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BEHAVIORAL HEALTH PROVIDERS AND ELECTRONIC HEALTH RECORDS: AN EXPLORATORY BELIEFS ELICITATION AND SEGMENTATION STUDY

by

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A DISSERTATION

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Major: Human Sciences

Under the Supervision of Professor John DeFrain

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BEHAVIORAL HEALTH PROVIDERS AND ELECTRONIC HEALTH RECORDS:

AN EXPLORATORY BELIEFS ELICITATION AND SEGMENTATION STUDY

Nancy Shank, Ph.D.

University of Nebraska, 2011

Advisor: John DeFrain

The widespread adoption of electronic health records (EHRs) is a public policy strategy to improve healthcare quality and reduce accelerating health care costs. Much research has focused on medical providers’ perceptions of EHRs, but little is known about those of behavioral health providers. This research was informed by the theory of reasoned action, and the technology acceptance model. This mixed methods research was conducted in two studies. The first study interviewed behavioral health providers (*n* = 32) to elicit beliefs about EHRs. Using the elicited beliefs from the first study, a survey of 38 Likert-scaled belief statements was administered to all behavioral health providers in Nebraska (*N* = 2,010). Using data from the sample (*n* = 667) the belief statements were reduced to four factors. The factors were used as a basis for a cluster analysis to create two market segments.

In the first study, most providers (81%) identified themselves as having positive overall opinions about EHRs and three themes emerged: (a) safety and quality of care, (b) security and privacy, and (c) delivery of services. Benefits and barriers were mentioned for each of these three areas, with the most frequently mentioned being benefits to client safety and quality of care (100%), privacy and security barriers (100%), delivery of services barriers (97%), and benefits to delivery of care in their practices (66%). 667

providers participated in the statewide survey to identify salient beliefs, reduced to four factors, that EHRs would (a) improve care and communication, (b) add cost and time burdens, (c) present access and vulnerability concerns, and (d) improve workflow and control. Using the factors as clustering variables returned a two-cluster solution: providers who had overall positive beliefs about EHRs (67%) and providers who had overall negative beliefs about EHRs (33%).

Based on the research, five key areas are highlighted that will likely impact behavioral health providers' perceptions of EHRs: (1) usability, (2) ease of use, (3) privacy and confidentiality, (4) cost, and (5) marketing.

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To Bryan and Cole

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CHAPTER 1: INTRODUCTION

Statement of Problem

The widespread adoption of electronic health records (EHRs)[1] promises to improve patient safety and quality of care. Medical providers' willingness to adopt EHRs has been the focus of much research because providers' acceptance is an important predictor of successful implementation. Despite the fact that mental health and substance abuse issues are an important component of health records, little is known about how behavioral health providers (i.e., health care professionals helping clients with mental health, psychosocial, and substance abuse issues) view electronic exchange of client records. Providers are often key decision makers regarding the decision to implement technology and are central to the success of an implementation. Effectively addressing the concerns and needs of behavioral health providers may persuade providers to implement systems; selectively targeting the divergence of demands may lead to greater acceptance. The purpose of this study is to explore behavioral health providers' views of electronically sharing client information and to develop characteristic profiles of providers based on their beliefs of the benefits and barriers to adopting EHRs.

Widespread sharing of electronic patient information has been a public policy goal since President George W. Bush's 2004 State of the Union address, during which he declared all Americans would have EHRs by 2014 (see *Private Health Records: Privacy Implications*, 2007). President Barack Obama has reiterated the goal and directed billions

[1] The term EHR is used throughout this document to refer to electronic information collected by clinicians with the expectation of sharing with other authorized clinicians and staff across healthcare organizations. Occasionally, the term electronic medical record (EMR) is used and it refers to electronic information collected by clinicians for sharing within one organization (National Alliance for Health Information Technology, 2008).

of federal dollars to support adoption of EHRs (American Recovery and Reinvestment Act, 2009).

Although the electronic exchange of personal information is deeply rooted in many other aspects of the American economy (e.g., financial transactions), patient health information has remained largely, a paper-based system. The reluctance of healthcare providers to move to electronic systems had seemed anachronistic, but unlikely to change due to indifference of physicians and patients alike. This began to change when several high profile reports critical of the U.S. healthcare system promoted EHRs as a means to reduce alarming rates of preventable medical errors and healthcare increases (Institute of Medicine, 1999, 2001). In the few healthcare systems where health information technologies had been implemented, outcomes were promising (Bates et al., 1998; Evans et al, 1998; Hunt, Haynes, Hanna, & Smith, 1998; Overhage, Tierney, Zhou, & McDonald, 1997). As adoption of EHRs accelerates, evidence has mounted that they will improve patient safety and quality of care by providing more immediate and comprehensive information about patients to providers (Wright et al., 2010). Total economic benefits of widespread adoption of EHRs may exceed $81 billion annually (Hillestad et al., 2005).

Preliminary results from a recent survey (Hsiao et al., 2009), indicated that over 40% of ambulatory physicians now use all or partial EMR systems: a 26% increase from two years ago. Large health care facilities and medical offices and practices owned by hospitals and health systems outpace smaller physicians’ offices without ties to these larger facilities (SK&A, 2010). Behavioral health providers have received less attention in surveys of EHR adoption but appear to be trailing medical provider adoption (Lefkovitz, 2009: Mojtabai, 2007; SK&A, 2010). There has been considerable research on medical provider adoption of EHRs, but little is known about behavioral health provider perspectives of electronically exchanging patient information.

Behavioral health is a distinct area of care of patients. Behavioral health care assists clients with mental health, psychosocial, and substance abuse problems. Behavioral health issues are prevalent: About 30% of working age adult Americans experience a mental disorder in the course of a year, with about 20% of those seeking and receiving treatment (Kessler et al., 2005). In 2006, mental disorders were one of the five most costly conditions to treat in the United States, exceeding $57 billion annually (U.S. Department of Health and Human Services, Agency for Healthcare Research and Quality, 2009). Approximately 9% of the population aged 12 or older has substance dependence or abuse problems, with 17% of these persons seeking and receiving treatment (U.S. Department of Health and Human Services, Substance Abuse and Mental Health Services Administration, 2008). The overall burden of substance abuse on society, including health- and crime-related costs and losses in productivity, exceed half a trillion dollars annually (U.S. Department of Health and Human Services, National Institutes of Health, 2008). Persons with behavioral health issues may also rely more heavily on other public systems such as Medicaid/Medicare payment, housing/homeless shelters, law enforcement and corrections (Chafetz, White, Collins-Bride, & Nickens, 2005; White, Chafetz, Collins-McBride & Nickens, 2006).

The physical well-being of persons with mental health issues is often neglected despite the fact that this population has a higher prevalence of physical disease and a higher mortality rate due to natural causes than does the general population (Brown, Inskip, & Barraclough, 2000; Dickey, Normand, Weiss, Drake, & Azeni, 2002; White et al., 2006). Mental health medications, one of the main treatments for people with mental health problems, may cause physical side effects such as obesity, diabetes, hypertension, and hyperlipidemia (Henderson et al., 2005; Meyer & Koro, 2004: Thakore, Mann, Vlahos, Martin, & Reznek, 2002; Weber, Gutierrez, & Mohammadi, 2009). The behavioral health population is susceptible to physically disadvantageous behaviors such as smoking, illicit drug use, binge drinking (Lasser, 2009; U.S. Department of Health and Human Services, Substance Abuse and Mental Health Administration, 2008). Persons with behavioral health needs are more likely to utilize hospital emergency departments (Larkin, Claassen, Emond, Pelletier, & Camargo, 2005), more likely to be admitted to the hospital (Rockett, Putnam, Jia, Chang, & Smith, 2005), and more likely to have adverse outcomes (e.g., death) following admittance (Daumit et al., 2006).

There have been repeated calls for improved communication between mental and medical health providers (Dickey et al., 2002; Farley, 2002; Institute of Medicine, 2006; Maj, 2008; Pincus, 2003; Pincus et al., 2007; Reynolds, Chesney, & Capobianco, 2006). Physicians believe behavioral health information is an important component of a patient's health record particularly for persons with chronic mental health conditions because these patients often require more lengthy visits, have more complicated histories, and are prescribed multiple medications (Rost, Humphrey, & Kelleher, 1994). Behavioral health providers, including psychiatrists, routinely refer patients to physicians for medical problems but have little ongoing communication after the initial contact due to time and reimbursement issues (Klusman, 2001). This lack of communication fails to realize positive patient outcomes that may result in the integration of care between mental and medical health providers (Lasser, 2009). Federal agencies are increasingly promoting a behavioral health and medical health system of services model under the rubric of public health (President's New Freedom Commission on Mental Health, 2003; U.S. Health and Human Services, Office of the Surgeon General, 1999; U.S. Health and Human Services, Substance Abuse and Mental Health Administration, 2007).

Purpose of the Study

The purpose of the study is to conduct an exploratory beliefs elicitation and segmentation study regarding behavioral health providers' perceptions of EHRs, specifically, the benefits and barriers of EHRS. To meet this purpose, the study will use a sequential mixed method design. Mixed methods research uses both qualitative and quantitative data in order to gain a more comprehensive understanding of a problem and answer questions that cannot be answered by either approach alone (Cresswell & Plano Clark, 2007).

Research Questions

The research questions guiding this inquiry are:

1. What do behavioral health providers believe are the benefits and barriers to EHRs?

2. Are there identifiable patterns about benefits and barriers that segment behavioral health providers into clusters?
3. How do beliefs about EHRs correlate with other variables such as socio-demographic, professional and practice characteristics, experience with electronic records and client information sharing, and perceived computer self-efficacy?
4. What is the relative contribution of provider beliefs about benefits and barriers in understanding segment beliefs?

The project has two phases: (1) Study 1: Qualitative beliefs elicitation and questionnaire; and (2) Study 2: Quantitative survey of behavioral health providers. Study 1 will involve semi-structured interviews (Appendix A) to elicit provider perspectives about benefits and barriers. Interviews will be transcribed and analyzed to create qualitative elements organized into theme areas. Interviewees will also complete a short socio-demographic questionnaire (Appendix B). Study 2 will involve the creation and administration of a survey (Appendix C) based on the Study 1 results. The survey will primarily use Likert-scaled responses so that attitudes may be quantitatively analyzed. The survey will also collect experiential and self-efficacy data and will be linked to archival socio-demographic and professional and practice information.

Significance of the Study

This study will contribute to an understanding of the adoption of EHRs by healthcare providers. The majority of research in this area has focused on medical providers. Little is known about how behavioral health providers view EHRs. This study will use an exploratory, mixed methods approach to identify salient beliefs about EHRs and identify and describe meaningful belief clusters.

Possible benefits of this research include contributing to a better understanding of behavioral health providers' expectations of EHRs which may impact in adoption decisions. This understanding may help policymakers create policies and programs that are responsive to behavioral health providers' needs and concerns. Additionally, this knowledge could assist EHRs vendors in ensuring that their products and marketing efforts meet the needs of providers.

Limitations of the Study

These studies will elicit and describe benefits and barriers of EHRs as perceived by behavioral health providers. However, the relationship between these beliefs and actual behaviors, such as the subsequent adoption or rejection of EHRs, will not be included as part of this study. This study seeks only to offer exploratory patterns of belief and will not tie those beliefs to actual behaviors. It is anticipated that future studies undertaken by the researcher will explore the explicit relationship between the elicited beliefs and eventual behaviors.

CHAPTER 2: LITERATURE REVIEW

This review of literature is divided into four sections. The first section presents the theoretical basis for focusing on beliefs as a valid predictive construct for adoption behaviors. The second section presents theories of technology acceptance and diffusion. The third section discusses the application of beliefs in market segmentation. The fourth and final section summarizes relevant studies of healthcare providers' beliefs about health information technology.

Beliefs

Researchers have long been interested in exploring how beliefs impact behavior. One of the most influential theories in predicting and describing that relationship is Ajzen and Fishbein's theory of reasoned action (1973), which was extended into the theory of planned behavior (Ajzen, 1991). The theory of reasoned action is a social cognitive theory based on the assumption that humans will behave rationally and use information to make behavioral decisions. The theory is essentially a series of hypotheses positing that an individual's beliefs form their attitudes about an object, and that these attitudes inform behavioral intentions, which in turn are predictive of actual behavior.

Beliefs are the characteristics, qualities, and attributes that an individual associates with an object. Beliefs are formed by exposure to information and past experiences. Individuals may hold any number of beliefs that include both negative and positive evaluations of the results of the behavior. The theory of reasoned action suggested that there are two belief constructs: behavioral and normative. *Behavioral beliefs* are the individual's positive and negative perceptions of the consequences of engaging in a behavior. *Normative beliefs* are the individual's assessment of important others' expectations that they should or should not engage in a behavior, along with the individual's motivation to comply with the expectations of these others. The primary difference between the theory of reasoned action and the theory of planned behavior is the addition of a third belief construct: control (Ajzen, 1991). *Control beliefs* are the individual's perceived self-efficacy and controllability to engage in a behavior (Ajzen, 2002).

At any given moment individuals are able to only attend to a limited number of beliefs (five to seven) when forming an attitude. The beliefs that form an individual's attitudes are referred to as *salient beliefs*. The salient beliefs of any given population are termed *modal salient beliefs* and may be identified through an elicitation study of a representative sample of the population (Ajzen & Fishbein, 1980). The recommended process is to elicit beliefs directly from the sample through open-ended questions, rather than pre-selecting belief statements for the population (Ajzen, 1991; Ajzen & Fishbein, 1980). Beliefs are grouped and counted through a content analysis to determine the most salient beliefs and included in a model set used to survey the population (Ajzen & Fishbein, 1980).

Elicitation studies are important because they provide a foundation for researchers to examine the thoughts and feelings of a population about a particular behavior. Researchers have specifically called for elicitation studies in health care that will provide contextualization for better understanding technology adoption behaviors (Holden & Karsh, 2010). Behavioral health providers likely take into account a number of beliefs in assessing EHRs. These beliefs may be influenced by a variety of factors including past experience with information technology, practice environment, information gleaned from professional resources, and interactions with other providers. These beliefs may mirror or diverge from those expressed by medical providers in other qualitative studies (Austin et al., 2006; Miller & Sim, 2004; Scheck McAlearney, Schweikhart, & Medow, 2004).

Technology Acceptance

Technology acceptance research focuses on individuals' decisions as to whether or not to use an available technology and it is one of the most mature research areas in contemporary information systems literature. One of the towering general theories that has been fruitfully applied to this area is innovation diffusion theory (Rogers, 1995). Innovation diffusion theory is, in actuality, a collection of theories that models many aspects of the uptake of new concepts, products, or actions (collectively, for Rogers, these are all termed *innovations*). In one component of innovation diffusion theory, Rogers postulated that attitudes are shaped by users' perceptions of five characteristics of an innovation: relative advantage, compatibility, complexity, trialability, and observability. Later researchers (Moore & Benbasat, 1991) added the construct of users' perception of the voluntariness. These characteristics are defined as:

- Relative Advantage – the degree to which an individual believes an innovation is better than the idea that it supersedes, including its impact on the individual's image or status.
- Compatibility – the degree to which an individual believes an innovation is consistent with existing values, past experiences, and needs of potential adopters.

- Complexity – the degree to which an individual believes an innovation is relatively difficult to understand and use.
- Trialability – the degree to which an individual believes an innovation may be experimented with on a limited basis.
- Observability – the degree to which an individual believes the results of an innovation are visible and communicable to others.
- Voluntariness - the degree to which use of the innovation is perceived as being freely determined by the potential user.

The theories of reasoned action and innovation diffusion have been popular starting points in information technology research. Their focus on user perceptions has been instructive in addressing one of the most vexing issues in information technology: The high failure rate of innovations due to user non-adoption (Lapointe & Rivard, 2006; Ram & Sheth, 1989). Davis' (1989) technology acceptance model (TAM) adapted Rogers' diffusion constructs specifically to information technology and has become one of the most widely researched models in information technology. TAM has been used to explain the adoption of a wide variety of information technologies such as voice mail, email, and software products (Adams, Nelson, & Todd, 1992). A meta-analysis of empirical studies confirmed the utility of the model in the physician population (Ma & Liu, 2004). The model relies on two of Roger's constructs, relative advantage and complexity (renamed *perceived usefulness* and *perceived ease of use)*, as parsimonious predictors of actual usage.

- Perceived Usefulness (Rogers' relative advantage) – the degree to which an individual believes that using a technology will enhance job performance (e.g., taking less time to accomplish a required task, producing higher quality work products).
- Perceived Ease of Use (Rogers' complexity) – the degree to which an individual believes that using a technology will be free of physical and mental effort.

Perceived usefulness and *ease of use* have been shown to be correlated with usage. *Perceived usefulness,* however, has repeatedly been significantly more strongly linked to usage than the *perceived ease of use* (Davis, 1989; Ma & Liu, 2004). In longitudinal studies, perceived ease of use receded in significance over time (Davis, Bagozzi, & Warshaw, 1989). In several studies of physicians, ease of use had no relationship with usefulness or attitude, leading the researchers to speculate that it is not a relevant construct for persons with high intelligence (Chismar & Wiley-Patton, 2002; Hu, Chau, Sheng, & Tam, 1999). These results have caused some researchers to call into question the *perceived ease of use* construct as a part of the model (Ma & Liu, 2004). Davis (1989) theorizes:

> the prominence of perceived usefulness makes sense conceptually: users are driven to adopt an application primarily because of the functions it performs for them, and secondarily for how easy or hard it is to get the system to perform those functions. For instance, users are often willing to cope with some difficulty of use in a system that provides critically needed functionality. Although difficulty of use can discourage adoption of an

otherwise useful system, no amount of ease of use can compensate for a system that does not perform a useful function (pp. 333-334).

