates are provided for all hypothesized paths along with each path's corresponding standard error (in parentheses) in Figure 5-7. Solid lines indicate statistically significant paths and dashed lines indicate non-significant paths. Most hypotheses were supported. First, for model 4a, subjective norm was not related to behavioral intention (hypothesis 1a - not supported) but was significantly related to perceived usefulness (hypothesis 1b - supported). Compatibility was positively related to perceived usefulness (hypothesis 2a - supported) and perceived ease of use (hypothesis 2b - supported). Perceived usefulness was positively related to attitude toward use (hypothesis 3a- supported) and behavioral intention (hypothesis 3b- supported).

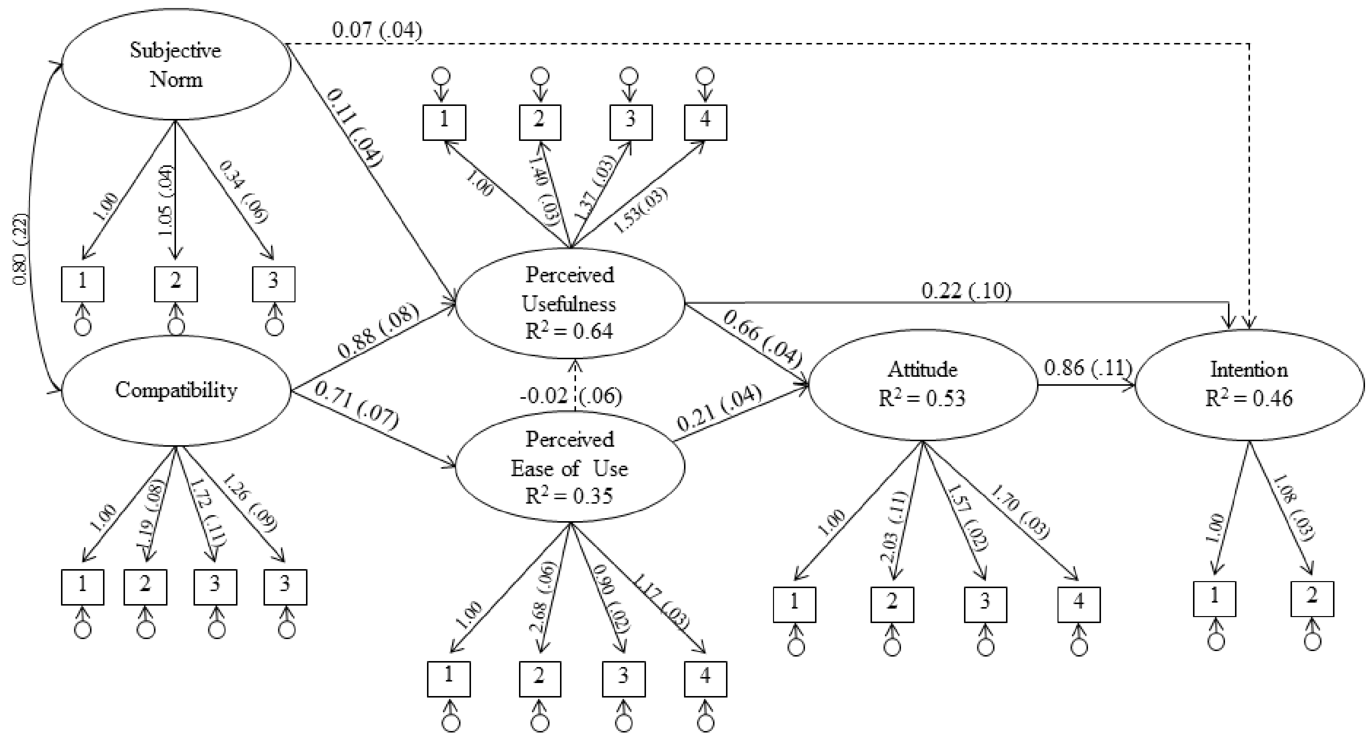
Perceived ease of use was positively related to attitude toward use (hypothesis 4a - supported) but not perceived usefulness (hypothesis 4b - not supported). Attitude toward use was positively related to behavioral intention (hypothesis 5 - supported). Model 4b included reliability as a predictor of perceived usefulness and perceived ease of use. Figure 6 indicates that reliability was significantly related to perceived usefulness (hypothesis 6a - supported) and perceived ease of use (hypothesis 6b - supported). Model 4c included a path from reliability to behavioral intention. Figure 7 shows that this path was not significant (hypothesis 7 - not supported).