One of TAM's great strengths is its simplicity and generality. However, it has been criticized for its inability to model the influence of external variables and barriers that may facilitate adoption (Venkatesh, Brown, Maruping, & Bala, 2008; Yarbrough & Smith, 2007). The unified theory of acceptance and use of technology model (UTAUT) formulates a model using constructs from theory of reasoned action, theory of planned behavior, innovation diffusion, TAM, and three additional models (motivational model, model of PC utilization, social cognitive theory) to create a unified technology model (Venkatesh, Morris, Davis, & Davis, 2003). The validated final model is essentially TAM with two additional constructs: *social influence* and *facilitating conditions*. The added constructs supply the influence of external variables and barriers that TAM had been criticized for ignoring.

Gatignon and Robertson (1989) demonstrated that adoption and rejection are independent constructs and explained by different combinations of variables. However, a relatively small number of researchers have supplemented innovation acceptance models with concepts of resistance to technology. Resistance researchers have criticized diffusion theorists for being pro-innovation and seeing resistance as an illogical obstacle that must be overcome by communication rather than a signal from users that the innovation does not meet their needs (Lapointe & Rivard, 2005; Sheth, 1981). Researchers have suggested that people do not resist change for no reason; rather they resist change because it presents a threat (Dent & Goldberg, 1999). Threats may include:

danger (Marakas & Hornik, 1996); loss of status, revenue, or power (Dent & Goldberg, 1999; Markus, 1983); or inequality in costs and benefits (Joshi, 1991). Ram and Sheth (1989) proposed two categories of types of resistance: functional barriers and psychological barriers. *Functional barriers* may be usage, value, or risk barriers. Usage barriers are those that require an unwelcome change to existing workflows, practices or habits. Value barriers are when a perceived performance to price ratio is unsatisfactory. Risk barriers are those involving undesirable physical, economic, functional, or social risk. *Psychological barriers*, the second of the two categories, comprises tradition and image. Tradition barriers are those in which the user feels adoption will result in deviation from established traditions. Image barriers are when a product's origin is perceived as unfavorable. Similar to the ease of use construct in the technology acceptance model, the usage barrier may be the most common cause of resistance (Ram & Sheth, 1989).

Using Ram and Sheth's taxonomy, Kleijnen, Lee, and Wetzels (2009) isolated antecedents to types of non-adopters (i.e., postponers, rejecters, and opponents). *Postponers* find an innovation acceptable, but decide not to adopt at an imminent point in time. *Rejectors* are disinclined toward adopting an innovation. *Opponents* are actively in disagreement that the innovation should be adopted by anyone. Most important to postponers was economic risk and usage barriers. Rejecters were influenced by economic risk, functional risk, social risk, usage barriers, and image barriers. Finally, opponents were influenced by physical risk, functional risk, social risk, tradition barriers, and image barriers. Laukkanen, Sinkkonen, and Laukkanen (2008) found that psychological barriers were higher determinants of resistance than were usage and value barriers. Shen, Huang, Chu, and Hsu (2010) integrated Ram (1989) and Ram and Sheth's (1989) perceived risk concepts into TAM using a benefit-cost framework. Measures of trust, behavioral introspection, and technology anxiety were risk antecedents to security concerns in mobile banking, and were significantly predictive.

Market Segmentation Based on Beliefs

Market segmentation is a technique that recognizes that the potential universe of users may be divided into definable sub-groups with different characteristics. Segmentation enables organizations to target messages to the needs and concerns of these subgroups. In his classic formulation of market segmentation, Wendell Smith describes the strategy, writing that market segmentation:

> consists of viewing a heterogeneous market (one characterized by divergent demand) as a number of smaller homogeneous markets in response to differing product preferences among important market segments. It is attributable to the desire of consumers or users for more precise satisfaction of their varying wants. (Smith, 1956, p. 6)

Segmentation, along with targeting and positioning are the "near-default steps in the formulation of a marketing strategy" (Sinha &Rosenthal, 2009, p. 245). Markets may be grouped in a variety of ways such as geographic, demographic, psychographic, product usage, and benefit (Haley, 1981; Weinstein, 1994). *Geographic segmentation* focuses on the physical location of users. When used purely, this approach essentially considers the market to be otherwise homogenous. User *demographic segmentation* uses individual or socio-economic characteristics to determine groups of consumers. Typical characteristics used in demographic segmentation include age, gender, family characteristics, income, and social class. *Psychographic segmentation* attempts to group users' lifestyle and personality traits. *Behavioral segmentation* focused on consumption patterns of users of the product. Finally, *benefit segmentation* focuses on what potential users are seeking in a product as the basis for determining behavior: Segments are identified by the benefits it wants to be satisfied.

Haley (1981) has argued that benefit segmentation should be used as the basis for segmenting a market because it identifies the reasons for the existence of market segments. Once the benefits-based segmentation is conducted, it is then be supplemented with other information such as geography, demography, psychography, and product usage. Benefit segmentation, as the name suggests, has largely focused on consumers' beliefs about positive aspects of adopting a product or service. One of the advantages benefit segmentation has over other methods is that its results may be more directly translated into messaging strategies (Calatone & Sawyer, 1978). A number of studies have also profitably incorporated the concept of problem analyses in segmentation (Evans, 1980; Lee, Morrin, & Lee, 2009; Van Auken & Lonial, 1984). Evans (1980) suggested that problems, in fact, may be even more important that benefits.

No studies were found that evaluated prospective EHRs users based on benefit segmentation or a combined benefit and barrier segmentation method: That is, based on the features of EHRs desired by behavioral health providers. Information about these clusters of users may be beneficial in creating communications about EHRs (Johnson, 1981).

Provider Perceptions of EHRs

Providers are often the decision makers about whether their organization will adopt EHRs, and their acceptance is key to successful implementation (Medicare Payment Advisory Commission, 2004). Lapointe and Rivard (2006) attributed physician resistance to clinical information systems as the critical sources of major organizational disruptions, and system abandonment. Quite a few studies have focused on medical health providers' perceptions; however, only a few studies have been conducted that focus on behavioral health providers' perceptions of EHRs.

Behavioral health providers perceived benefits and barriers. An examination of the literature found only three studies focusing on behavioral health providers' perceptions of EHRs. The most recent of the three, Salomon and colleagues (2010), surveyed psychiatric clinicians' post-implementation views of the EHR implemented in their outpatient mental health clinic. Nine factors were identified including: data security, data sensitivity, data quality erosion, data quality enrichment (quantity and clarity), xenophobia (concerns about non-mental health providers), altered behaviors in recording client information in the record, personal comfort with security, efficiency (saves or wastes time), and personal importance of confidentiality. The second survey (Lefkovitz, 2009), available only as an executive summary, reported that behavioral health and human service organizations perceived high benefits of electronic medical records and inter-operability with medical/primary care systems, but that cost was a significant barrier. The third behavioral health-focused study (Walter, Cleary, and Rey, 2000) reported results from a survey of providers at an Australian mental health organization. Most of these providers viewed electronic medical records positively and believed electronic medical records made their job easier and more efficient, improved client care, improved communication with other staff, and were effective for documenting and accessing client progress and staff activity. A minority of providers believed electronic medical records were time-consuming and took more effort than they were worth.

Medical provider perceived benefits and barriers. Within the medical health domain, a number of studies have been conducted examining medical health providers' acceptance of technology, in general, as well as their acceptance of specific health information technologies (e.g., computerized physician order entry systems, EHRs, electronic medical records). Medical healthcare providers perceive an array of benefits and barriers in adopting electronic health and medical records. Identified benefits include: improved access to medical record information and improved quality of information; improved efficiency, productivity, and workflow; improved accuracy for coding; improved patient care and communication; high patient acceptance; improved coordination of care of patients with other providers and more timely referrals; improved ability to detect medication errors; and the ability to act on test results in a timely fashion (Austin et al., 2006; Aydin, Rosen, & Felitti, 1994; Gans, Kralewksi, Hammons, & Dowd, 2005; Marshall & Chin, 1998; Scheck McAlearney et al., 2004; Wright et al., 2010). In a systematic literature review of physician perceptions of health information technology, in general (i.e., not limited to electronic medical or health records), Yarbrough and Smith (2007) identified five categories of barriers: interruption of traditional practice patterns, lack of evidence regarding benefits, organizational issues, and system-specific issues. In studies specifically about physician attitudes about adopting electronic health and medical records, found similar types of barriers: interruption of practice patterns/ patient relationship (Audet et al., 2004; Austin et al., 2006; Aydin et al.,1994; Eley, Fallon, Soar, Buikstra, & Hegney, 2008; Gans et al., 2005; Miller & Sim, 2004; Penrod & Gadd, 2001); lack of evidence regarding benefits (Audet et al., 2004); lack of financial wherewithal and technology reluctance (Audet et al., 2004; Aydin et al., 1994; Eley et al., 2008; Gans et al., 2005; Miller & Sim, 2004; Scheck McAlearney et al., 2004); software, system, and standards limitations and constraints (Audet et al., 2004; Gans et al., 2005; Miller & Sim, 2004). Table 1 summarizes these studies. In addition to Yarbrough and Smith's categories of barriers (2007), researchers have found only mild concerns about privacy and security (Gans et al., 2005; Penrod & Gadd, 2001; Wright et al., 2010).

Table 1

Medical Healthcare Provider-Identified Benefits and Barriers of Electronic Records

Study	Population	Technology	Benefits	Barriers
Audet, Doty, Peugh, Shamasdin, Zapert, & Schoenbaum, 2004 (Likert-scaled survey)	Physicians	Electronic medical records and other health information technologies		Cost of system implementation and maintenance Lack of local, regional, and national standards Lack of time to consider acquiring, implementing, and using a new system
Austin, Pier, Mitchell, Schattner, Wade, Pierce, &	Medical doctors	Handheld computers	Enhanced productivity Enhanced quality of patient care and service	Lack of required computer skills Unfamiliarity with resources

Study	Population	Technology	Benefits	Barriers
Klein, 2006 (Interviews)				Problematic for patients with English as a second language Problematic for patients with poor eyesight Reduced rapport between GP and patient Lack of required Internet access and speed Unacceptable to elderly patients
Aydin, Rosen, & Felitti, 1994 (Likert-scaled survey)	Nurse practitioners and physician assistants	Electronic medical records	Increase in overall ease/quality of department's work	Makes job more stressful
Eley, Fallon, Soar, Buikstra, & Hegney, 2008 (Likert-scaled survey)	Nurses	Health information and computer technology		Too many work demands IT does not fit with other demands Not enough computers Lack of IT support Lack of IT knowledge
Gans, Kralewksi, Hammons, & Dowd, 2005 (Likert-scaled survey)	Medical group practice administrators	Electronic health records	Improved access to medical record information Improved workflow Improved patient communications Improved accuracy for coding evaluation and management procedures Improved drug refill capabilities Reduced medication errors Improved charge capture Improved clinical decision making Improved claim submission process	Security and privacy concerns Lack of support from practice administration Inability to evaluate, compare, and select appropriate EHR Practice staff does not have skills or training to use EHR Inability to integrate EHR with practice billing/claims system Lack of support from practice non-physician providers Insufficient time to select, contract, install, implement EHR Lack of support from practice clinical staff Insufficient return on investment from EHR system Available EHR

Study	Population	Technology	Benefits	Barriers
				software does not meet the practice's needs
Marshall & Chin, 1998 (Likert-scaled survey)	Clinicians	Electronic medical records	Improved overall quality of care Improved quality and content of clinician-patient interaction Ability to act on test results in a timely fashion Ability to coordinate care of patients with other providers Improved timeliness of referrals Improved ability to detect medication errors	
Miller & Sim, 2004 (Interviews)	Medical records managers and physician champions	Electronic medical records		High initial cost and uncertain financial benefits High initial physician time costs Challenges with technology usability Difficult complementary technological changes and inadequate support Inadequate electronic data exchange Lack of incentives Physicians' attitudes
Penrod & Gadd, 2001 (Likert-scaled survey)	Physicians	Electronic medical records	Improved availability of medical record	Increased time to enter orders Reduced rapport with patients Reduced patient privacy Reduced physician autonomy
Scheck McAlearney, Schweikhart, & Medow, 2004 (Focus groups)	General health practitioners	Electronic mental health records on handheld device	Improved time efficiency Reduced paperwork Improved quality of information High patient acceptance Improved patient engagement (through visual medium)	Physical constraints: physical factors and age Perceptual constraints: discomfort with technology, discomfort with device, device not user-friendly, preference for paper, preference for personal

Study	Population	Technology	Benefits	Barriers
				computers
Wright, Soran, Jenter, Volk, Bates, & Simon, 2010 (Likert-scaled survey)	Physicians	Health information exchange	Reduced healthcare costs Improved patient care Time saving for physicians	Concerns about privacy and security

Other Characteristics of Users

Studies of general technology use (i.e., not specific to health information technology or to the provider population) have examined the relationship between attitudes and use with age, gender, and education, with older studies sometimes finding relationships (Dyck & Smither, 1994; Gilroy & Desai, 1986; Igbaria & Parasuraman, 1989; Laguna & Babcock, 1997; Wilder, Mackie, & Cooper, 1985). More recently and particularly among users of health information technology, studies have found no relationship between gender or age, and the overall attitudes towards computers and/or electronic medical records (Audet et al., 2004; Aydin et al., 1994; Brown & Coney, 1994; Clayton, Pulver, & Hill, 1994; Dansky, Gamm, Vasey, & Barsukiewicz, 1999).

Providers who have implemented electronic medical records tend to rate benefits more highly and barriers as less of a problem than do those providers who have not implemented electronic medical records systems (Gans et al., 2005; Scheck McAlearney et al., 2004; Wright et al., 2010). The practice setting also appears to be a factor in physician acceptance of electronic medical records, with physicians at larger practices being more positive about adoption (Audet et al., 2004).

Behavioral Health Provider Belief Elicitation

No studies of behavioral health providers were found that elicited belief statements directly from behavioral health providers themselves, thus forming a sound basis for understanding attitudes and adoption (Ajzen & Fishbein, 1980). The goal of the present study is to explore behavioral health providers' views of the benefits and barriers of sharing patient records electronically. Findings could have implications for providers, policy makers, and vendors who are working to develop health information exchanges.

CHAPTER 3: METHODOLOGY

The purpose of this research is to elicit behavioral health providers' beliefs about EHRs, and to identify and describe patterns of those beliefs. A mixed methods, sequential design will be conducted in two parts. The first study (Study 1) will identify beliefs about the benefits and barriers of EHRs through 32 semi-structured interviews. The second study (Study 2) will survey approximately 2,000 behavioral health providers to present quantitative representative data and identify clusters of beliefs.

Study 1 – Beliefs Elicitation of Population Subset

The beliefs of behavioral health providers will be probed to explore their perspectives about the benefits and barriers to EHRs. Consistent with the recommendations of Ajzen and Fishbein (Ajzen, 1991; Ajzen & Fishbein, 1980), the study relies on a subset of the population to elicit beliefs. Beliefs are obtained through open-ended questions about the advantages and disadvantages associated with the behavior. In this study, the behavior is the use of EHRs.

Measures

The primary measures used in this study were a background questionnaire and a structured interview. The background questionnaire included 17 items assessing participant demographics and experience (gender, age, highest level of education, year of graduation, years in practice, non-provisional licenses and certificates), primary practice and professional characteristics (number of hours worked per week, number of clients seen each week, type of employment contract, type of practice setting, and total numbers of behavioral health care and medical records staff employed by the practice), personal and occupational use of technology (computer use at home and at work, varieties of software used), and current health information exchange practices used personally and by others at one's place of practice (phone, fax, mail, or use of an electronic medical records system).

The structured interview focused on four areas:

1. The benefits of a system that allows providers to electronically exchange client behavioral health information with other health care providers.
2. The barriers of a system that allows providers to electronically exchange client behavioral health information with other health care providers.
3. Who providers believe should be part of the decision-making process regarding adopting and implementing an electronic system for behavioral health information.
4. The likelihood that the interviewee and others in the practice would use an electronic sharing system if it were developed.

Follow-up questions and probes were designed to elicit as much information as possible regarding the four focal questions. Interviewers also prompted respondents to think about the perceived benefits and barriers at several levels: for providers and their organizations, for clients, and for the system of care. At the end of the interview, participants were asked if they had any other comments about sharing behavioral health information that had not yet been covered in the interview.

After the interview, participants were asked for information about the size of their practice or organization, including the number of full-time equivalent behavioral health providers and number of medical records staff. These questions were not included on the survey because it was suspected that some providers might need to direct the researchers to others in their organization to gather that information.

Sample

A mixed sampling procedure was used to select 32 participants representing types of providers based on similarity of probable use of EHRs. The three stratification categories were: (a) Prescribers: psychiatrists, Advanced Practice Registered Nurses (APRNs), and physician assistants (PAs); (b) Non-prescriber clinicians: psychologists, licensed mental health professionals (LMHPs), licensed independent mental health professionals (LIMHPs), and licensed drug and alcohol counselors (LADCs); and (c) Non-prescriber nurses: psychiatric registered nurses (RNs). All of the participants, except those in the third category, psychiatric registered nurses, were identified from a list (N = 504) of behavioral health providers, practicing in southeast Nebraska, compiled by the University of Nebraska Medical Center Health Professions Tracking Service. This list included 28 psychiatrists (6%), 11 APRNs (2%), 3 PAs (1%), and 107 psychologists (21%). It also included 355 persons designated as licensed professionals (70%), most of whom held multiple licenses: LMHPs (n =318), LIMHPs (n = 102), and LADCs (n = 58). Individuals were randomly ordered within each of the three categories of providers. Given that a random sampling would have over-represented the non-prescribing professions (comprising 92% of the list), the sample was stratified. Potential participants were telephoned in that randomly determined order until recruitment targets were met.

The Health Professions Tracking Service list did not include psychiatric nurses who had not obtained an advanced degree. To obtain a sample of psychiatric nurses, five organizations were identified that employed psychiatric nurses. These organizations identified a total of 84 psychiatric nurses who were not APRNs (and thus not on the Health Professions Tracking Service list). Each of these psychiatric nurses was sent a letter through their organization, informing them of the study and asking for volunteer participants. Fifteen psychiatric nurses from three of the five organizations volunteered by the deadline indicated in the letter: 4 nurses from the largest organization (n = 73 employed psychiatric nurses), 2 from the second largest (n = 10) and 1 from a smaller organization (n = 4). Not represented were 2 organizations employing 6 and 4 nurses.

Thus, the sampling frame totals for each category of provider was: (a) Prescribers, 8%, (b) Non-prescriber clinicians, 92%, and (c) Non-prescriber RNs, 17%. Based on discussions with key informants, it was anticipated that professionals within these categories would have differing perspectives on EHRs because of the unique ways in which they work with clients and their information. Therefore, a stratified sampling that would over-represent the smaller professional categories was planned.

Procedures

Interview candidates were phoned during the spring 2009, apprised of the general purpose of the research, and invited to participate in the interviews. Those agreeing to participate made an appointment for an in-person or phone interview. Prior to the interview, study information, a consent form, and the quantitative background questionnaire was mailed or faxed to participants. Respondents were asked to complete these materials and fax or give them to the interviewer at the time of the interview.

Three senior researchers conducted the interviews. The researchers developed and followed a semi-structured interview protocol and conducted at least one interview in conjunction with one of the other researchers to ensure similarity across the interviews. Participants answered semi-structured interview questions designed to yield in-depth responses about their experiences, perceptions, opinions, and feelings about the benefits of and barriers to participating in EHRs sharing. They also were asked whether they were willing to be contacted in the future for feedback on interview findings. The interviews were transcribed by the University of Nebraska Lincoln Bureau of Sociological Research.

Analysis

Interviews were conducted and recorded either face-to-face (n = 15) or over the phone (n = 17). Approximately 16 hours of interviews were conducted, ranging from 11 minutes to 48 minutes, with a mean interview time of 29 minutes. Interviews were conducted over a 10 week period, during which time the coding scheme was created and evolved, and completed interviews were transcribed and coded. Researchers used a qualitative software program, Atlas.ti 6, to facilitate data storage, coding, retrieval, comparing, and linking. An inductive analysis was used to discover behavioral healthcare providers' beliefs. The use of inductive analysis allows researchers to discover the patterns, themes, and categories emerging from behavioral healthcare providers' perspectives. Data coding began with convergence – looking at recurring regularities and then by examining divergences. Upon completion of all the interviews and coding, the researchers reached consensus on the major themes and the codes that comprised each theme. Reliability was assessed by computing the inter-rater agreement on development of themes and on coding of a sample of interviews. Four interviews were randomly selected and assigned to a second coding by another researcher. Overall, coders demonstrated 100% agreement in coding interviews for the presence of major themes. Validity of the themes was assessed by inviting participants to comment on a summary of the theme categories, particularly providing feedback on the accuracy and appropriateness of the overall theme categories. Only one participant responded to a researcher initiated request for feedback and that response was positive.

Study 2 – Belief Segmentation

The beliefs elicited during Study 1 formed the basis of the second study: Belief segmentation. The study explored the generalizability of the beliefs statements and created profiles of patterns of beliefs. Continuing to follow Ajzen and Fishbein's theory of reasoned action and theory of planned behavior (Ajzen, 1991; Ajzen & Fishbein, 1980), the study relied on the results of the elicitation study to survey the population (Ajzen & Fishbein, 1980). The survey results were used to group similar statements and identify cluster characteristic profiles of providers. The sequence of factor and cluster analyses have been conducted to identify market segments in a wide variety of areas such as tourism (Boo & Jones, 2009), mobile phone services (Sohn & Kim, 2008), automobile insurance (Hosseini, Harmon, & Zwick, 1991), office systems (Powers & Sterling, 2008), and computer terminals (Moriarty & Reibstein, 1986).

Measures

The survey comprised 52 items within five components: (a) belief-based perspectives on EHRs; (b) shortened version of the Computer User Self-Efficacy Scale (Cassidy & Eachus, 2002); (c) satisfaction rating of EHRs systems; (d) checklist of current means of sharing client information (e.g., fax, phone, mail, electronic records); and (e) overall supportiveness for widespread adoption of EHRs. The survey was piloted with ten behavioral health providers to ensure the statements and terms were appropriately phrased and understandable.

Belief-based perspectives of EHRs. Consistent with Ajzen and Fishbein, the relatively large set of beliefs elicited from the subsample of the population were grouped, categorized, and counted (Ajzen, 2006; Ajzen & Fishbein, 1980). A smaller portion of this large set was selected to form the modal salient set from which a Likert-scaled questionnaire was constructed. There are no clear rules about the process for selecting the modal salient set from the total belief set. Ajzen and Fishbein (1980) offer several alternatives: (a) use the 10-12 beliefs most frequently mentioned, (b) select all the beliefs that meet a selected frequency threshold, or (c) select a certain percentage of the total number of beliefs elicited. Of the three alternatives suggested by Ajzen and Fishbein (1980), this study followed the second method by selecting all beliefs that met a pre-selected frequency. For this study, all beliefs that were mentioned by more than two providers were included. This approach improved the likelihood that all salient modal beliefs have been identified. Based on the qualitative results from Study 1 beliefs elicitation, it was expected that provider beliefs would result in four factors. To ensure that each anticipated factor was represented by an adequate number of variables (i.e., the factor is adequately over determined); the set of questions was re-examined to ensure that each of the four themes were represented by at least four measured variables (Fabrigar, Wegener, MacCallum, & Strahan, 1999). The use of elicited belief statements in Study 1 contributed to confidence that the variables in Study 2 were relevant and reduced the likelihood that irrelevant variables would distort results with spurious or obscured factors. The final survey included 38 belief statements, with between 6 and 19 variables representing each of the four themes. The statements were roughly split between positively (n = 18) and negatively (n = 20) worded statements.

Shortened version of the Computer User Self-Efficacy Scale. Self-efficacy beliefs have been shown to contribute to behavioral intentions, because individuals must believe that they have the capability or skills to achieve a task as part of an intention to successfully undertake a behavior. Self-efficacy is typically domain-specific. That is, an individual may have high levels of self-efficacy in one area, such as driving a car safely or diagnosing a client’s mental health, but may not feel efficacious in another area, such as flying an airplane or using a computer. Therefore, this study included eight items from a general computer self-efficacy scale adapted from Cassidy and Eachus (2002). To reflect new technologies and terminologies, the wording of some questions was updated and some items removed. Because the scale is unidimensional, items may be removed without severely diminishing its validity (S. Cassidy, personal communication, November 18, 2009).

Satisfaction rating of EHR systems. Past research has suggested that providers who use electronic medical record systems tend to focus on the benefits of the systems more than the barriers, as compared to providers who have not implemented electronic medical record systems (Gans et al., 2005; Scheck McAlearney et al., 2004). Therefore, two items were included to assess first, whether the respondent had past experience with EHRs, and second, to assess the satisfaction with past use of EHRs using a Likert-scale.

Checklist of current means of sharing client information. Respondents were asked to identify their current means of sharing client records with providers outside their practice. Providers were asked to *check all that apply* from a list (e.g., fax, phone) and were also provided an *other* category. The question was adapted from a similar question used in Study 1.

Overall supportiveness for widespread adoption of EHRs. A summative statement regarding overall support for the adoption of EHRs was included. This Likert-scaled item provided a general statement that summarized behavioral health providers' attitudes about the acceptability of EHRs and was used as a criterion variable for missing value calculations.

Comment section. The final item on the survey was a free text area where respondents were invited to provide additional comments about the survey or electronic sharing of client information.

In addition to the data gathered directly from participants, data used in the present study included previously gathered data. That data was provided by the Health Professions Tracking Service and included practice and professional information. The data (e.g., type of practice setting and work relationship, type of professional licensure, degree type, etc) is gathered annually by the Tracking Service. Because the Tracking Service survey is a part of the state's Health Alert Network and because Center staff rely on a number of information sources to update records (e.g., state records, associations, media), this list of behavioral health professionals is believed to be the most up-to-date and comprehensive currently available.

Sample

There are just over 2,000 (*N* = 2,010) behavioral health practitioners in Nebraska. An invitation to participate in the survey was sent to all practicing psychiatrists, psychologists, licensed mental health practitioners, licensed alcohol and drug counselors, and advanced practice registered nurses with behavioral health specialization. The list of practicing behavioral health providers (de-duplicated of dual-licensed providers) was generated by the Health Professions Tracking Service. An invitation to participate in the study was sent to all providers on the list.

Procedures

The survey was produced on an internet-accessible, password protected website and also produced in a paper survey. The Dillman (2000) method was used to maximize response rates. All providers were sent a letter announcing a forthcoming invitation to participate in the survey. Four days later participants were sent the letter of invitation that included the URL and password to take the on-line survey. Three to four days later those with email addresses received an additional invitation with the URL. Sixteen days after the first communication a postcard reminder, again with the URL and password, was sent. Two weeks later the final contact, a letter and paper survey, was made with a coded, stamped, return envelope. When an invitee completed the survey, they received no further recruitment contacts.

In all recruitment communications, participants were invited to contact one of the researchers if they had any difficulties or questions. 26 individuals made phone or email contact (two of these individuals made 2 contacts). The majority of the contacts were individuals who were experiencing difficulties accessing the web-based survey (n = 12) or who did not want to complete an online survey and requested a paper survey (n = 5). Other contacts were for notification of retirement, relocation, illness, or death (n = 4); confirmation that the online survey they had completed had been received (n = 4); and notification of a name or address change (n = 1).

From the sampling frame (N = 2,010), 674 individuals responded to the survey (n = 400 through the on-line survey; n = 274 through the paper-based survey). Using the American Association for Public Opinion Research Response Rate 2 method (American Association for Public Opinion Research, 2009) the response rate was 34%. This rate is similar to recent organizational response rates (i.e., mean of 35% in 2005) in published refereed management and behavioral science journals (Baruch & Holtom, 2008).

Analysis

Using SPSS 18 for Windows, the data underwent a two-phase analysis to identify provider beliefs: a factor analysis followed by a cluster analysis. A factor analysis followed by a cluster analysis is a fairly common sequence in social science research. The factor analysis reduces highly correlated variables into a smaller set of data that are less correlated and may be used to create scores for the cluster analysis. The benefit of the factor-then-cluster sequence is that it reduces the correlation between the original, larger number of variables, and may result in simplified clusters that have more meaning and greater interpretability. The cluster analysis, based on factor scores, is used to classify groups of similar individuals. These groups (or “clusters”) may provide valuable insight into the socio-demographic differences in beliefs about EHRs. A drawback of this approach is that factor analysis may blur the cluster relationships; it assumes the variables have a normal distribution as will the resulting factors (Aldenderfer & Blashfield, 1984).

In the first phase of the analysis, the 38 belief statements were subjected to a factor analysis. The goal of the factor analysis is to decrease the number of beliefs statements into a comprehensible, smaller set of variables. Common factor analysis and principal component analysis are the two most widely used models for factoring a set of variables. Factor analysis is the preferred method when the researcher’s goal is to detect latent constructs (Widaman, 1993). Latent constructs are unobserved variables that are not directly measured, but influence measured responses. Factor analysis presumes that latent constructs exist, cannot be measured directly, and are the cause of covariance among measured variables. Although some researchers have claimed that factor analysis and principal components analyses are virtually interchangeable and result in empirically indistinguishable findings (Velicer & Jackson, 1990), others continue to demonstrate differential solutions and demonstrate the superiority of factor analysis over principal components analysis for determining underlying constructs (Bentler & Kano, 1990; Snook & Gorsuch, 1989; Widaman, 1993).

An exploratory factor analysis was conducted. An exploratory factor analysis is more appropriate than a confirmatory factor analysis when the researcher does not have a strong theoretical or empirical basis upon which assumptions could be made about the number of factors or the specific variables within these factors (Fabrigar et al., 1999). An exploratory factor analysis enables the data to drive the solution, rather than a priori assumptions about the data structure. This prevents a researcher from excluding possible factors that may emerge. The Chi square goodness-of-fit test, along with Bartlett's test of sphericity (tests whether the variables are noncollinear and therefore cannot be factored because the result would be as many factors as there are variables), and Kaiser-Meyer-Olkin Measure of Sampling Adequacy (measures the common variance among all the variables), provide information about whether the data may be factored and whether the result fits the data.

The generalized (weighted) least squares (WLS) extraction method was the primary extraction technique applied to the data. WLS was appropriate for the Likert-scaled belief statements since Likert items are typically treated as ordinal data. However, the solution generated by the WLS extraction was compared to the results of a variety of other extraction methods. Methodologists promote performing factor analyses using a variety of extractions to assess the stability of the solution (Tabachnick & Fidell, 2001). The WLS was compared to both the maximum likelihood (ML) method and unweighted least squares (ULS). A drawback of ML is that it requires a normal distribution and larger sample sizes (Wolins, 1995). ULS works well with smaller sample sizes and does not require rigorous adherence to assumptions of normality making it particularly well-suited for exploratory analysis and a better extraction for ordinal data (Wolins, 1995).

Factor analysis may be conducted using a variety of rotations to orient the data in multidimensional space to simplify the result into a more interpretable solution. Rotations are generally divided into two categories: orthogonal and oblique. Orthogonal rotations assume the factors are uncorrelated, while oblique rotations assume factors are correlated and recognize this correlation in the rotation (Finch, 2006). There is considerable debate about which category of rotation is preferred: Some have suggested that orthogonal rotations are simple and easy to understand, often lead to the same conclusion, and therefore are to be preferred (Nunnally & Bernstein, 1994). Other researchers have argued that oblique rotations provide superior solutions because they appropriately recognize covariance among variables and provide additional statistical information including estimates of correlations among common factors that are helpful in interpreting the solution (Fabrigar et al., 1999). Since correlation among the belief statements was anticipated, an oblique rotation was utilized to properly recognize the interrelatedness of variables. The correlations were inspected to confirm high correlation. There is no prevailing oblique rotation preference. The widely-used Promax rotation, available in SPSS, was applied. In the Promax rotation, high loading variables are maintained in the same pattern as found in the orthogonal solutions, but decreased for variables with low loadings.

Multiple methods may be used to evaluate the fit of factors in a generated solution. The number of factors ultimately selected should represent a parsimonious solution that is plausible. Traditionally, selecting too few factors has been judged a more serious problem than selecting too many, because solutions may obscure model structures by inappropriately combining constructs (Fabrigar et al., 1999). Over the years a number of popular rules for specifying and evaluating factors have been widely used. Three of the most popular are the Kaiser-Guttman criterion, Scree tests, and Chi square tests. The suitability of each of these three methods has been questioned (Hu & Bentler, 1999). The Kaiser-Guttman criterion (eigenvalue >1) selects factors that have eigenvalues from the original correlation matrix that are greater than 1. Critics believe that the eigenvalue greater-than-one rule is overly-mechanistic and leads to both over- and under-factoring (Finch & West, 1997). The Scree test is a visual assessment of the successive contribution of eigenvalues to the solution. The number of factors is based on where the eigenvalues level off. Scree test critics find the visual assessment too subjective (Fabrigar et al., 1999). It is recognized, however, that the number of factors retained in a solution remains a substantive as well as statistical decision process and should ultimately be evaluated on its ability to parsimoniously interpret the data in a meaningful way (Browne & Cudeck, 1989). Results will be described in the next chapter.

The second phase of the data analyses was a cluster analysis. The goal of the cluster analysis was to identify market segments within the population having similar belief construct profiles. The research question cluster analyses answer is whether participants may be grouped based on similar values for variables. That is, cluster analyses create an unknown subdivision of a population into homogeneous subgroups (Lorr, 1983).