Across all of the models, there was evidence to support nine out of 12 hypotheses when they were tested with structural equation modeling. Combined with the results of the zero-order correlations, which provided evidence to support all 12 hypotheses, hypothesis 1a, 4b, and 7 were partially supported because, although they were significantly related to their intended criterion variables, these predictors did not account for unique variance in the outcome when controlling for the influence of other variables.

Model Comparison. Relevant statistical and theoretical evidence was used to determine which model provided the best approximation to the data. Collectively, the evidence suggests that model 4b is the most practically and theoretically defensible.

Table 6 provides statistical evidence to evaluate the three models. Since all models have essentially the same model fit according to RMSEA, SRMR, and TLI, the AIC and ECVI provide evidence for which model is best in a statistical sense. Initial evidence suggests model 4a is the most plausible because it has the lowest AIC and the ECVI point estimate does not overlap with the 90% confidence interval for either model 4b or 4c. However, one issue with the ECVI is that it considers the number of free

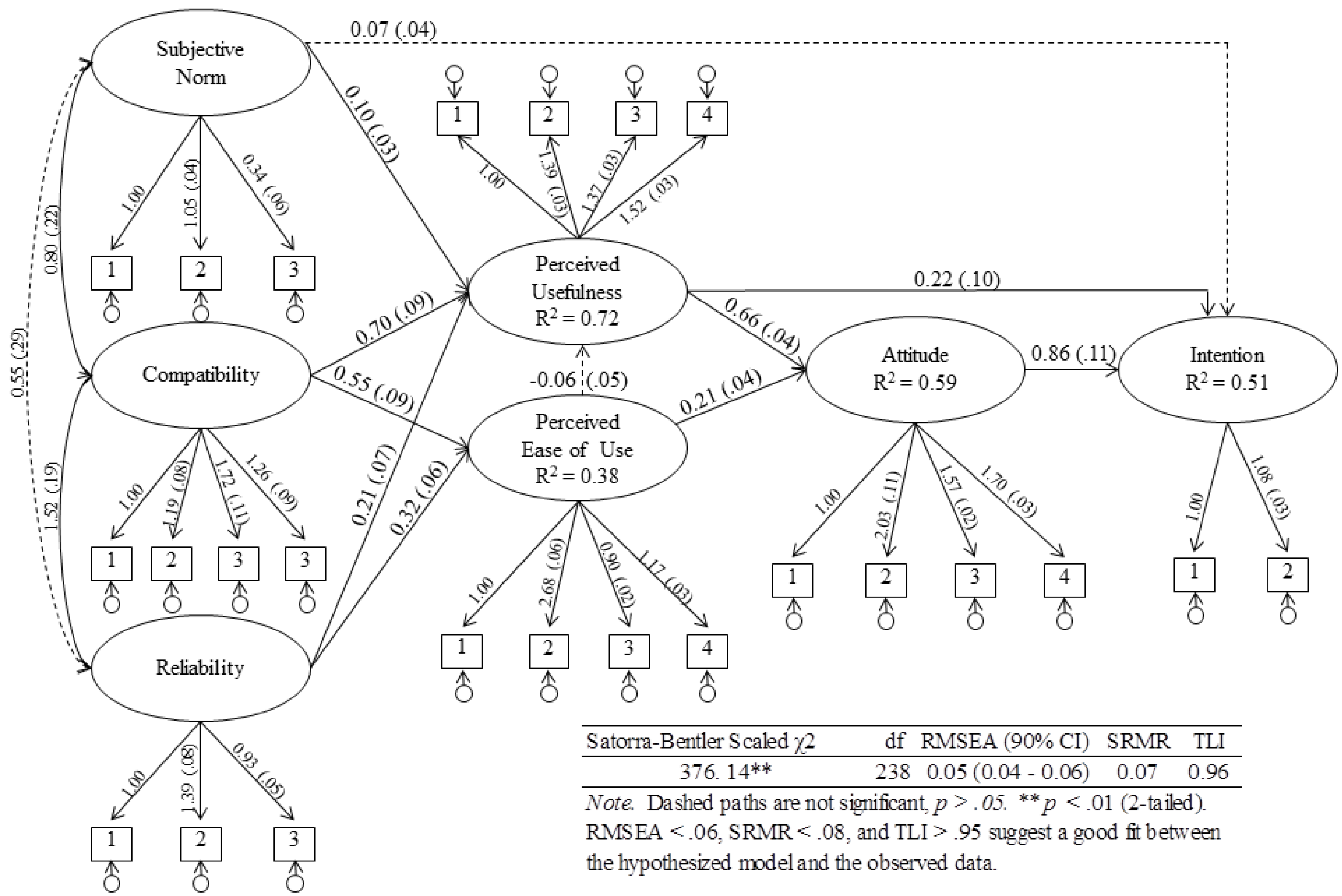
Figure 5. Results for Research Model 4a



Satorra-Bentler Scaled $\chi 2$	df	RMSEA (90% CI)	SRMR	TLI
277.39**	179	0.05 (0.04 - 0.06)	0.08	0.97

Note. Dashed paths are not significant, $p > .05$. ** $p < .01$ (2-tailed). RMSEA < .06, SRMR < .08, and TLI > .95 suggest a good fit between the hypothesized model and the observed data.

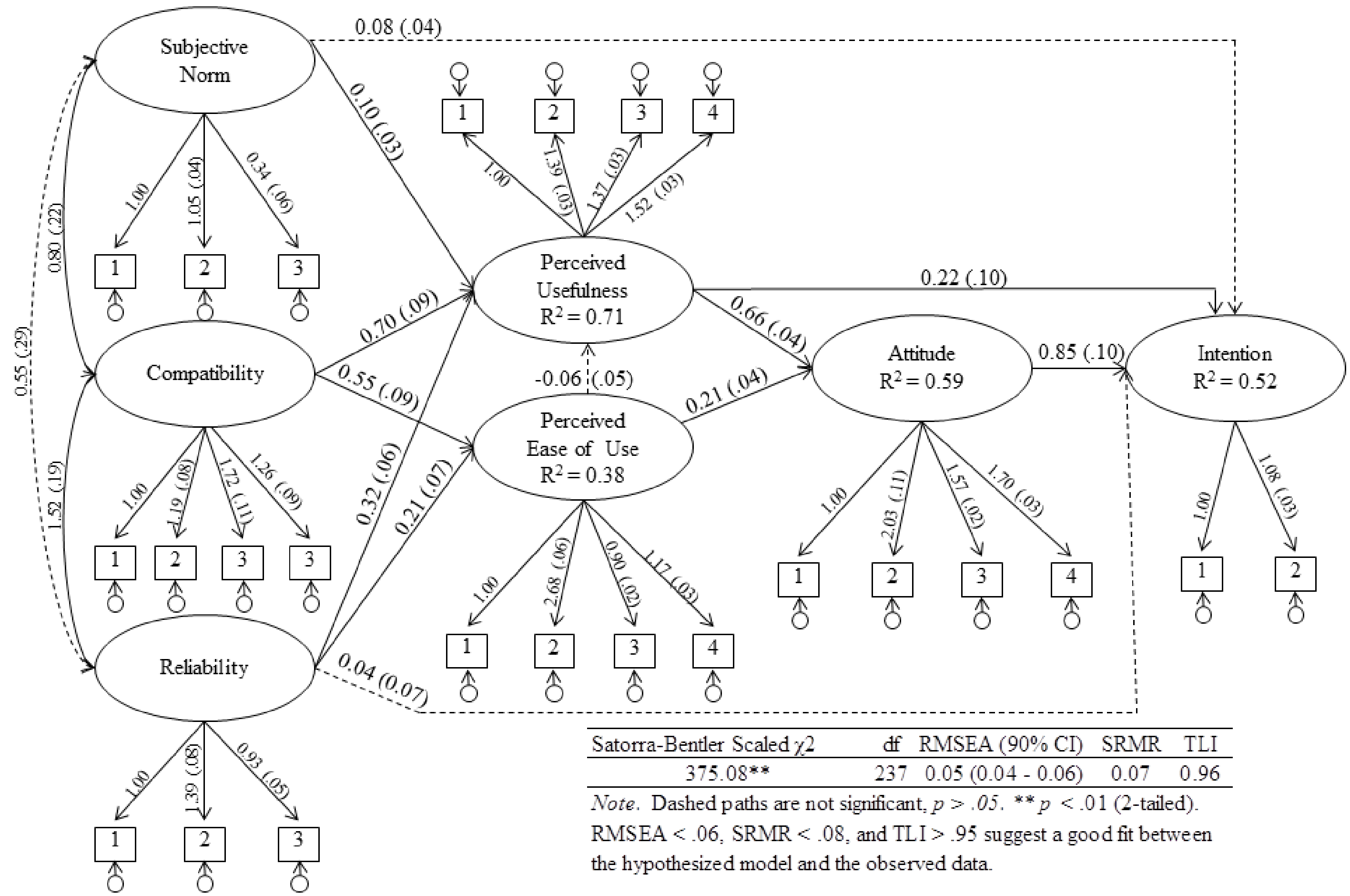
Figure 6. Results for Research Model 4b



Satorra-Bentler Scaled χ2	df	RMSEA (90% CI)	SRMR	TLI
376. 14**	238	0.05 (0.04 - 0.06)	0.07	0.96

Note. Dashed paths are not significant, $p > .05$. ** $p < .01$ (2-tailed). RMSEA < .06, SRMR < .08, and TLI > .95 suggest a good fit between the hypothesized model and the observed data.