As was true with the factor analysis, cluster analysis requires the researcher to make a number of decisions about analytic procedures that may have substantial impacts on the results. Since the cluster analysis was based on the results from a factor analysis, the determination of how factor weights were to be calculated for each individual was an important question. Two additional decisions in cluster analyses are which similarity measure, and which partitioning method to use. The variables of interest for this study were the groupings of individuals based on their scores (answers) on the belief statements. Scores for the factors were generated for each respondent using an exact weighting process (Grice, 2001a). To obtain the exact weighted scores, the least squares weights (or *factor score coefficients*) were multiplied by respondents' scores for each variable. Using the factor score coefficient matrix for the weights, rather than the structure or pattern matrix, provides superior representations, particularly when the factors are oblique (Grice, 2001a, 2001b).

The two-step cluster method was used to classify the data. Of the three cluster procedures that may be used to cluster data (i.e., hierarchical cluster analysis, *k*-means cluster, and two-step cluster), two-step cluster is the approach recommended for exploratory clustering (SPSS, 2010). The log-likelihood criterion distance proximity measure was used to assess distances of an individual's scores across factors. The Schwarz Bayesian Criterion was used to determine the optimal number of clusters. Many researchers approach cluster analyses assuming that valid clusters exist in the data, and therefore, do not test the significance of the cluster solution. However, cluster analysis always finds clusters, whether or not they are valid (Dubes & Jain, 1979). Therefore, significance tests of the cluster solution were conducted. Although it may be tempting to use standard hypothesis testing techniques directly on the variables used for clustering, this approach often returns invalid significance (Dubes & Jain, 1979; Milligan & Mahaljan, 1980). Instead, following Milligan (1996), statistical validity of the cluster solution was tested using internal criterion analysis and external criterion analysis. Internal criterion analyses use information obtained from within the clustering process to assess how well the variables cluster. For this study, the structure silhouette measure of cohesion and separation was used (Kaufman & Rousseeuw, 1990). The structure silhouette measures the closeness of variables in one cluster to each other compared to the other clusters. External criterion analyses test for significant differences between the clusters using variables not included in the cluster analysis. In this study, demographic/professional variables were used for the external criterion analyses, since they were not used in the clustering, but may be expected to be different within cluster solutions.

Next, the role of benefits beliefs in comparison to barriers beliefs was examined. The same criterion variable as was used to test statistical validity was again employed, this time to make comparisons between the full-beliefs model and nested models that use beliefs-only or benefits-only variables. Nested and non-nested linear regressions were run to examine the predictive abilities of the models and the strength of the independent contributions of each belief factor.

The results of the cluster analysis were then summarized in a market segmentation matrix. The matrix identifies the key characteristics of each market segment. Face validity of the solution was then examined using widely-accepted characteristics of good market segmentation (Wedel & Kamakura, 2000).

The mixed methods, sequential research design described in this chapter will explore what behavioral health providers believe about EHRs, what differences there are in beliefs depending on provider characteristics, which beliefs relate to each other, and the profiles of providers with similar patterns of beliefs. It is expected that the results of this exploratory study form initial understandings as to behavioral health providers' interests and reluctance. This information may be helpful in designing electronic behavioral health records and in determining what assurances and incentives may be useful to spur adoption.

CHAPTER 4: RESULTS

Study 1 – Beliefs Elicitation of Population Subset

Demographics

The recruited sample (*n* = 32) of behavioral health providers comprised professionals from each of the three category types: prescribers (psychiatrists, APRNs, PAs); non-prescriber clinicians (Psychologists, LMHPs, LIMHPS, LPCs, LADCs); and non-prescriber nurses (psychiatric RNs) (Table 2). The largest category represented was non-prescriber clinicians (44%), followed by prescribers (31%), and then non-prescriber nurses (25%). The desired oversampling of the first and third categories was successful.

Table 2

Participant Characteristics – Study One

	n	%
Professional License		
Psychiatrists, APRNs, PAs	10	31%
Psychologists, LMHPs, LIMHPS, LPCs, LADCs	14	44%
Psychiatric RNs	8	25%
Practice Setting		
Clinic (free-standing)	7	22%
Hospital (non-federal)	6	19%
Ambulatory care clinic	2	6%
In-home	2	6%
Regional center	2	6%
School/University	2	6%
Administrative agency	1	3%
Agency staff	1	3%
Clinic (hospital)	1	3%
County institution	1	3%
Group health plan	1	3%
Long-term care facility	1	3%
Non-profit facility	1	3%
Public health	1	3%
State institution	1	3%

	n	%
VA facility	1	3%
Own practice (no other specified)	1	3%

The sample represented a wide variety of primary practice settings. The participants were fairly evenly split between men (*n* = 17) and women (*n* = 15). The group was highly educated with almost half (47%) having attained doctorates (i.e., M.D., Ph.D., or Psy.D). The participants appeared to be sophisticated users of practice-related technologies: 50% of the respondents (*n* = 16) reported regularly using an electronic medical records system and nearly one-third (*n* = 10) reported regularly using lab systems. However, only a minority of respondents (*n* = 6) reported using an electronic medical records system to exchange client data with providers at other facilities (Table 3).

Table 3

Mode of Exchanging Client Health Information

	n	%
Fax	29	91%
Phone	28	88%
Mail	23	72%
E-mail	6	19%
EMR system	6	19%
Rely on others to do it	5	16%
Other	1	3%
Did not say	1	3%

When asked whether they would be positively or negatively disposed to adopting EHRs, most providers were positive. Of providers who summarized their overall opinion about EHRs, 81% (*n* = 21) characterized themselves as positive. Three (12%)

characterized themselves as having an overall negative opinion. Two providers (8%) characterized themselves as both positive and negative during their interviews. Six providers did not provide overall positions on their supportiveness.

Providers were asked whether they believed that behavioral health providers faced different benefits and barriers than medical providers. Most providers (59%) believed that behavioral health was different from medical health. Of those providers, most (79%) believed that behavioral health information is more sensitive and the client more vulnerable. Some providers (32%) believed that the subjectivity of behavioral health information makes electronic sharing a more complicated process.

Interviews on the benefits and barriers of electronically sharing client records revealed three major themes: quality and safety, privacy and security, and delivery of services (Table 4). All 32 providers (100%) discussed benefits and a little over half (59%) specified barriers of relating to client safety and quality. Within the privacy and security theme, all 32 providers (100%) talked about barriers while 22% cited benefits. For delivery of services, 97% offered barriers and 66% discussed benefits.

Table 4

Themes Regarding Perceptions of EHRs

Theme	Description	% Citing Benefits	% Citing Barriers
Quality and Safety	Care is delivered so as to prevent harm and achieve positive outcomes.	100%	59%
Privacy and Security	Client information is only accessible to those with the need and right.	22%	100%

Theme	Description	% Citing Benefits	% Citing Barriers
Delivery of Services	Behavioral health organizations and providers operate in a time and cost efficient manner.	66%	97%

Theme 1: Quality and Safety

Providers discussed quality and safety benefits of EHRs more than they discussed the barriers: all 32 providers offered at least one benefit that would be achieved, and only 19 providers offered barriers. Benefits discussed included that EHRs would: lead to improved continuity and quality of care; improve treatment and quality of care by having information more immediately available; and improve providers' ability to more appropriately treat and respond to medication issues. Providers also expressed concerns about EHRs, including that they might adversely impact relationships with their clients and lead to miscommunication among providers.

Providers expected that electronic exchange of information would provide more complete and immediate information about behavioral health clients which would improve quality and continuity of care. Providers believe they offer good care already, but speculated that more complete information would help them provide better care:

> *If I don't get all the information and miss something, then I'm not going to understand a person's behavior.*
>
> * * * * *
>
> *The clearer the information and better the information that is available at that time will help the care itself.*
>
> * * * * *

Continuity of care is a main part of all of this. Because everybody gets to know what is wrong with the patient . . . and if the primary care provider can get the information just like the psychiatrist then it is better treatment for the patient.

* * * * *

There are so many more variables that could be causing the person's behavior. That's why coordination is helpful, because there are so many other things that could be going on.

* * * * *

It prevents you from reinventing the wheel and having to do entirely new assessments if you already have a recent one.

Providers noted that EHRs would improve the immediacy of access to client information. They discussed that having the client information more readily available would assist in providing needed care and might free clinician time for client care:

There's a disruption of care because you have to wait a half hour while we're trying to contact the hospital and having the hospital fax over information . . . It can be several months before we get [the information].

* * * * *

We spend a lot of time re-faxing things, requesting information, making phone calls requesting that information . . . It takes away from the time we could be spending on client treatment needs.

Behavioral health providers discussed a benefit in having more comprehensive information about clients' medications. Providers noted that their clients may receive drug prescriptions from other behavioral and medical providers. Being unaware of the other drugs could result in unaccounted-for side effects and interactions:

> *If [the client] has a heart condition . . . there are going to be certain medications we want to avoid. General physicians should have [mental health] information because there's a lot of medication they give that may make a person quite depressed.*
>
> * * * * *
>
> *Just having a record of what's working for them would be a great benefit instead of starting over.*

Providers also expressed patient safety and quality of care barriers. The most frequent concern was that the provider–client relationship would suffer if EHRs required providers to divert attention from the clients to a computer:

> *If I'm spending all of my time looking at my keyboard typing as I'm interviewing you that really cuts into the relationship that we're supposed to be developing.*

Another patient safety and quality of care barrier providers mentioned was that EHRs would result in miscommunications with other providers. Providers mentioned miscommunications grounded in over-reliance on written information (rather than interpersonal) and in other providers wrongly interpreting information:

It's not face-to-face so there always can be miscommunication because of that.

* * * * *

If you have major depression, once that's down there someplace, then every time somebody looks to see what the diagnosis is, they just transfer that to the next health form that it's on, even though those things may be only very temporary.

The quality and safety benefits were decisive for some providers. Some providers remarked that improved quality and safety should be the primary reason (and for some the only valid reason) that EHRs should be adopted:

Quality of treatment is the umbrella reason. In my end of the business, we have people with fairly complex problems that are receiving services from an array of different providers. Those services need to be integrated and coordinated toward a common goal. And that requires a lot of communication.

* * * * *

The only reason for exchanging would be for the maximum benefit of different people having different areas of expertise, medical, versus psychiatric, versus nutrition that contribute to the whole of treating an individual. Otherwise, there isn't any reason for it. There would be no reason to exchange information with somebody that wasn't potentially going to be helpful in treating the client's overall needs.

Theme 2: Security/Privacy

Every provider mentioned security and privacy when discussing adopting EHRs. More providers discussed the barriers than benefits of security and privacy: Only 7 providers offered at least one benefit, while all 32 providers offered at least one barrier. The most frequently mentioned security and privacy benefit was that, compared to paper-based systems, EHRs enabled improved tracking of who accessed information and prevented access by unauthorized persons. The main privacy and security barriers were that information could be illegitimately accessed by others, patients would be reluctant to consent to electronic sharing, and providers would face significant legal barriers that all but preclude electronic sharing.

Some providers believed that electronic systems would be an improvement over paper-based records. Providers particularly discussed the relative advantages EHRs offered in controlling user access and tracking:

> *I call Walgreens and I say, "I'm an RN from this hospital, and I need to verify John Smith's meds." Well, Walgreens doesn't know who I am, [yet they provide patient information over the telephone].*
>
> * * * * *
>
> *That's always my fear with a fax; if I hit the wrong number, is that fax going to go to the wrong place? Then I have confidential information going where it shouldn't go.*

All providers mentioned that they had concerns about privacy and security. Some providers, in fact, identified privacy and security as the single most important barrier to adopting electronic behavioral health records sharing:

Confidentiality is always the most important factor.

* * * * *

The biggest drawback is in some way that data [is] being compromised or shared in inappropriate ways or reaching the wrong person.

* * * * *

I just got a notice from my credit card company that they were sending me a new one because hackers had gotten in to secure information, so I guess no one's really safe.

Another privacy and security barrier providers identified was client reluctance to consent to electronic sharing. Providers characterized client reluctance as "patients are legitimately concerned about what happens to their health care information" and "they get worried about the CIA and FBI and other agencies spying on them":

Behavioral health still has stigma attached to it. And having records and being able to send them at the speed of light to probably anywhere. People don't always want that to happen. They want to keep it private for employment reasons and whatever. So, until mental health is de-stigmatized, I think there is always going to be a problem.

* * * * *

We're not going to exchange their information without an informed consent. And the getting of that informed consent could be a challenge therapeutically. It might even damage the treatment relationship in some cases.

Finally, providers identified privacy and security legal barriers. For some providers, federal privacy laws are the biggest barrier and other providers worried about their own legal liability:

HIPAA. HIPAA, HIPAA, HIPAA. That's about the first 3 or 4 problems in the way.

* * * * *

I'm the one whose hide is on the line if confidentiality is breached. Therefore I'm not going to put that trust in somebody else because if the confidentiality is breeched, I'm probably the one that will get the lawsuit, not them.

Overall, although some security and privacy benefits were identified, barriers were discussed in more of the interviews. One provider summed up concerns about privacy and security vulnerabilities in electronic sharing:

Anybody is going to be concerned about security issues because paper can be easily accessed, but only by a limited number of people. Anything that's computerized may be harder to access but can be accessed by millions of people. So you probably have a higher degree of difficulty but a wider scope of who could get to it.

Theme 3: Delivery of Services

Every provider, except one, discussed benefits and barriers within the delivery of services theme. Providers discussed barriers more than they discussed the benefits: all 32 providers offered at least one barrier and only 21 providers offered benefits. Most of the benefits providers discussed revolved around the belief that electronic records would result in time and cost saving for their practices. Providers were concerned that barriers to the delivery of care included: staff would be reluctant to use EHRs, systems would be too costly and time consuming to implement and support, and there are not EHR products available that meet the use and reliability needs of behavioral health providers.

Some providers believed that electronic systems would result in time and cost savings for providers and their practices. Providers also believed that EHRs could result in less time spent on sending and requesting information and improved efficiencies in providing care:

> *The age old question 'Where's the chart?' doesn't have to be asked anymore. You have pretty much instant access; as soon as a provider electronically signs the record then that information is accessible to you. It frees the provider up from having to look for things. I think it just makes it tremendously efficient to access information, that's probably the biggest benefit.*
>
> * * * * *

It saves me time. It saves the probation officers time. . . . We're not chasing each other on the phone; we're not sending emails back to each other saying, "Hey, do you think I can get this information?"

* * * * *

Trying to track down that paperwork and documentation can be very time consuming and costly. . . . So there's a financial benefit.

* * * * *

Patients' needs can be exchanged before the visit starts so care can be provided in a more efficient way.

All of the providers mentioned at least one delivery of services barrier. Providers predicted that staff would be reluctant to adopt systems because of a variety of factors, such as age, discomfort with computers, and an unwelcome deviation from training and practice:

Some people are very good physicians or very good nurses or therapists but the moment they see a computer they freeze.

* * * * *

A lot of providers in mental health have just very rigid ideas about exchanging information and being overly protective of client information and I think that that would only add to their over protectiveness.

Another delivery of services barrier providers discussed was concern that EHRs would be too costly and time consuming to implement and operate. Providers were also skeptical that EHRs would fit within their workflows:

Cost, number 1? Yeah.

* * * * *

I think this is going to take a heck of a long time to set up. If you have to go in and put all the information on each person. . . . I wouldn't want to do [that].

* * * * *

[EHRs] would be laborious for me to have to input information electronically to be able to send it. . . . I do all my clinical work and all of the secretarial work.

* * * * *

The efficiency of the system depends on every person being able to use or wanting to. If 10% of people are resistant . . . then it becomes an inefficient system and you still have to do paperwork system in addition to the electronic.

Providers discussed vendor-specific barriers. Providers were skeptical that EHRs could accommodate the narrative-rich nature of behavioral health information. Providers were also concerned that EHRs may not be reliable:

You can't template someone's psychological history. You can't do that.

* * * * *

I've had multiple times where I'd done an assessment and I'm almost done with the assessment and the computer crashes. . . . Okay well that's a

> *whole hour of work. . . . And I'm like going, "Okay, I have to start this all over. You've got to be kidding."*

Overall, delivery of service issues offered somewhat contradictory predictions about the impact of EHRs on practices: Some providers believed that EHRs would save time and money, but most were worried that it would be too costly for them to implement and use:

> *When you're talking about mental health you're talking about small offices. You're talking about providers who cannot handle large overhead which electronic systems tend to bring into the overall expense of an office.*

Summary

The purpose of the first study was to discover and describe behavioral health providers' perceptions about the barriers and benefits of electronically sharing client records. Behavioral health providers offered numerous specific benefits and barriers that were categorized into three themes: quality and safety, privacy and security, and delivery of services. Among the benefits discussed, all providers mentioned quality and safety benefits, two-thirds discussed benefits in the delivery of services, and only fewer than one in ten offered benefits in privacy and security. Of the barriers, privacy and security concerns were mentioned by all providers, nearly all providers mentioned the challenges for delivery of services, and over half the providers cited challenges to quality and safety.

Overall, behavioral health providers in this study were positive about electronic sharing: 81% (n = 21) characterized themselves as positive, which according to the technology acceptance model (Davis, 1989) has positive implications for the adoption of EHRs: Providers who have positive attitudes about adopting EHRs will be likely to adopt. Further research would be needed to determine whether these findings may be generalized to a larger population.

This study provides two pieces of evidence that behavioral health providers have differing perceptions about the benefits and barriers of electronic sharing than medical providers. First, a majority of the behavioral health providers (59%) stated that they do face different challenges than do medical providers because their client information tends to be more sensitive and narrative rich. Second, the patterns of responses in this study indicate that behavioral health providers are more concerned about privacy and security than are medical providers: 100% of behavioral health providers voiced concerns about privacy and security with a number of them labeling it their most important concern. This is consistent with previous discussions of the privacy and security challenges that behavioral health providers face (*Cost and Confidentiality*, 2008; *Privacy and Confidentiality*, 2005; Salomon et al., 2010; U.S. Department of Health and Human Services, Office of the Surgeon General, 1999). In qualitative studies of medical providers, (Austin et al., 2006; Miller & Sim, 2004; Scheck McAlearney et al., 2004), none identified privacy and security as a unique issue. Even surveys that explicitly sought physician concerns about privacy and security did not result in identification of it as a major issue: In Wright et al.'s survey, 55% of physicians responded they were *concerned* (and only 16% *very concerned*) about privacy and security, leading the authors to conclude that for the physicians, privacy and security were not a "major concern" (p. 69).

Cost and staff time concerns were frequently mentioned as significant barriers to adopting electronic records. Just as smaller medical practices have much lower adoption rates of EHRs (SK&A, 2010), small behavioral health practices may also have challenges based on their small size: Well over half of all psychiatrists and psychologists report individual practice as their primary or secondary employment setting (Duffy et al., 2004). Cost saving approaches such as shared computing services may be needed to achieve the economies of scale needed to address cost and expertise issues of these small practices. It is not known what an acceptable cost for behavioral health providers may be. In one study a majority of medical providers (2/3 of respondents) were unwilling to pay a suggested hypothetical fee of $150 (Wright et al., 2010).

Our participant sample reported high use of electronic medical records (50%) within their organizations. Past studies have suggested that providers who use electronic medical record systems tend to focus on the benefits of the systems more than the barriers as compared to providers who have not implemented electronic medical record systems (Gans et al., 2005; Scheck McAlearney et al., 2004).

In summary, three themes (i.e. safety and quality of care, security and privacy, and delivery of services) were identified from interviews with 32 behavioral health providers. Most behavioral health providers were positive about sharing electronic client records. This was a unique, exploratory study that adds to the existing literature on electronic medical records by showing that some barriers (e.g., security and privacy) may be a greater concern for the behavioral health community.

Study 2 – Belief Segmentation

Demographics

Data from 674 respondents were collected in Study 2 – the statewide survey of behavioral health professionals. Since the study focused on belief statements, individuals who did not respond to any of the belief statements (*n* = 7) were deleted from the sample, resulting in a final sample of 667. The sample size was adequate for the factor and cluster analyses, well exceeding the minimum of 300 cases for factor analysis suggested by Tabachnick and Fidell (2001). Others have suggested that sample size adequacy may best be ensured by the over-determination of factors (having at least four variables contributing to each expected factor) (Fabrigar et al., 1999). Every factor in this study exceeds that recommendation.

The final sample was on average, female (70%), midlife (71% between the ages of 29 to 59 years of age), highly educated (95% having at least attained a master’s degree), licensed as a mental health practitioner (69%) at an outpatient facility (69%). Most providers’ preferred addresses (70%) were located in large metropolitan areas with populations exceeding 250,000. The most popular current means of sharing client behavioral health information were fax (91%), phone (84%), and mail (82%). Providers reported a mean of 26.85 hours per week seeing clients (SD = 15.47). Descriptive statistics of the sample are presented in Table 5.

Table 5

Participant Characteristics – Study Two

Characteristic	Category	*n*	Valid %
Gender (*n* = 666)			
	Male	198	30
	Female	468	70
Age (*n* = 666)			
	29-39	122	18
	40-49	124	19
	50-59	228	34
	60-69	162	24
	69+	30	5
Educational Highest Degree (*n* = 658)			
	Associate's	10	2
	Bachelor's	21	3
	Master's	449	68
	Post Master's	4	1
	Doctorate	129	20
	Medical Doctor	45	7
Professional Licensure (*n* = 666)[a]			
	Licensed Mental Health Practitioner	457	69%
	Licensed Professional Counselor	212	32%
	Licensed Independent Mental Health Practitioner	191	29%
	Licensed Master Social Worker	127	19%
	Licensed Alcohol and Drug Counselor	124	19%
	Psychologist	98	15%
	Doctor of Medicine/Doctor of Osteopathic Medicine	45	7%
	Advanced Practice Registered Nurse	21	3%
	Licensed Marriage and Family Therapist	20	3%
	Compulsive Gambling Counselor	11	2%
	Physician Assistant	5	1%

Characteristic	Category	*n*	Valid %
	Certified Master Social Worker	1	0%
Practice Setting (*n* = 648)			
	Outpatient	447	69%
	Educational	60	9%
	Inpatient/Residential	51	8%
	Correctional	33	5%
	Federal Facility	22	3%
	Other	35	5%
Urban to rural continuum (*n* = 666)			
	Counties in metro areas of 250,000 to 1 million population	467	70%
	Counties in metro areas of fewer than 250,000 population	2	0%
	Urban population of 20,000 or more, adjacent to a metro area	7	1%
	Urban population of 20,000 or more, not adjacent to a metro area	122	18%
	Urban population of 2,500 to 19,999, adjacent to a metro area	14	2%
	Urban population of 2,500 to 19,999, not adjacent to a metro area	38	6%
	Completely rural or less than 2,500 urban population, not adjacent to a metro area	16	2%
Current Sharing Method (*n* = 630)[b]			
	Fax	570	91%
	Phone	527	84%
	Mail	518	82%
	E-mail	214	34%
	Electronic behavioral health records system	63	10%
	Rely on others to do it for me	89	14%
	Other	37	6%

Characteristic	Category	*n*	Valid %

[a] The total number of license types reported exceed the sample size because most behavioral health professionals maintain more than one license type.
[b]The total current means of sharing client behavioral health information exceeds sample size because most behavioral health professionals reported using multiple means of sharing information.

When compared to the population of all 2,010 behavioral health providers in Nebraska, the sample closely approximated the population on many characteristics. The gender distribution was not significantly different from the population ($X^2(1) = .012$, $p = .912$). The average age in the sample ($M = 52.35$, $SD = 11.284$) was similar to that of the population ($M = 51.72$, $t(665) = 1.430$, $p = .153$). The educational attainment was not significantly different from the population ($X^2(5) = 7.097$, $p = .214$). The professional licensure for most categories was not significantly different: psychologists ($X^2(1) = .312$, $p = .576$), licensed mental health practitioners ($X^2(1) = .551$, $p = .458$), licensed professional counselors ($X^2(1) = .710$, $p = .399$), licensed marriage and family therapists ($X^2(1) = .188$, $p = .665$), licensed master social workers ($X^2(1) = .010$, $p = .921$), certified master social workers ($X^2(1) = 1.000$, $p < .001$), advanced practice registered nurses ($X^2(1) = .217$, $p = .642$), and physician assistants ($X^2(1) = 1.339$, $p = .247$). Several categories of licensure categories were over-represented in the sample: licensed independent mental health practitioners ($X^2(1) = 6.857$, $p = .009$), compulsive gambling counselors ($X^2(1) = 4.204$, $p = .040$), licensed alcohol and drug counselors ($X^2(1) = 4.080$, $p = .043$). Only one licensure category was under-represented in the sample: doctors of medicine or osteopathic medicine ($X^2(1) = 4.619$, $p = .032$). The practice setting was not significantly different from the population ($X^2(5) = .011$, $p = 1.000$).

Data Irregularities and Validity

Data were inspected for irregularities that could impact the statistical validity of data analysis. Irregularities examined included missing values, out-of-range values, outliers, and skew. First, descriptive univariate data were inspected for missing values. Following Tabachnick & Fidell (2001), missing data were tested for mean differences by constructing a dummy variable with two groups: cases with missing belief statement ratings and cases without missing belief statement ratings. Each missing belief statement was dummy-coded into a categorical response/no response variable. The categories of response/no response were then compared for mean differences against the overall support for EHRs rating. No significant differences between responders and non-responders were found for 34 of the 38 belief statements. However, differences were found for 4 of the 38 belief statements*: Improve your access to client medical/physical health records* ($F(1,654) = 8.035$, $p = .005$, $MSE = 1.818$), *Lead to more complete client information* ($F(1,654) = 4.494$, $p = .034$, $MSE = 1.827$), *Improve your practice's office work flow* ($F(1,654) = 4.505$, $p = .034$, $MSE = 1.827$), and *Be resisted by staff at your practice* ($F(1,654) = 21.928$, $p < .001$, $MSE = 1.780$). To approximate responses for these missing belief statements, a regression equation was constructed to predict missing values for the four variables that showed significant differences between incomplete responses and complete responses. Predictor variables for the regression included all the other belief statement scores as well as the overall support score.

Next, all belief responses were examined for out-of-range values. Two belief statements had out-of-range values. Both were values predicted based upon the missing value regression. To bring responses in range, they were recoded as the closest most acceptable score.

The presence of outliers in the belief data set was evaluated because outliers may impact correlations and therefore distort factor analyses. A univariate analysis, followed by a multivariate analysis was conducted. Methodologists suggest that both univariate and multivariate analyses be conducted prior to deciding what actions to take regarding outliers (Tabachnick & Fidell, 2001). The univariate analysis identified specific variables that had scores with extreme values when compared to the rest of the sample. The multivariate analysis looked for cases that had extreme scores on multiple variables in comparison to other cases.

The univariate analysis was conducted on the 38 belief questions and yielded one outlier variable, *Be resisted by some providers*, that had three cases of standardized scores (z scores) exceeding the +/- 3.29 score recommended as a cutoff by Tabachnick and Fidell (2001). Tabachnick and Fidell (2001) suggest that if a researcher is convinced that the outliers are a legitimate part of the population, steps should be taken to reduce the impact of the outliers: variables transformed and scores changed. Because the participants are behavioral health providers from the sampling frame, it is clear that they are a legitimate part of the population and were therefore included. The outlier univariate scores were replaced with the most extreme acceptable value (Tabachnick & Fidell, 2001), recoding from 1.0 to 1.70, and adequately reducing the standard deviation of the z score from -4.17 to -3.28.

The multivariate analysis identified 31 subject response outliers. A logistic regression was used to discover what items contributed to the cases having outlier status. The cases were dummy coded as either outliers (n = 31), non-outliers (n = 534), or having missing belief values (n = 133). Extreme scores on 9 belief statements were meaningfully divergent from the population ($p < .05$) and contributed to the multivariate outlier status (Table 6). The outliers believed more strongly that the rest of respondents there are specific negative outcomes of using electronic records. The three most meaningful divergences from the population were that outlier subjects agreed more strongly that EHRs may: *Be misused by third party payers, Force you to use an overly templated behavioral health record*, and *Be resisted by clients*. To address the multivariate outliers, Tabachnick and Fidell (2001) guidance was followed. They recommend that if the researcher is convinced the outliers belong to the population and thus reluctant to delete the cases, that subsequent analyses be run with and without the outlier cases. The factor analysis was first run with the outlier multivariate cases and then with the cases to assess the impact of the outliers. As will be reported later, the multivariate outlier cases had only a minimal impact on the factor solution.

Table 6

Summary of Logistic Regression Analysis of Variables Contributing to Outlier Cases in Sample

Predictor	*B*	*S.E.*	*Exp(B)*
Be misused by third party payers	.934	.359	2.544
Force you to use an overly-templated behavioral health record	.784	.388	2.189
Be resisted by clients	.713	.358	2.040

Predictor	*B*	*S.E.*	*Exp(B)*
Make you become too reliant on technology that could crash	-.634	.288	.531
Compromise your professional ethics	-.684	.301	.505
Improve your clients' safety	-.693	.330	.500
Be impractical because behavioral health information cannot be captured by checkboxes and dropdown lists	-.698	.265	.498
Result in more data entry errors in client records	-.791	.317	.453
Improve the quality of care your clients receive	-.931	.325	.394

The final data irregularity examined was skew. It has been widely observed that psychological and behavioral data is often skewed. However, many statistical processes, including factor analysis assume data are normally distributed. Non-normal distributions may lead to under-factoring. West, Finch, and Curran (1995) recommend that significant skewness (>2) and kurtosis (>7) be addressed since this magnitude of non-normality may distort subsequent analysis. No beliefs items were found to exceed the recommended limits: skewness ranged from .74 to -1.2, and kurtosis ranged from 2.0 to – 1.1.

In order to assure that the ordinal status of the belief statements was appropriately reflected, all responses were forced into a response category of between 1 and 5. In other words, particularly for the missing value calculations, the resulting factor scores did not comply with possible response choices. This was also executed on responses on the paper based survey that were non-conclusively a specific number. For example, those that straddled two ordinal choices. All values were recoded to the nearest acceptable response choice.

Descriptive Results

Respondents were asked to rate their level of agreement with statements about EHRs. Each question asked respondents to use a Likert-scaled response (1 = *Strongly disagree*; 2 = *Disagree*; 3 = *Neither agree nor disagree*; 4 = *Agree*; 5 = *Strongly agree*) to rate 38 statements:

> *Imagine a system that enables you to electronically share client information with medical and behavioral health providers at other organizations, who have the appropriate release of information. From your perspective, such an electronic sharing system would…*

The means and standard deviations, reported in Table 7, indicate strongest agreement ($M > 4.00$) with three statements: *Be resisted by some providers*, *Improve coordination of care among all providers working with the same client*, and *Improve your access to client medical/physical health records*. Providers did not have an equivalent level of disagreement ($M < .2$) with any of the statements.

Table 7

Providers Beliefs

Belief Statement	*Mean(SD)*
Be resisted by some providers	4.12(.73)
Improve coordination of care among all providers working with the same client	4.07(.92)
Improve your access to client medical/physical health records	4.01(.86)
Improve your ability to track medication history	3.93(.89)
Provide more complete information to help with your diagnoses and treatment planning	3.89(.98)
Lead to more complete client information	3.85(.96)
Reduce duplicating client evaluations, assessments, or tests that have already been conducted by other providers	3.83(1.03)

Belief Statement	*Mean(SD)*
Improve your communication with other providers	3.81(.96)
Streamline your access to client information/records	3.80(.94)
Be resisted by staff at your practice	3.56(1.13)
Be misused by third party payers	3.48(1.02)
Increase your legal vulnerability	3.47(1.04)
Be time consuming for your practice to implement	3.40(1.13)
Make you become too reliant on technology that could crash	3.32(1.14)
Force you to use an overly templated behavioral health record	3.30(1.02)
Improve the quality of care your clients receive	3.25(1.09)
Cost your practice too much to implement	3.24(1.06)
Result in extra work for you on a daily basis	3.15(1.11)
Improve your practice’s office work flow	3.14(1.06)
Be resisted by clients	3.13(.99)
Be impractical because behavioral health information cannot be captured by checkboxes and dropdown lists	3.13(1.15)
Save costs for your practice in the long run	3.11(1.10)
Increase the time your practice spends on transcriptions	3.09(1.08)
Be difficult because your practice lacks the technological expertise to implement and maintain	3.08(1.24)
Improve your clients’ safety	3.07(1.07)
Improve your clients' satisfaction with the admissions process	3.06(1.00)
Improve your practice’s billing accuracy	3.02(1.03)
Result in more data entry errors in client records	2.97(.93)
Require more training than you have time for	2.95(1.10)
Reduce the time you spend on paperwork	2.94(1.15)
Create more time for client care	2.94(1.10)
Disrupt your own work flow	2.88(1.10)
Compromise your professional ethics	2.76(1.15)
Disrupt your relationships with your clients	2.58(1.02)
Negatively influence treatment plans	2.56(0.97)
Improve your ability to control who has access to your clients' information	2.53(1.15)
Improve privacy and security of confidential client information	2.52(1.10)
Be difficult for you due to your apprehensions about computer technology	2.47(1.23)

Note: Likert scaled responses were 1=*Strongly disagree*; 2=*Disagree*; 3=*Neither agree nor disagree*; 4=*Agree*; 5=*Strongly agree*.

Three steps were taken to validate and begin exploration of the belief statement responses. First, overall patterns of supportive or non-supportive responses were converted into a new score. Next, this overall supportive or non-supportive score was compared to the single item response asking individuals to rate their overall support of EHRs. Finally, differences in support based on provider characteristics were analyzed.

In the first step, groupings of the positively and negatively worded statements were examined further to explore respondents' overall support or non-support of EHRs. Responses to the negative belief statements were reverse coded and the final response categories reworded to: 1 = *Highly negative*; 2 = *Negative*; 3 = *Neither positive nor negative*; 4 = *Positive*; 5 = *Highly positive*. This enabled an overall support/non-support score to be calculated for each individual from the sum of responses for all 38 belief statements. Scores could range from 38 (highly negative) to 190 (highly positive). Actual summed scores ranged from 38 (the most highly negative score possible) to 189 (1 less than the most highly positive score possible) (M = 118, SD = 26.97). The reliability of the supportive and non-supportive belief statements was assessed with Cronbach's alpha, a measure of internal consistency among variables. The Cronbach's alpha for the 18 positive items was .950, and for the negative items was .945, exceeding the recommended score of .70 and thus suggesting internal consistency among the belief statements.