Figure 7. Results for Research Model 4c



Satorra-Bentler Scaled $\chi 2$	df	RMSEA (90% CI)	SRMR	TLI
375.08**	237	0.05 (0.04 - 0.06)	0.07	0.96

Note. Dashed paths are not significant, $p > .05$. ** $p < .01$ (2-tailed). RMSEA < .06, SRMR < .08, and TLI > .95 suggest a good fit between the hypothesized model and the observed data.

parameters in a model in the calculation such that models with more free parameters will have larger ECVI values. Given the large difference in the degrees of freedom between model 4a (179) and 4b (238), this significant result could be due to a difference in the number of parameters estimated rather than a substantive difference. Therefore, it is necessary to also examine individual path estimates and the proportion of variance accounted for in the endogenous variables by the exogenous variables when determining which model to retain.

The results of model 4b indicated that reliability was significantly related to perceived usefulness and perceived ease of use. Furthermore, the amount of variance explained in perceived usefulness increased from 64% to 72%, perceived ease of use increased from 35% to 38%, attitude increased from 53% to 59%, and behavioral intention increased from 46% to 51% by adding reliability. These increases are substantial considering that only one additional variable was different between model 4a and model 4b. While this evidence suggests that model 4b better explains the psychological phenomenon of technology acceptance, there is currently no formal test to see if a change in R^2 is statistically significant between two structural equation models. However, many of these increases are fairly large and if researchers are ultimately interested in better understanding the factors that influence one's behavioral intention to use a piece of technology, then model 4b appears to provide a more useful representation of this phenomenon than does model 4a, despite the statistical evidence from the ECVI and AIC suggesting that model 4a is better.

Conceptually, compatibility and reliability are distinct constructs. Compatibility assesses an individual's perception of how relevant the technology is to one's job

(Venkatesh & Davis, 2000), whereas reliability refers to a person's perception of a system's reliability and responsiveness during normal operations. Although these two constructs are significantly correlated, r (259) = 0.50, $p < .01$, the relationship suggests that they are distinct and both important to understand antecedents of perceived usefulness and perceived ease of use. The path estimates show that both variables are differentially important in determining one's perceived usefulness and perceived ease of use, such that compatibility has a greater influence on perceived usefulness and perceived ease of use compared to reliability but that reliability explains additional variance in these variables after controlling for the influence of compatibility. Therefore, model 4b appears to provide a better representation to the data than does model 4a after considering other statistical measures, conceptual definitions, and theory.

Finally, based on a Satorra-Bentler scaled chi-square difference test, it appears that adding an additional path from reliability to behavioral intention (i.e., moving from model 4b to model 4c) does not significantly improve model fit (Bryant & Satorra, 2012). It was only possible to conduct this test between these two models because they are nested. Furthermore, the individual path estimate for reliability to behavioral intention was not statistically significant. In summary, it appears that model 4b is the most useful and plausible of the three models to capture the process of tablet computer acceptance among pediatricians.

Exploratory Analyses

Based on earlier research (Ducey et al., 2011), tablet computer use was conceptualized as having two factors: individual and team use. Exploratory factor analysis (EFA) was used to examine the factor structure of the tablet computer use scale.

EFA was appropriate because I was interested in determining the dimensionality of the items and which items loaded on which factor(s). Given these objectives, EFA is more appropriate than confirmatory factor analysis (CFA) because, although I wrote items for specific factors and had tentative ideas about which items should load on each factor, I had no evidence besides face validity to identify items that would load only on the intended factor. Moreover, Fabrigar and Wegener (2012) suggest that when researchers are examining new items, it is appropriate to run an EFA before a CFA. An EFA with maximum likelihood estimation indicated that the scale was unidimensional. The first factor had an eigenvalue of 2.97 and accounted for approximately 60% of the variance. The second factor extracted had an eigenvalue of 0.80 and accounted for 15% of the variance. Given this result, I did not attempt to rotate the solution because a single general tablet computer use factor rather than two distinct factors appeared to provide the best representation of the data.

Given the small number of people ($N = 89$) in the sample who currently used tablet computers in their medical practice, it was not possible to formally test the relationship between behavioral intention and actual use in a structural equation framework. However, the zero-order correlation between behavioral intention and individual tablet computer use (r (87) = 0.51, $p < .01$) and team tablet computer use (r (87) = 0.42, $p < .01$) was statistically significant. These results provide support for hypothesis 9a and 9b. In addition, behavioral intention significantly correlated with general tablet computer use, r (87) = 0.50, $p < .01$. Finally, I explored the relationship between tablet computer use and job satisfaction by calculating correlations. Results indicated that individual (r (87) = 0.04, *ns*), team (r (87) = 0.07, *ns*), and total (r (87) = 0.06, *ns*) tablet computer use were not related to job satisfaction.

Chapter 4: Discussion

The present study examined an extended Technology Acceptance Model to understand factors that influence tablet computer adoption among pediatricians operating in a variety of settings including academic medicine, university hospitals, and private practice. After evaluating three equally plausible structural equation models with statistical, empirical, and conceptual evidence, results indicated that model 4b (Figure 6) best captured the process of tablet computer acceptance among pediatricians. Specifically, the final model indicated that individual (i.e., perceived usefulness), organizational (i.e., subjective norm), and device (i.e., compatibility, reliability) characteristics collectively influenced physicians' intentions to adoption tablet computers in their medical practices. However, in the current sample compatibility was relatively more important than subjective norm and reliability in determining participants' perceptions of usefulness and ease of use. In addition, perceived usefulness was relatively more important when determining one's attitude toward using tablet computers. All of these results are in accordance with previous research that has extended the Technology Acceptance Model by including these external variables as predictors of perceived usefulness and perceived ease of use. Moreover, exploratory analyses found that behavioral intention was significantly related to actual tablet computer use but that actual use had no effect on job satisfaction. Also, tablet computer use is better conceptualized as a single construct rather than being comprised of individual and team tablet computer use.

The only hypothesized paths that did not approach significance in the final model were between subjective norm and behavioral intention and perceived ease of use and perceived usefulness. For the first non-significant relationship, it is plausible that important coworkers do not directly influence one's behavioral intention to use a tablet computer because participants also independently evaluate a system in order to determine if they will use a given piece of technology. This explanation is consistent with the final model. It shows that pediatricians considered subjective norms when determining tablet computers' perceived usefulness and ease of use, but important others did not directly influence intention to adopt tablet computers. Furthermore, previous research that has tested this path has found mixed results. The results of the current study combined with four other studies that have examined this relationship (Chau & Hu, 2001, 2002; Wu et al., 2008; Yi et al., 2006), reveal that the path has been non-significant in three out of five cases.

Second, the path from perceived ease of use to perceived usefulness was not statistically significant. This result was unexpected because prior research using a vote counting strategy to review all available evidence on the TAM in the healthcare industry found that this relationship was statistically significant in 10/12 studies (Holden & Karsh, 2010). Given previous research, there are a number of possible explanations for this non-significant finding. First, this result may have been due to random error. Alternatively, given the relatively large mean for perceived ease of use, it is possible that most participants believed that tablet computers would be easy to adopt. In this case, the non-significant relationship could be due to range restriction. This final explanation appears most plausible. Future research should explore this reasoning to determine if the relationship of perceived ease of use to perceived usefulness is moderated by device complexity such that the relationship is statistically significant when individuals are considering adopting a complex device but non-significant with a device that is easy to learn to operate.

Theoretical and Practical Contributions

This study contributes to our theoretical understanding of technology adoption in organizations in a variety of ways. First, the results indicate that the Technology Acceptance Model provides a parsimonious way to model tablet computer adoption among pediatricians. Prior research has not examined the viability of the TAM to predict tablet computer use. Therefore, this study contributes to the literature by suggesting that the TAM generally applies very well for this new piece of technology. However, additional research is needed with other samples besides pediatricians to confirm this conclusion. Also, the research models considered in this study demonstrate that it is necessary to consider individual, organizational, and device characteristics when modeling determinants of perceived usefulness and perceived ease of use. Most prior research has considered variables from one or two of these categories. However, the results from the current study suggest that in combination, the three types of variables influence behavioral intention via perceived usefulness and perceived ease of use. These external variables accounted for a substantial proportion of the variance in perceived usefulness (72%) and perceived ease of use (38%). Moreover, this study suggests that external variables primarily influence one’s behavioral intention to adopt a piece of technology through the TAM constructs, rather than directly influencing behavioral intention, as indicated by the lack of support for hypothesis 1 in model 4a and hypothesis

7 in model 4c. Finally, although previous researchers have qualitatively reviewed the evidence for the TAM in healthcare (e.g., Holden & Karsh, 2010), this study contributes to the literature to ultimately provide enough data to meta-analytically estimate the key relationships in the TAM for healthcare settings, specifically with physicians because research is needed in this area (see Future Research section).