In the second step, to further validate the belief statements, the summed belief score was compared to responses to the single item overall attitude question asked in the survey (i.e., *Overall, rate your support for creating a system that would enable providers* *to electronically share client information in a secure manner*). The overall attitude response choices were: 1=*Not supportive*; 2=*Somewhat not supportive*; 3=*Neutral*; 4=*Somewhat supportive*; and 5 =*Very supportive*. The mean score of 3.50 (SD = 1.36) indicates slight support for EHRs. It would be expected that there would exist a significant positive relationship between an individual's summed score and their response to the overall attitude question. Spearman's rho was used to calculate the correlation since Likert-scaled variables may not be assumed to measure responses at equal intervals. The results indicate a strong relationship between the summed belief scores and the overall support question, $r(561) = .83$, $p < .001$.

Finally, analyses of the differences in summed belief scores among respondent types were then conducted to understand overall patterns of support for electronic records. A Spearman's rho correlation was conducted for the quantitative independent variables of age, summed computer self-efficacy, and satisfaction with previously-used electronic records. An ANOVA was conducted for the categorical variables of gender, provider professional category, organizational type, location along urban and rural continua, and web versus paper survey responders.

Age. A Spearman's rho correlation between age (M = 52.35, SD = 11.284) and overall beliefs about electronic records (M = 118.13, SD = 26.97) was significant ($r(562) = -.247$, $p < .001$). Older responders were more likely to have negative beliefs about EHRs than were younger respondents.

Gender. An ANOVA revealed no significant difference between men and women in their overall attitude toward electronic records, $F(1, 562) = 2.646$, $p = .104$, $MSE = 725.981$).

Professional licensure. Overall attitudes toward EHRs did not vary significantly based on professional licensure: psychiatrists, $F(1, 563) = 1.491$, $p = .223$, $MSE = 726.831$; APRNs, $F(1, 563) = .056$, $p = .812$, $MSE = 728.682$; PAs, $F(1, 563) = .044$, $p = .833$, $MSE = 728.697$; psychologists, $F(1, 563) = .001$, $p = .981$, $MSE = 728.754$; and licensed professionals, $F(1, 563) = .644$, $p = .423$, $MSE = 727.923$.

Organizational type. There were significant mean differences in the summed beliefs among providers based on the type of primary practice ($F(5, 541) = 5.510$, $p < .001$, $MSE = 688.535$). Pairwise comparisons using Least Significant Difference procedure (with a minimum mean difference = 7.617) revealed that respondents from corrections and federal facilities were most positive (corrections: $M = 132.22$, $SD = 23.77$; federal: $M = 131.53$, $SD = 20.77$) and were significantly more positive than respondents from schools, outpatient facilities, and those in the *other* category. Respondents from inpatient facilities were the third most positive group ($M = 128.18$, $SD = 24.98$) and were also significantly more positive than those from outpatient facilities and those in the *other* category (but statistically equivalent to those from schools).

Location along urban to rural continua. There were no significant differences in overall attitude based on three classifications of urban/rural location of providers: Rural Urban Community Area Code, ($F(14, 549) = 1.305$, $p = .199$, $MSE = 722.623$);

Urban Influence Code, ($F(7, 556) = 1.047$, $p = .397$, $MSE = 727.682$); and the Rural Urban Continuum Code, ($F(6, 557) = 5.510$, $p = .414$, $MSE = 727.988$).

Computer self-efficacy. Responses to the negative computer self-efficacy statements were reverse coded and the final response categories reworded to: 1 = *Highly negative*; 2 = *Negative*; 3 = *Neither positive nor negative*; 4 = *Positive*; 5 = *Highly positive*. An overall computer self-efficacy score was then calculated from the sum of scores for the eight computer self-efficacy statements. This resulted in a possible range of scores from 8 (highly negative) to 40 (highly positive). The summed self-efficacy scores suggested overall slightly positive feelings about computer self-efficacy ($M = 26.38$, $SD = 7.135$). A Spearman's rho correlation between the summed computer self-efficacy score and overall beliefs about electronic records suggests that feelings of computer self-efficacy were positively correlated to responses supportive of electronic records $r(553) = .498$, $p < .001$.

Web versus paper survey responders. Providers responding via the web survey were more positive about electronic records with a mean attitude score of 123.26 ($SD = 23.94$), whereas those who answered via the mail survey had a mean attitude score of 111.09 ($SD = 29.27$). The difference was significant, $F(1,563) = 29.468$, $p < .001$, $MSE = 692.508$).

Satisfaction with electronic records. A Spearman's rho correlation between satisfaction with electronic records, if previously used, and overall beliefs about electronic records was $r(310) = .570$, $p < .001$. This finding is similar to previous research that indicates previous positive experiences with electronic records may make providers more positive about EHRs.

Assessment of Suitability of Data for Factor Analysis

The factorability of the 38 belief statements was then assessed by examining the Spearman's rho correlation matrix of the 38 belief statements. All of the items were significantly correlated at $p < .001$. Most of the items (89%) were at least weakly correlated (> |.32|), meaning that the overlap in variance among the factors warranted use of the oblique, rather than orthogonal, rotation (Tabachnick & Fidell, 2001). None of the correlations exceeded .90, thus reducing concerns about multicollinearity. Over 93% of the 703 correlations ranged from |.30| to |.75|. Several items had significant, but weak correlations (less than .30) with many other belief statements. The item with the weakest correlations to the other items was *Be resisted by some providers* which was correlated less than |.40| with each of the other belief statements.

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and the Bartlett Test of Sphericity were conducted to ensure that the data were suitable for factoring. The KMO analysis yielded a very satisfactory index of .976, and the Bartlett Test was highly significant ($X^2 = 14416.701$, $df = 703$, $p < .001$). The initial and final communalities for each variable are represented in Table 8. Initial communalities were estimated as the R-square (i.e., the squared multiple correlation) value for each item serving as the dependent variable in a regression equation in which all the other variables are independent variables. In other words the initial communality multiplied by 100 measures the percent of a belief statement's variance that can be predicted from the remaining 38 belief statements. The final communalities are essentially the R-square value for each item as dependent variable with the factors serving as independent variables. Therefore, when the final communality is multiplied by 100, it measures the percent of a belief statement's variance that may be predicted by the underlying factors. Most of the initial communalities generated (89%) are low to moderate (.40 to .70). Three items had low (<.50) final communalities, indicating that they may be unrelated to the other belief statements or that another factor could be identified with additional statements added for future research (Costello & Osborne, 2005). Those statements were *Improve your practice's billing accuracy*, *Increase the time your practice spends on transcriptions*, and *Be resisted by some providers*. Given the over determination of factors and the over 500 cases, the low communalities did not present major data analytic concerns (MacCallum, Widaman, Zhang, & Hong, 1999). The item correlations, KMO, Bartlett's Test, and communalities, along with the over determination of variables, confirmed that the items share some variance and are suitable for factoring (Fabrigar et al., 1999).

Table 8

Initial and Final Communalities for the 38 Belief Statements

Belief Statement	Initial	Final
Provide more complete information to help with your diagnoses and treatment planning	.700	.770
Disrupt your own work flow	.684	.769
Improve coordination of care among all providers working with the same client	.713	.767
Streamline your access to client information/records	.715	.765
Improve privacy and security of confidential client information	.657	.758
Improve your practice's office work flow	.668	.743

Belief Statement	Initial	Final
Disrupt your relationships with your clients	.678	.742
Lead to more complete client information	.669	.731
Compromise your professional ethics	.644	.722
Cost your practice too much to implement	.631	.718
Improve your communication with other providers	.669	.717
Improve your access to client medical/physical health records	.645	.712
Be time consuming for your practice to implement	.621	.708
Negatively influence treatment plans	.636	.696
Force you to use an overly templated behavioral health record	.586	.687
Save costs for your practice in the long run	.633	.686
Result in extra work for you on a daily basis	.613	.685
Improve the quality of care your clients receive	.626	.679
Reduce the time you spend on paperwork	.576	.641
Improve your clients' satisfaction with the admissions process	.558	.640
Be difficult because your practice lacks the technological expertise to implement and maintain	.544	.634
Improve your ability to track medication history	.582	.633
Require more training than you have time for	.567	.628
Improve your ability to control who has access to your clients' information	.508	.627
Increase your legal vulnerability	.551	.622
Be misused by third party payers	.532	.618
Make you become too reliant on technology that could crash	.524	.597
Create more time for client care	.511	.587
Be impractical because behavioral health information cannot be captured by checkboxes and dropdown lists	.520	.574
Improve your clients' safety	.514	.563
Result in more data entry errors in client records	.488	.542
Reduce duplicating client evaluations, assessments, or tests that have already been conducted by other providers	.490	.537
Be resisted by clients	.465	.514
Be resisted by staff at your practice	.438	.510
Be difficult for you due to your apprehensions about computer technology	.409	.500
Improve your practice's billing accuracy	.407	.492

Belief Statement	Initial	Final
Increase the time your practice spends on transcriptions	.400	.451
Be resisted by some providers	.252	.315

Belief Statement Factor Analysis

A common factor analysis on the 38 belief statements was conducted using weighted least squares (WLS), factoring with Promax (oblique) rotation. The default kappa value of 4 was applied (Fabrigar et al., 1999). Four factors with eigenvalues > 1 created a solution accounting for 56.66% of the variance. All items, except one, had extraction communalities of greater than .45. The one item with a lower communality was *Be resisted by some providers*, with a communality of .315. The pattern matrix, which measures the "the unique relationships between the individual factors and items, excluding the overlapping effects of other factors" was interpreted because this research is primarily interested in ascertaining the unique relationships between the factors and items. (Finch, 2006, p. 42).

Four factors emerged from the pattern matrix when observing pattern matrix loadings of greater than or equal to |.40| (Table 9). The factors were beliefs that electronic records would: *Improve care and communication*, *Add cost and time burdens*, *Present access and vulnerability concerns*, and *Improve workflow and control*. The first factor explained 45% of the variance, the second factor 6% of the variance, the third factor 3% of the variance, and the fourth factor 2% of the variance. Each factor had multiple variables with moderate to high loadings (>.50), indicating reliable definition. The pattern matrix generated one multivocal item (*Improve privacy and security of confidential client information*) that loaded negatively on Factor 3 (*Present access and vulnerability* *concerns*) and positively on Factor 4 (*Improve workflow and control*). Three beliefs statements failed to load into the solution: *Be resisted by some providers*, *Negatively influence treatment plans*, and *Save costs for your practice in the long run*.

Table 9

Belief factor and Loadings

Factor	Loadings 1	2	3	4
Factor 1: Improve care and communication				
Improve your access to client medical/physical health records	.926	.062	.015	-.099
Improve coordination of care among all providers working with the same client	.925	.073	.043	.013
Provide more complete information to help with your diagnoses and treatment planning	.916	.114	.023	.024
Lead to more complete client information	.854	.102	-.088	-.036
Improve your ability to track medication history	.797	-.035	.085	-.001
Improve your communication with other providers	.768	-.046	.026	.058
Streamline your access to client information/records	.740	-.069	.008	.094
Reduce duplicating client evaluations, assessments, or tests that have already been conducted by other providers	.609	.097	-.001	.200
Improve the quality of care your clients receive	.423	-.093	-.035	.326
Improve your clients' safety	.400	.091	-.211	.266
Factor 2: Add cost and time burdens				
Be difficult because your practice lacks the technological expertise to implement and maintain	.148	.838	.052	.069
Be time consuming for your practice to implement	.078	.818	-.014	-.063
Result in extra work for you on a daily basis	.015	.681	.012	-.142
Cost your practice too much to implement	.068	.676	.212	.014
Disrupt your own work flow	-.076	.671	.036	-.101
Require more training than you have time for	-.053	.662	.141	.083
Be resisted by staff at your practice	.082	.488	.215	-.048
Be difficult for you due to your apprehensions about computer technology	-.027	.465	.226	.130
Increase the time your practice spends on transcriptions	-.012	.449	.105	-.110

Factor	Loadings 1	2	3	4
Factor 3: Present access and vulnerability concerns				
Be misused by third party payers	.160	.014	.727	-.172
Increase your legal vulnerability	.011	.026	.655	-.133
Force you to use an overly-templated behavioral health record	.011	.168	.629	-.011
Compromise your professional ethics	-.271	.076	.581	.061
Make you become too reliant on technology that could crash	-.017	.265	.535	.075
Be resisted by clients	-.040	.194	.461	-.050
Disrupt your relationships with your clients	-.329	.244	.452	.131
Be impractical because behavioral health information cannot be captured by checkboxes and dropdown lists	-.103	.261	.441	.020
Result in more data entry errors in client records	-.069	.309	.408	.039
Improve privacy and security of confidential client information	-.036	.175	-.611	.519
Factor 4: Improve workflow and control				
Improve your ability to control who has access to your clients' information	-.109	.224	-.372	.715
Improve your practice’s office work flow	.206	-.277	.156	.575
Improve your practice’s billing accuracy	.188	.132	-.067	.529
Create more time for client care	.077	-.319	.161	.523
Improve privacy and security of confidential client information	-.036	.175	-.611	.519
Improve your clients' satisfaction with the admissions process	.225	-.073	-.030	.490
Reduce the time you spend on paperwork	.121	-.331	.092	.474

Confirmation of the appropriate number of factors was assessed through three methods: a visual assessment using the Scree plot, the Chi square goodness-of-fit analyses, and applying alternative factor analyses and comparing those results to the solution. First, a Scree plot of eigenvalues against the number of factors was produced. The Scree plot is a visual representation of the decreasing eigenvalues as factors are added. Each steep angle in the plot indicates that the added factor has made a significant contribution to the model. The Scree plot for this study's factors levels off between factors 3 and 4, and then again between 5 and 6 (Figure 1). This suggests that either two or four factors may be an appropriate solution (Cattell & Vogelmann, 1977).

Figure 1

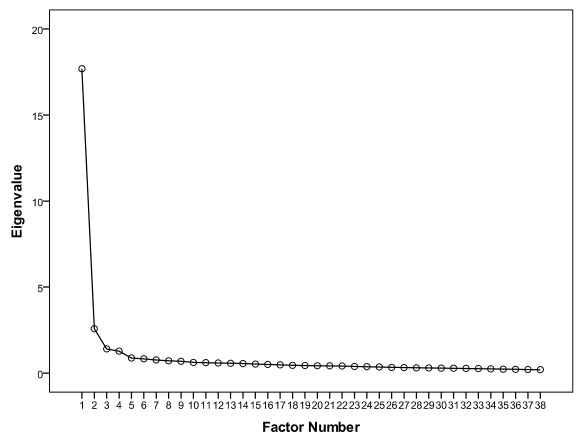

Figure 1. Scree plot suggests that either two or four factors may be an appropriate number of belief factors for the provider responses.

Next, the results of the goodness-of-fit tests were examined. The test measures whether the solution varies significantly from the correlation matrix. The solution did vary significantly ($X^2 = 847.693$, $df = 557$, $p < .001$), suggesting that the solution is valid.

Finally, the stability of a factor solution was assessed by conducting additional factor analyses using other extraction and rotation methods, even those that are not best suited to the particulars of the data set. The rotations used were varimax, promax, and quartimax. Varimax, an orthogonal rotation, is the most commonly used rotation and maximizes the variance of loadings on each factor. Promax, an oblique rotation, maintains high loading variables in the same pattern as generated in the orthogonal solution, but decreases relationships for variables with low loadings. Quartimax is an orthogonal rotation that maximizes the variance of loadings on each variable, resulting in the first factor being most general and the remaining factors often creating subclusters. In addition to three alternate rotations, an additional extraction, namely maximum likelihood, was also applied. Maximum likelihood works well for smaller samples (< 300), but may have a tendency to create more factors than are optimal (Wolins, 1995). There was little difference between the WLS solution and the varimax (either using WLS or the maximum likelihood extraction) and the promax using the maximum likelihood extraction. Each of the analyses resulted in four factor solutions with statements grouping in the same general pattern. The quartimax rotation (both using WLS and maximum likelihood) resulted in a very large, single factor that contained most of the statements, and three additional factors with very few belief statements, all of which were multi-vocal with the first factor. Finally, the direct oblimin rotation using the maximum likelihood extraction also resulted in four factors, but presented in a different ordering (i.e., the second factor in the WLS solution is the first solution in the direct oblimin rotation with maximum likelihood extraction, and the fourth factor is the third factor). The general stability of the results, even with less than optimal extractions and rotations, reinforces the interpretability of the solution.

The impact of the previously identified 39 multivariate outlier cases on the solution was examined next. The cases were deleted from the data set, leaving 526 cases to analyze. The WLS factor analysis was re-run. The solution without the outlier cases was very similar to the solution including the outlier cases. The solution explained slightly more of the variance (59% as compared to 57%), had a similar range of communalities, and resulted in a similar four factor solution. This result suggests that the multivariate outlier cases had only a minimal impact on the factor solution.