Practically, the results suggests that important people (i.e., subjective norm), the compatibility between the device and work demands, and the reliability of the device impact perceptions of usefulness and ease of use. These two attitudinal variables ultimately influence one's attitude toward tablet computers, one's behavioral intention to use the device, and actual use. Organizations interested in providing tablet computers to physicians and residents may consider designing training programs to increase employees' ratings regarding subjective norms, compatibility, and reliability prior to implementing an organization-wide IT investment initiative. For example, conducting a brief orientation that discusses the functionality of tablet computers and provides devices preloaded with work-relevant applications (e.g., Epocrates, Medscape) may enhance perceptions of compatibility. Also, it may be possible to demonstrate that key personnel support the use of tablet computers by having them lead these training sessions. As a result of this type of training, tablet computer adoption rates may improve by increasing perceptions of the external variables assessed in this study. Second, the results are of interest to tablet computer device manufacturers and app developers. In order to increase sales of tablet computers to physicians and hospitals, these individuals need to ensure that the software and hardware support critical work-related tasks and are very reliable.

Limitations

This study suffered from a number of limitations. First, the data violated the assumption of multivariate normality. However, the modified data analysis strategy involving robust standard errors and the Satorra-Bentler scaled chi-square appeared to be the best solution given current evidence. Second, all of the data used in the SEM analyses were single-source (self) and cross-sectional. Therefore, it is not possible to infer any causal flow to the proposed models. However, given the extensive research literature on the Technology Acceptance Model, the current research model provides a plausible and useful representation of the process of technology acceptance among pediatricians. Third, some people may disagree with the decision to retain model 4b instead of model 4a because model 4a had more favorable ECVI and AIC values. Although this is a legitimate criticism, it is equally important to consider theoretical and conceptual reasons for determining the best model. Ultimately, the inclusion of reliability improves our understanding of the antecedents of two critical constructs in the Technology Acceptance Model. Finally, it is possible that using a sample of pediatricians and only examining tablet computers limits the generalizability of the results and conclusions. The extensive research literature on the Technology Acceptance Model in healthcare suggests that this is only a minor concern. For example, the results are remarkably consistent across different samples of healthcare professionals and/or technologies. Table 1 emphasizes this point by showing that the TAM works well for physicians, public health nurses (Chen et al., 2008), medical staff (Melas et al., 2011), and physiotherapists (Van Schaik et al., 2002), among others. Given the diversity of these samples, it is reasonable to assume that the results obtained in a sample of pediatricians generalize to other medical specialists who may be interested in using tablet computers in areas such as internal medicine, dermatology, and plastic surgery.

Future Research

There are three key areas in which to conduct future research on technology adoption and more specifically technology adoption in the healthcare industry. First, researchers should consider including other individual (e.g., image, self-efficacy, IT knowledge), organizational (e.g., training, type of healthcare setting, technical support), and device (e.g., operating system, size, cost) characteristics as predictors of perceived usefulness and perceived ease of use. These variables represent a small number of possible constructs to add to the Technology Acceptance Model. Refer to Table 2 for a complete list of variables that have been previously considered in the TAM and the results for each variable. Given the current state of the literature, it appears we have a good understanding of what variables influence perceived usefulness. However, additional work needs to examine the factors that influence perceived ease of use.

Previous researchers have praised this “added variables approach” to better understand the factors that predict healthcare IT adoption and use (Holden & Karsh, 2010, p. 167). I agree that including additional variables will ultimately improve our understanding of the psychological process of technology adoption. However, once there is enough available evidence, researchers need to move beyond adding variables with little theoretical justification to formalized theory building. Specifically, once variables have been consistently replicated with a variety of different samples and technologies, researchers need to develop a coherent and theoretically meaningful framework to expand our understanding of technology adoption. Currently, no one has attempted to organize the many unique predictors of perceived usefulness or perceived ease of use beyond individual, organizational, and device characteristics. Given the large quantity of research in this tradition, it appears that an inductive theory building approach holds promise to expand the Technology Acceptance Model (Locke, 2007).

Finally, research using the TAM in healthcare has nearly reached the point of aggregating similar studies to meta-analytically estimate path coefficients for this specific industry. Prior meta-analyses on the TAM either ignored industry as a moderator (e.g., Ma & Liu, 2004) or coarsely classified companies by industry (e.g., King & He, 2006). It is important to meta-analytically estimate the paths in the TAM separately for healthcare because some researchers have questioned the applicability of the model in this context (e.g., see Chismar & Wiley-Patton, 2003). Therefore, it appears that researchers may benefit from a healthcare-focused meta-analysis to determine if the TAM is an appropriate theory of technology adoption among healthcare professionals.

Conclusions

The present study examined variables that influence tablet computer adoption in a sample of pediatricians. Comparisons of three alternative and equally plausible structural equation models indicated that individual, organizational, and device characteristics collectively influenced physicians' behavioral intention to adopt tablet computers. This research extends the Technology Acceptance Model by showing that subjective norms, compatibility, and reliability explain 72% of the variance in perceived usefulness. Additionally, compatibility and reliability explain 38% of the variance in perceived ease of use. These results are consistent with previous research and extend the literature on technology adoption by modeling determinants of the two core attitudinal constructs in the Technology Acceptance Model. Future research should examine other variables that may influence perceived usefulness and perceived ease of use, with the goal of ultimately developing a formal inductive theory that expands the Technology Acceptance Model.

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Appendices

Appendix A: Recruitment Email

Dear Dr.______________,

My name is Adam Ducey and I am doctoral student in industrial-organizational psychology at the University of South Florida. I am currently working on a research project (USF IRB #PRO 8065) examining pediatricians' attitude towards tablet computers (e.g. Apple iPad, Samsung Galaxy Tab). I request your participation in this research.

In order to participate in this research study, you don't need to use a tablet computer in your medical practice, but you must be a resident or physician in pediatrics or Med-Peds. Participation in the study involves the completion of a brief (10-15 minute) and anonymous online survey which can be accessed at your convenience from this link:

https://www.surveymonkey.com/s/pediatriciantabletstudy

Should you participate in this study, you can enter into a drawing to receive one of ten $10 Amazon.com gift cards. Also, upon request I can provide you a summary of my results.

Your response is extremely valuable to me and I greatly appreciate your time and contribution to this research. Should you have any questions concerning this study, please contact me, Adam Ducey, at aducey@mail.usf.edu.

Thank you,
Adam Ducey

Doctoral Student
Industrial/Organizational Psychology
University of South Florida
4202 East Fowler Avenue, PCD 4118G
Tampa, FL 33620-7200

Appendix B: Subjective Norm Scale

Physicians that Currently Use a Tablet Computer

1. Physicians who influence my clinical behavior think that I should use a tablet computer in my medical practice.
2. Physicians who are important to me think that I should use a tablet computer in my medical practice.
3. In general, medical facilities have supported the use of tablet computers.

Physicians that Currently Do Not Use a Tablet Computer

1. Physicians who influence my clinical behavior think that I should use a tablet computer in my medical practice.
2. Physicians who are important to me think that I should use a tablet computer in my medical practice.
3. In general, medical facilities would support the use of tablet computers.

Appendix C: Compatibility Scale

Physicians that Currently Use a Tablet Computer

1. Using a tablet computer is compatible with all aspects of my work.
2. I think that using a tablet computer fits well with the way I like to work.
3. Using a tablet computer fits into my work style.
4. In my job, usage of my tablet computer is important.

Physicians that Currently Do Not Use a Tablet Computer

1. Using a tablet computer would be compatible with all aspects of my work.
2. I think that using a tablet computer would fit well with the way I like to work.
3. Using a tablet computer would fit into my work style.
4. In my job, usage of a tablet computer is important.

Appendix D: Reliability Scale

Physicians that Currently Use a Tablet Computer

1. It is fast to search for medical information on a tablet computer.

2. Applications on the tablet computer load quickly.

3. Tablet computer applications reliably handle my queries.

Physicians that Currently Do Not Use a Tablet Computer

1. It would be fast to search for medical information on a tablet computer.

2. Applications on the tablet computer would load quickly.

3. Tablet computer applications would reliably handle my queries.

Appendix E: Perceived Usefulness Scale

Physicians that Currently Use a Tablet Computer

1. Using a tablet computer in my job helps me to accomplish tasks more quickly.
2. Using a tablet computer improves my job performance.
3. Using a tablet computer in my job increases my productivity.
4. Using a tablet computer enhances my effectiveness on the job.

Physicians that Currently Do Not Use a Tablet Computer

1. Using a tablet computer in my job would help me to accomplish tasks more quickly.
2. Using a tablet computer would improve my job performance.
3. Using a tablet computer in my job would increase my productivity.
4. Using a tablet computer would enhance my effectiveness on the job.