Factor Scores

The multi-item factors generated by the factor solution were used to create scores for the cluster analysis. Following Grice (2001a), exact regression scores were calculated for each individual by multiplying factor score coefficients by respondent's scores for each of the 38 belief statements. Descriptive statistics for the exact regression factor scores are displayed in Table 10. Expected because of the high correlations among item responses and the resulting factors, Spearman's rho indicated that the factor scores were also highly correlated (Table 11). The two positive factors, *Improve care and communication*, and *Improve workflow and control*, were significantly positively correlated with each other, and were negatively correlated with the two negative factors, *Add cost and time burdens* and *Present access and vulnerability concerns*. The two negative factors, *Add cost and time burdens* and *Present access and vulnerability concerns*, were positively correlated with each other.

Table 10

Belief Factor Descriptive Statistics

Factor	Low	High	*M (SD)*
Factor 1: Improve care and communication	.44	5.35	3.86(.93)
Factor 2: Add cost and time burdens	.53	5.48	3.02(1.05)
Factor 3: Present access and vulnerability concerns	1.50	6.77	4.19(1.02)
Factor 4: Improve workflow and control	2.16	7.36	4.68(1.02)

Table 11

Belief Factor Correlations

Factor	1	2	3	4
Factor 1: Improve care and communication				
Factor 2: Add cost and time burdens	-0.69**			
Factor 3: Increase access and vulnerability concerns	-0.66**	0.72**		
Factor 4: Improve workflow and control	0.69**	-0.68**	-0.59**	

** denotes significance at p<.001

Cluster Analysis of Providers

The two-step cluster analysis, using the log-likelihood criterion distance proximity measure and Schwarz Bayesian Criterion, was employed. The analysis returned a two cluster model (Table 12). The largest cluster (67%) comprised respondents with positive beliefs about EHRs. The most important belief factor for this cluster was: strong agreement that EHRs will improve care and communication (Factor 1), skepticism of the statement that EHRs would result in added cost and time burdens (Factor 2), belief that EHRs would improve workflow and access (Factor 4), and moderate concerns that EHRs would increase access and vulnerability (Factor 3). This group was named *Positives*. The smaller cluster (33% of the sample) had negative beliefs about EHRs. For this group the most important belief was that EHRs would add cost and time burdens (Factor 2), followed by strong concerns about access and vulnerability concerns (Factor 3), skepticism with the statement that EHRs will result in improved workflow and control (Factor 4), and some skepticism that EHRs will improve care and communication (Factor 1). This group was named *Negatives*.

Table 12

Two Cluster Belief Solution with Factors in Order of Importance

Cluster 1: Positives 67.4%	Cluster 2: Negatives 32.6%
Factor 1: Improve care and communication (*M* = 4.32)	Factor 2: Add cost and time burdens (*M* = 4.14)
Factor 2: Add cost and time burdens (*M* = 2.48)	Factor 3: Present access and vulnerability concerns (*M* = 5.22)
Factor 4: Improve workflow and control (*M* = 5.17)	Factor 4: Improve workflow and control (*M* = 3.65)
Factor 3: Present access and vulnerability concerns (*M* = 3.69)	Factor 1: Improve care and communication (*M* = 2.91)

The quality of the two cluster solution was assessed using one measure of internal criterion analysis and two tests of external criterion analysis. The internal criterion analysis measure used was the structure silhouette and cohesion of separation. The two tests of external validity were differences between the two cluster groups for variables not used in the cluster analysis, and linear regression models of variables included and not included in the cluster model.

Internal criterion analysis was assessed by examining the structure silhouette of cohesion and separation (Kaufman & Rousseeuw, 1990). As the factors in one cluster demonstrate closer relationships with one another compared to those in the other cluster, then the model is found to be of greater quality, scaled at poor, fair, and good. The two cluster solution in this study had a *good* rating. This suggests the solution was able to satisfactorily distinguish clusters.

Next, tests of external validity were conducted. In the first test, variables not used in the cluster analysis were employed to determine whether meaningful differences existed between the two clusters for these variables. It may be expected that membership in the two clusters may have differences in demographic and professional characteristics. That is, that Positives and Negatives may comprise different population profiles. Variables selected for testing included age, computer self-efficacy, satisfaction with past experience with EMRs, overall support for EHRs, and practice setting type.

Age was significantly associated with cluster group. Younger providers (M = 50.36) were more likely to be in the Positives group than older providers (M = 54.85), $F(1,562) = 20.76$, $p < .001$, $MSE = 120.33$. Providers with more confidence in their computer skills (M = 28.58) were more likely to be in the Positives group than were providers less confident in their computer skills (M = 22.46), $F(1,553) = 100.99$, $p < .001$, $MSE = 44.90$. Providers with positive past experiences with EMRs (M = 3.72) were more likely to be in the Positives group than were providers with less satisfactory experiences with EMRs (M = 2.50), $F(1,308) = 99.89$, $p < .001$, $MSE = .852$. In response to the single question about overall characterization of support for EHRs, providers who rated themselves as being supporters of EHRs (M = 4.23) were more likely to be in the Positives group than were providers who rated themselves as being non-supporters (M = 2.02), $F(1,561) = 779.85$, $p < .001$, $MSE = .78$. Finally, practice setting type also had a relationship to cluster membership ($X^2(5) = 18.10$, $p = .003$), however the only significant difference within the group was Corrections providers, fewer of whom were in the Negatives group than was expected. Several variables tested did not have a significant relationship to the cluster membership including: gender ($X^2(1) = .79$, $p = .43$); professional license category ($X^2(5) = 2.78$, $p = .734$); and measures of urban to rural location (Rural Urban Community Area Code: $X^2(14) = 21.08$, $p = .100$; Urban Influence Code: $X^2(7) = 6.17$, $p = .520$; Rural Urban Continuum Code $X^2(6) = 3.75$, $p = .711$).

The second test of external criterion analysis was a series of nested and non-nested linear regressions using overall support for EHRs as the dependent variable. Using overall support for EHRs as a proxy for group membership was reasonable since there was a significant difference between the two cluster groups, $F(1, 561) = 779.85$, $p < .001$, $MSE = .78$, all the variables used were highly correlated with the overall support (Table 13), and there is face validity that those who report high overall support for EHRs will likely cluster into the Positives group and those who report low overall support for EHRs will likely fall into the Negatives group.

Table 13

Summary Statistics, Correlations and Results from Segmentation Model Variables Against Overall Support of EHRs

	Mean(SD)	Relationship to Overall Support Item	Regression Weights
Ordinal Variables			
Age		0.20**	0.00
Factor 1: Improve care and communication	3.86(.93)	0.76**	0.42**
Factor 2: Add cost and time burdens	3.02(1.05)	-0.74**	-0.22*
Factor 3: Present access and vulnerability concerns	4.19(1.01)	-0.72**	-.029**
Factor 4: Improve workflow and control	4.68(1.02)	0.68**	0.21*
Computer self-efficacy		0.47**	-0.00
Satisfaction with EMRs		0.53**	0.13*
Categorical Variables			

	Mean(SD)	Relationship to Overall Support Item	Regression Weights
Practice Setting (with Outpatient as Comparison)		$F(4,632) = 4.97$, $p < .001$	
School			-0.16
Inpatient			-.02
Corrections			0.30
Federal			0.59
Other			-0.11

*$p < .03$
**$p < .001$

The multiple regression model with all segmentation variables produced $R^2 = .72$, $F(12, 278) = 58.22$, $p < .001$, indicating that the model accounts for 72% of the variance of scores of overall support for widespread adoption of EHRs (Table 14). All of the variables, with the exception of age and practice setting had significant independent contributions to the model. Next, the well-performing all-variable model was compared to a beliefs-only model to determine whether there was a significant difference in explanatory power when demographic and professional variables were removed from the model. In other words, would knowing the beliefs an individual holds predict support as well as knowing beliefs and having demographic and professional information? The beliefs-only model had an R^2 of .70, $F(4, 286) = 169.94$, $p < .001$ and performed as well as the full model R^2 change = .01, $F(8, 278) = 1.40$, $p < .195$. In the next test, the all-variable model was compared to demographic and professional data only. Although other market segmentation studies have used demographic and professional data only to divide markets, in this study there was a significant deterioration in predictive ability using only the demographic/professional variables, R^2 change = -.37, $F(4, 278) = 89.72$, $p < .001$. The only variables with significant independent contribution to the demographic/ professional model were computer self-efficacy and satisfaction with EMRs used. The results indicate that demographic/professional data alone were not able to predict overall support for EHRs as well as that data when combined with beliefs data. Next, a non-nested analysis was conducted comparing the beliefs-only model to the demographic/ professional model. Predicted scores were computed for each model and compared using Hotelling's t-test for non-independent correlations. The correlation between these two models was $r = .63$, $p < .001$. The beliefs-only model accounted for significantly more variance among overall EHR support than did the demographic/professional model, $t(282) = 9.04$, $p < .01$.

Table 14

Nested Regression Model Testing Contribution of Belief Factors and Demographic/Professional Characteristics

Variables	Full Model	Beliefs-only Model	Demographic/ professional Model
Factor 1: Improve care and communication	0.42**	0.43**	
Factor 2: Add cost and time burdens	-0.22*	-0.27**	
Factor 3: Present access and vulnerability concerns	-.029**	-0.30**	
Factor 4: Improve workflow and control	0.21*	0.23**	
Age	0.00		-0.01
Computer self-efficacy	-0.00		0.04**
Satisfaction with EMRs	0.13*		0.52**
Practice Setting (with Outpatient as Comparison)			

Variables	Full Model	Beliefs-only Model	Demographic/ professional Model
School	-0.16		-0.21
Inpatient	-.02		-0.11
Corrections	0.30		-0.27
Federal	0.59		-0.11
Other	-0.11		-0.38
Regression and Significance	*F*(12, 278) = 58.22, *p* < .001	*F*(4, 286) = 169.94, *p* < .001	*F*(8, 282) = 18.80, *p* < .001
R^2	0.72	0.70	0.35
Change in R^2		*F*(8, 278) = 1.40, *p* < .195	*F*(4, 278) = 89.72, *p* < .001

*$p < .03$
**$p < .001$

The Role of Benefits and/or Barriers

There has been some debate about which has a greater predictive ability: benefits or barriers. The next analyses tested benefits against barriers. First, the full-beliefs model was tested against the benefits-only model, and then the full-beliefs model was tested against a barriers-only model. Neither reduced model performed as well as the full-beliefs model (Table 15). Next, the benefits-only model was tested against the barriers-only model. The correlation between these two models was $r = .77$, $p < .001$. There was no significant difference between the predictive abilities of the models, $t(560) = .5$, $p < .05$.

Table 15

Nested Regression Model Testing the Contribution of Benefits and Barriers Beliefs

Variables	Full-beliefs Model	Benefits-only Model	Barriers-only Model
Factor 1: Improve care and communication	0.50**	0.81**	
Factor 2: Add cost and time burdens	-0.26**		-0.57**
Factor 3: Present access and vulnerability concerns	-0.36**		-0.55**
Factor 4: Improve workflow and control	0.20**	0.40**	
Regression and Significance	$F(4, 558) = 347.23$, $p < .001$	$F(2, 560) = 485.28$, $p < .001$	$F(2, 560) = 467.79$, $p < .001$
R^2	0.71	0.63	0.62
Change in R^2		$F(2, 558) = 77.17$, $p < .001$	$F(2, 558) = 85.50$, $p < .001$

*$p < .03$
**$p < .001$

All four belief factors had significant contributions to the model (Table 16). Factor 1 (Improve care and communication) has the largest beta weight and may be interpreted to mean that each added point in an individual's Factor 1 score results in a .50 increase in an individual's *Overall support of widespread adoption of EHRs* score.

Table 16

Summary Statistics, Correlations and Results from Regression of Belief Factors Against Overall Support Of EHRs

Factor	*Mean(SD)*	Correlation with Overall Support	*b*	*B*
Factor 1: Improve care and communication	3.86(.93)	0.76**	.503	0.34**
Factor 2: Add cost and time burdens	3.02(1.05)	-0.74**	-.259	-0.20**
Factor 3: Present access and vulnerability concerns	4.19(1.01)	-0.72**	-.359	-0.27**
Factor 4: Improve workflow and control	4.68(1.02)	0.68**	.201	0.15**
(Constant)			2.915	

**$p < .001$

Next, the full (four factor) model was compared to sequential models, each successive model eliminating one of the four factors. Each of the four reduced models was significant and accounted for a substantial proportion of variance in overall support. However, none of the reduced models performed as well as the full model (Table 17).

Table 17

Nested Regression Model Testing the Contribution of Each Belief Factor

Variables	Full-beliefs Model	Remove 1	Remove 2	Remove 3	Remove 4
Factor 1: Improve care and communication	0.50**		0.56**	0.62**	0.60**
Factor 2: Add cost and time burdens	-0.26**	-0.36**		-0.44**	-0.33**

Variables	Full-beliefs Model	Remove 1	Remove 2	Remove 3	Remove 4
Factor 3: Present access and vulnerability concerns	-0.36**	-0.48**	-0.47**		-0.37**
Factor 4: Improve workflow and control	0.20**	0.39**	0.28**	0.28**	
Regression and Significance	$F(4, 558) = 347.23$, $p < .001$	$F(3, 559) = 377.20$, $p < .001$	$F(3,558) = 347.23$, $p < .001$	$F(3,558) = 401.54$, $p < .001$	$F(3,558) = 443.49$, $p < .001$
R^2	0.71	0.67	0.70	0.68	0.70
Change in R^2		$F(1, 558) = 85.75$, $p < .001$	$F(1, 558) = 26.73$, $p < .001$	$F(1, 558) = 59.09$, $p < .001$	$F(1, 558) = 18.00$, $p < .001$

*$p < .03$
**$p < .001$

EHR Market Segmentation of Behavioral Health Providers

Using the results of the cluster analyses, it is possible to create a matrix (Table 18) that summarizes the solution. The approach of segmenting based on the beliefs and supplementing with descriptive demographic and professional data follows Peltier and Schribrowsky (1997). The utility of the information can be seen clearly. Promoters of electronic records have a large, receptive segment of Positives. Providers in this group are relatively younger, support widespread adoption of EHRs, are confident computer users, have positive past experiences with EMRs, and are proportionally represented throughout practice settings. The benefits they expect from EHRs are improved care and communication, and improved workflow and control in their practice. This group doubts that EHRs will be an added cost and time burdens, and have moderate concerns about access and vulnerability. Those wishing to promote EHRs to the smaller group have a greater challenge. The Negatives are relatively older, are not supportive of widespread adoption of EHRs, and have had negative experiences with EMRs. This group sees few benefits to EHRs. Their concerns are that EHRs will add costs and time burdens, present access and vulnerability issues. They are skeptical of the claims that EHRs will improve workflow and control, or improve care and communication.

Table 18

Benefit and Barrier Summary Segmentation Matrix

Positives	Negatives
67%	33%
Relatively Younger	Relatively Older
Supportive of widespread adoption of EHRs	Not supportive of widespread adoption of EHRs
Fairly confident in their computer skills	Not confident in their computer skills
Positive experience with EMRs	Negative experience with EMRs
Equivalent proportional membership of all settings	Fewer Corrections personnel than expected are Negatives
Most importantly strongly believe EHRs will improve care and communication among providers	Most importantly believe EHRs will be an added cost and time burdens
Doubt that EHRs will be added cost and time burdens	Strong concerns about access and vulnerability
Believe EHRs may result in improved workflow and control	Skeptical that EHRs will result in improved workflow and control
Moderate concerns that EHRs will increase access and vulnerability	Skeptical that EHRs will improve care and communication among providers

Within the market segmentation literature, there are widely-accepted criteria by which clusters may be judged in their ability to provide satisfactory market segments (Wedel & Kamakura, 2000). The six criteria are:

- Identifiability – segments recognize distinct groups;
- Substantiality – segments are large enough to be worth considering;
- Accessibility – segments may be reached;
- Stability – segment remains intact long enough for identification, implementation of a marketing strategy, and evaluation of the strategy;
- Responsiveness – segment members respond differently to marketing messages; and,
- Actionability – the segments are attractive to core competencies of firms wishing to satisfy needs within the market.

Identifiability. This criterion was satisfied since the two clusters represent distinctive groups of customers. Providers within both segments were identifiable based on their beliefs about EHRs. Measures for distinguishing the beliefs were sufficient.

Substantiality. The solution created two segments representing 67% and 33% of the population. Both segments represent sizable proportions of the behavioral health provider population. Thus, this criterion is satisfied.

Accessibility. Behavioral health providers in either cluster may be reached through promotional and distributional marketing efforts. Secondary data about behavioral health providers, such as contact information, is available that would aid in contacting providers in either segment. This criterion is met.

Stability. Segments must be static in time so that the segments may be identified and marketing strategies executed. The expectation of marketers addressing these two segments would be that providers in the Negatives group would be susceptible to change.

Stability is needed over a long enough period that the group may be addressed, but does not necessarily need to extend for a longer period beyond that. Ajzen and Fishbein (1980) theorize that belief stability is a function of the strength of the belief, the length of time the belief has been held, whether it is reinforced by others important to the individual, its relationship to other attitudes and beliefs, and its clarity or structure. Based on the clear distinctions in the belief profiles, it is difficult to imagine that segment membership is fungible.

Responsiveness. It may be expected that members of the two segments will respond to messages differently. The importance of the four belief factors were differentially ordered for both segments. The Positives cluster, with the predominant belief that EHRs will lead to improved care and communication would surely respond positively to a message reinforcing that belief, while the Negatives group will likely respond at best indifferently, since it is not as important a belief and does not address their primary concern, or at worst skeptically.