Appendix F: Perceived Ease of Use Scale

Physicians that Currently Use a Tablet Computer

1. Learning to operate my tablet computer is easy for me.

2. My interaction with my tablet computer is clear and understandable.

3. It is easy for me to become skillful at using my tablet computer.

4. I find my tablet computer easy to use.

Physicians that Currently Do Not Use a Tablet Computer

1. Learning to operate a tablet computer would be easy for me.

2. My interaction with a tablet computer would be clear and understandable.

3. It would be easy for me to become skillful at using a tablet computer.

4. I would find a tablet computer easy to use.

Appendix G: Attitude toward Use Scale

Physicians that Currently Use a Tablet Computer

All things considered, my using a tablet computer in my medical practice is:

Good: __: __:__:__:__:__:__: Bad

Wise: __: __:__:__:__:__:__: Foolish

Favorable: __: __:__:__:__:__:__: Unfavorable

Positive: __: __:__:__:__:__:__: Negative

Physicians that Currently Do Not Use a Tablet Computer

All things considered, using a tablet computer in my medical practice would be:

Good: __: __:__:__:__:__:__: Bad

Wise: __: __:__:__:__:__:__: Foolish

Favorable: __: __:__:__:__:__:__: Unfavorable

Positive: __: __:__:__:__:__:__: Negative

Appendix H: Behavioral Intention Scale

Physicians that Currently Use a Tablet Computer

1. Assuming I have access to a tablet computer, I intend to use it in my medical practice.
2. Given that I have access to a tablet computer, I predict that I would use it in my medical practice.

Physicians that Currently Do Not Use a Tablet Computer

1. Assuming I have access to a tablet computer, I intend to use it in my medical practice.
2. Given that I have access to a tablet computer, I predict that I would use it in my medical practice.

Appendix I: Individual Tablet Use Scale

1. How frequently do you use a tablet computer in your medical practice when interacting with patients (e.g., share lab results, growth curves, or instructional videos)?
2. How frequently do you use a tablet computer for medical educational purposes (e.g., access podcasts, articles, or slideshow presentations related to medical research)?
3. How frequently do you use a tablet computer to access or input information related to patient care (e.g., use a tablet computer to input info in electronic health record system, calculate drug interactions/dosing/side-effects, or verify/annotate labs)?

Appendix J: Team Tablet Use Scale

1. How frequently do you use a tablet computer to collaborate with other individuals when interacting with patients (e.g., team-based coordination of care with other physicians, physician assistants, nurses; share information with the patient or patient's family members)?
2. How frequently do you use a tablet computer to collaborate with other health professionals for medical education purposes (e.g., share podcasts, articles, or slideshow presentations related to medical research)?

Appendix K: Job Satisfaction Scale

Think of your job in general. All in all, what is it like most of the time? In the blank beside each word or phrase below wrote,

Y for "Yes" if it describes your job

N for "No" if it does not describe it

? for "?" if you cannot decide

___ Good

___ Undesirable (R)

___ Better than most

___ Disagreeable

___ Makes me content

___ Excellent

___ Enjoyable

___ Poor

Appendix L: Demographics Questions

1. Age (in years)?

2. Gender

Male

Female

Prefer not to answer

3. Ethnicity

White/Caucasian

Black/African American

Hispanic/Latino(a)

Asian/Pacific Islander

Native American

Prefer not to answer

Other (please specify)

4. Years practicing as a pediatrician

5. What is your professional position?

Intern

Resident

Fellow

Attending physician (1 – 5 years)

Attending physician (> 5 years)

Other (please specify)

Appendix L (continued)

6. Current practice setting

Academic/Medical School

University Hospital

Community based private practice

Other (please specify)

Appendix M: Institutional Review Board Approval Letter

RE: **Exempt Certification** for IRB#: Pro00008065
Title: Predicting Tablet Computer Use: An Extended Technology Acceptance Model
USF Graduate Medical Education Committee approval received by the IRB on 6/14/2012.

Dear Mr. Ducey:

On 5/28/2012 the Institutional Review Board (IRB) determined that your research meets USF requirements and Federal Exemption criteria as outlined in the federal regulations at 45CFR46.101(b):

(2) Research involving the use of educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures or observation of public behavior, unless:
(i) information obtained is recorded in such a manner that human subjects can be identified, directly or through identifiers linked to the subjects; and (ii) any disclosure of the human subjects' responses outside the research could reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, or reputation.

As the principal investigator for this study, it is your responsibility to ensure that this research is conducted as outlined in your application and consistent with the ethical principles outlined in the Belmont Report and with USF IRB policies and procedures. Please note that changes to this protocol may disqualify it from exempt status. Please note that you are responsible for notifying the IRB prior to implementing any changes to the currently approved protocol.

The Institutional Review Board will maintain your exemption application for a period of five years from the date of this letter or for three years after a Final Progress Report is received, whichever is longer. If you wish to continue this protocol beyond five years, you will need to submit a new application. When your study is completed, either prior to, or at the end of the five-year period, you must submit a Final Report to close this study.

We appreciate your dedication to the ethical conduct of human subject research at the University of South Florida and your continued commitment to human research protections. If you have any questions regarding this matter, please call 813-974-5638.

Sincerely,

John A Schinka, Ph.D.

John A. Schinka, Ph.D., Chairperson
USF Institutional Review Board