Actionability. Identification of the two segments should provide guidance for decisions about how effective promotional or outreach efforts may be. Organizations attempting to reach either segment will have a better understanding of how the segments may fit into their goals, portfolios, and implementation strategies.

Summary

The purpose of this exploratory study was to discover and describe behavioral health providers' perceptions of the benefits and barriers to EHRs. The 38 belief statements, gleaned from qualitative interviews conducted in Study 1, were reduced to four factors regarding providers' expectation that EHRs would: (a) Improve care and communication, (b) add cost and time burdens, (c) present access and vulnerability concerns, and (d) improve workflow and control.

A cluster analysis of providers, based on the four factors, produced two clusters: a cluster of providers with overall positive beliefs about EHRs (67%) and a second cluster of providers with overall negative beliefs about EHRs (33%). The clusters differed both on their agreement with the factor items as well as the order of factor importance. The most significant factor for the positive cluster was the strong belief that EHRs will improve care and communication among providers. They doubt that EHRs will result in added cost and time burdens, believe EHRs may result in improved workflow and control, and have moderate concerns that EHRs will increase access and vulnerability. The most significant factor for the negative cluster was the belief EHRs will add cost and time burdens. Providers in the negative cluster had strong concerns about access and vulnerability, were skeptical that EHRs would result in improved workflow and control, and were skeptical that EHRs would improve care and communication among providers.

The groups were different on a number of demographic and professional characteristics. Positive providers were relatively younger, were confident in their own computer skills, and when they had worked with EMRs had positive experiences. Providers in the negative cluster were relatively older, not confident in their own computer skills, and had negative experiences with EMRs they had used.

The present study results indicate a more cautious view of EHRs among behavioral health providers than among the general medical provider population. In

Wright and colleague's (2010) statewide survey of physicians' perceptions of EHRs, most physicians were somewhat positive or very positive that EHRs would improve the quality of patient care (86%), be timesaving for clinicians (76%), and reduce healthcare costs (71%). In the present study, several items related directly to the areas explored in the physician statewide survey. One item asked behavioral health providers for their level of agreement that EHRs would improve the quality of care: only 47% strongly agreed or agreed. Two items related directly to clinician time savings: 36% strongly agreed or agreed that EHRs would reduce the time they spent on paperwork, and 38% strongly agreed or agreed that EHRs would result in extra work for them on a daily basis. One item related to savings in healthcare costs (i.e., *Reduction in duplicating client evaluations, assessments, or tests that had already been conducted by other providers*) to which 75% strongly agreed or agreed. The survey did not, however, ask a more general overall healthcare costs question, making direct comparison impossible. In another recent study, Saloman and colleagues (2010) surveyed psychiatric clinicians' views of an implemented EHR. This study differed somewhat from the present study since it looks at post-implementation perceptions of a specific EHR rather than pre-implementation perceptions. However, there were some similar items that provide an interesting comparison. Of the post-implementation clinicians, 28% agreed that compared to paper records, electronic records safeguard confidentiality better. In this study the providers were less certain that EHRs improved confidentiality: 19% agreed that EHRs would improve privacy and security of confidential client information and 21% that EHRs would improve clinician ability to control who has access to client information. The post-implementation clinicians were less confident that EHRs would result in more complete information (61%) than those in this study: 73% believed that EHRs would lead to more complete information. Finally, the post-implementation clinicians appeared to have less concern that EHRs would decrease patients' willingness to divulge confidential information (19% agreed). In this study, 36% of behavioral health providers believed that EHRs would be resisted by clients.

CHAPTER 5: DISCUSSION

This two study research project was designed to explore behavioral health providers' perceptions about the benefits and barriers of using EHRs. There is a national push toward the adoption of EHRs, but little is known about how behavioral health providers view sharing clinical information with each other and with medical providers. It is helpful to understand underlying belief structures because beliefs form attitudes that in turn impact behavioral intentions, and subsequently behaviors (Ajzen & Fishbein, 1973). The present research is significant because it explores an area that has, heretofore, received scant attention, despite the fact that behavioral health providers have lagged in their adoption of EHRs and behavioral health records contain information that may be essential for other providers to have when treating shared clients. For example, multiple medications are frequently a part of treatment for people with mental health problems (Ananth, Parameswaran, & Gunatilake, 2004; Maidment & Parmentier, 2009; Morrato et al., 2007). Clients may receive medications from behavioral health providers for mental health and substance abuse issues, as well as from medical providers for the physical side effects of those medications (Henderson et al., 2005; Meyer & Koro, 2004; Thakore et al., 2002).

The present research was conducted as a mixed methods, two study design. The first study was a qualitative study designed to ascertain modal salient beliefs of a representative sample of the population (Ajzen & Fishbein, 1980). The second study used the elicited beliefs from the first study to quantify providers' beliefs and use the information to segment them based on belief factors. There have been no belief elicitation studies of behavioral health providers regarding EHRs, despite calls for such studies by other researchers (Holden & Karsh, 2010).

Study One – the Foundational Study

The first study identified three themes behavioral health providers mentioned when discussing the benefits and barriers of using EHRs: (a) safety and quality of care, (b) security and privacy, and (c) delivery of services. Most providers (81%) identified themselves as having positive overall opinions about EHRs, and all providers discussed benefits to client safety and quality of care as a benefit of EHRs. However, all providers also discussed privacy and security barriers, and all but one provider discussed delivery of services barriers. Two-thirds of providers (66%) also discussed benefits to delivery of care in their practices. There appeared to be some divergence of opinion on whether the benefits would outweigh the barriers, and which themes would be most important in that determination. Some providers stated that benefits to quality and safety of client care was the deciding factor while other providers believed that vulnerabilities to privacy could not be overcome; some believed that EHRs would result in cost and time savings for their practices, while others believed that EHRs would result in cost and time expenses that could not be overcome. These initial findings appeared to create a reasonable foundation from which to further explore providers' beliefs and discover whether patterns in those beliefs might be identifiable.

Study Two – Factors and Segmentation

The focus of the second study was discovering providers' patterns of agreement or disagreement with 38 belief statements about EHRs, generated from the first study.

Through an exploratory factor analysis, the belief statements reduced to four factors, based on providers' beliefs that EHRs would: (a) improve care and communication, (b) add cost and time burdens, (c) present access and vulnerability concerns, and (d) improve workflow and control. These four factors approximated the four most discussed theme areas from the first study. Factor 1: Improve care and communication, tracked closely to the discussions of all providers about quality and safety benefits to clients. Factor 2: Add cost and time burdens, appeared to represent the 97% of providers mentioning barriers to their practice's delivery of services. Factor 3: Present access and vulnerability concerns, tracked the discussions of all providers about barriers based on concerns about privacy and security. Finally, Factor 4: Improve workflow and control, was similar to the 66% of providers who discussed benefits to their practice's delivery of services. The two discussion areas not represented by the factoring were the least-mentioned areas in the first study: barriers based on concerns about client quality and safety (mentioned by 59% of providers), and benefits to privacy and security (mentioned by 22% of providers).

The four identified factors included two that focused on benefits and two on barriers. The benefits factors were, Factor 1: Improve care and communication, and Factor 4: Improve workflow and control. These factors may relate most directly to UTAUT's performance expectancy (TAM's perceived usefulness) and effort expectancy (TAM's perceived ease of use). The two barrier factors were, Factor 2: Add cost and time burdens, and Factor 3: Present access and vulnerability concerns.

A cluster analysis was conducted to ascertain whether there were patterns in the providers' factor-scored responses. Definitive clusters would mean that the factors did provide a means of distinguishing among providers. The cluster analysis returned a two-cluster solution. The largest cluster, named Positives, comprised 67% of the sample. The smaller cluster, named Negatives, comprised 33% of the sample. The most important of the belief factor for the Positives was strong agreement that EHRs would improve care and communication: Compare this belief to the skepticism among Negatives that EHRs would improve care and communication, which was the least important factor for them. The most important of the belief factor for the Negatives was that EHRs would add cost and time burdens. In contrast, Positives were skeptical that EHRs would add cost and time burdens and this skepticism was the second most important factor for them. Positives had moderate concerns about privacy and security, but for Negatives significant concerns about privacy and security were the second most important factor. Improved workflow and control were the third most important factor for both Positives and Negatives but, perhaps predictably, Positives believed EHRs would contribute to gains in workflow while Negatives were skeptical that EHRs would be beneficial.

There were demographic and professional differences between Positives and Negatives. A significant difference in age was found between Positives and Negatives. The age differential was significant, but relatively small: Positives had a mean age of 50 years of age and Negatives of 55 years of age. No difference was found for gender. There have been mixed findings regarding the impact of age and gender on computer acceptance, with some finding no relationship and others finding a significant relationship. In UTAUT, age is theorized to play a moderating role (Venkatesh et al., 2003). The influence of performance expectancy on behavioral intention is more salient for younger, male workers. The influence of both effort expectancy and social influence on behavioral intention is more salient for older, female workers.

Similar to previous studies examining health information technology acceptance, Positives were more likely to be confident in their computer skills and have had positive past experiences with EMRs (Gans et al., 2005; Scheck McAlearney et al., 2004). Dansky and colleagues (1999) found that computer experience was a significant predictor of perceived usefulness for EMRs for physicians and mid-level practitioners. In UTAUT, computer self efficacy and behavioral intention have a nonsignificant relationship when the effort expectancy construct is considered (Venkatesh et al., 2003). Perhaps related to concepts of comfort with technology, it is interesting to note that providers who responded using the web survey were more positive about EHRs, than were providers who completed the paper survey.

Benefits and Barriers as Organizing Constructs

This study asked providers to consider benefits and barriers to adoption. Although benefits to innovation have received considerable attention in the diffusion and adoption literatures, barriers to innovation have received much less notice, despite their playing distinct roles in user acceptance (Gatignon & Robertson, 1989). There are few examples of benefits and barriers being considered simultaneously. In one exception, individuals' perceived ability to use an innovation positively impacted evaluative and behavioral responses, and satisfaction with existing behavior increased resistance and reduced likelihood of adoption (Ellen, Bearden, & Sharma, 1991). This research considered both benefits and barriers to create a model that explained 71% of the variance in overall support for EHRs. The benefits and barriers model outperformed alternate models that used benefits only, beliefs only, or demographic/professional characteristics only. The benefits and barriers model (with all four factors) outperformed any model that excluded one of the factors. The benefits and barriers model performed equally well when compared to a full model of benefits and barriers and demographic/professional characteristics. For parsimony, the benefits and barriers model may be preferred. This study confirms the importance of both benefits and barriers in exploring provider beliefs.

Usefulness and Ease of Use

In the acceptance literature, TAM researchers have repeatedly found that usefulness is the strongest predictor of technology acceptance (Ma & Liu, 2004). Usefulness, particularly in terms of usefulness in improving client care and communication among providers (Factor 1) and improving practice workflow and control (Factor 4) were the two benefits-focused factors that emerged from the study. Factor 1 was the most important distinguishing factor for the Positives group and had the largest independent contribution to overall support of EHRs in the four factor multiple regression ($b = .50$). Within Factor 1 (Improve care and communication), the highest loading elements of usefulness were*: Improve your access to client medical/physical health records* (.926), *Improve coordination of care among all providers working with the same client* (.925), *Provide more complete information to help with your diagnoses and treatment planning* (.916), *Lead to more complete client information (.854), and Improve your ability to track medication history* (.797). Within Factor 4 (Improve workflow and control), the highest loading items were: *Improve your ability to control who has access* *to your clients' information* (.715), *Improve your practice's office work flow* (.575), and *Improve your practice's billing accuracy* (.529). The findings in this study are consistent with other TAM studies that have found the construct of usefulness an important predictor in technology acceptance.

Resistance literatures suggest that usage barriers (similar to TAM's ease of use construct) would be the most common cause of resistance (Ram & Sheth, 1989). That is, if an innovation is not easy to use, it will be rejected. In the present study, providers were not presented a specific product to evaluate in terms of ease of use; however a number of general questions related to general conceptions of ease of use were asked and primarily captured in Factor 2 (Add cost and time burdens) and Factor 3 (Present vulnerability concerns). Factor 2 was the most important distinguishing factor for Negatives and Factor 3 was second most important. Factor 3 had the second highest independent contribution to overall support of EHRs in the four factor multiple regression (b = -.36). Within Factor 2 (Add cost and time burdens), the items with the highest loadings were: *Be difficult because your practice lacks the technological expertise to implement and maintain* (.838), *Be time consuming for your practice to implement* (.818), *Result in extra work for you on a daily basis* (.681), *Cost your practice too much to implement* (.676), *Disrupt your own work flow* (.671), *Require more training than you have time for* (.662). All of these, except for *Cost your practice too much to implement*, have face validity for concerns about ease of use. Within Factor 3 (Present vulnerability concerns), the items with the highest loadings were: *Be misused by third party payers* (.727), *Increase your legal vulnerability* (.655), and *Force you to use an overly-templated behavioral health* *record* (.629). Only one of these three, *Force you to use an overly-templated behavioral health record*, appears to be related to ease of use.

TAM suggests that usefulness has a direct relationship to acceptance and that ease of use is a likely antecedent to usefulness (Ma & Liu, 2004). The present study does not provide further evidence as to the relationship between usefulness and ease of use, but rather provides contextualization regarding what behavioral health providers consider usefulness and ease of use to mean for them. But concepts appear to be relevant to providers in their evaluation of EHRs.

Recurrent Issues

This study identified a number of recurrent issues regarding EHRs. Among the most striking, as they relate to the widespread adoption of EHRs by behavioral health providers are: privacy and confidentiality, and cost. These two concepts will be described next.

Privacy and confidentiality. This study found that behavioral health providers may have more heightened concerns about privacy and security of information than do medical providers. This is not surprising given that behavioral health providers face more stringent federal privacy requirements for sharing substance abuse and alcohol treatment information (Public Health Service Act, 42 U.S.C. Part 2). Nearly all states have statutes addressing confidentiality of mental health records and information, as well (U.S. Health and Human Services, Office of the Surgeon General, 1999). In the interviews conducted in the present study, a majority of the providers (59%) believed that they faced different challenges in using EHRs than did medical providers, primarily because their information is more sensitive and the client more vulnerable (79%). In the first study, all providers offered concerns about privacy and confidentiality of client information being a barrier. For some it was the single most important determination as to whether they were willing to support EHRs. In the second study, there were two privacy and confidentiality belief questions, that EHRs would: (a) *Improve privacy and security of confidential client information*, and (b) *Improve your ability to control who has access to your clients' information*. In response to the first question only one in five providers (21%) *Agreed* or *Strongly agreed* that EHRs would improve their ability to control who has access to their clients' information, while over half (51%) *Disagreed* or *Strongly disagreed* with the statement. When asked whether EHRs would improve provider ability to control access to client information, fewer than one in five (19%) *Agreed* or *Strongly agreed*, while nearly half (48%) *Disagreed* or *Strongly disagreed*. Interestingly, these two questions were separated in the factor analysis. The first question, *EHRs will improve privacy and security of confidential client information*, had a strong negative loading (-.611) in Factor 3: Present access and vulnerability concerns. The second question, *EHRs will improve your ability to control who has access to your clients' information*, had the strongest loading among those in Factor 4: Improve workflow and control. For Negatives, Factor 3 was the second most important factor for cluster determination, but both Negatives and Positives have concerns in this area (Negatives, M = 5.22; Positives, M = 3.69). Factor 4 was the third most important factor for both Negatives and Positives, with the groups having dramatically different means (Negatives, M = 3.65; Positives, M = 5.17). Although the Positive and Negatives appear to disagree on the severity of the privacy concerns, it is clearly an issue for both groups. This finding is consistent with others' regarding the concern for privacy and confidentiality in behavioral health information *(Cost and Confidentiality*, 2008; *Privacy And Confidentiality Issues*, 2005; Salomon et al., 2010; U.S. Department of Health and Human Services, Office of the Surgeon General, 1999). Unless providers have assurance that protections are in place, it may be expected that they will be reluctant to use EHRs.

Cost. The second issue is that of cost to implement. In the first study a number of providers indicated that EHRs were simply too costly to implement. In the second study a single factor, Factor 2 (Add cost and time burdens), emerged addressing this issue. Concern about added cost and time burdens was the most significant distinguishing factor for Negatives, who evidenced dramatically differing means that did Positives (Negatives, M = 4.14; Positives, M = 2.48). The highest loading items in this Factor were: *Be difficult because your practice lacks the technological expertise to implement and maintain* (.838), *Be time consuming for your practice to implement* (.818), *Result in extra work for you on a daily basis* (.681), *Cost your practice too much to implement* (.676), *Disrupt your own work flow* (.671), *Require more training than you have time for* (.662). All of these items appear to relate to costs to implement and maintain EHR systems, in terms of financial investments and staff costs. Indeed, these systems are not inexpensive: Studies suggest that office-based EHRs cost approximately $25,000 - $45,000 per provider to implement and approximately $3,000 - $9,000, annually per provider to maintain the system (Congressional Budget Office, 2008). Further, smaller practices typically pay more per provider than do larger offices and practices. Most providers implementing

EHRs experience a drop in productivity of between 10 – 15% for at least several months as systems are implemented. For small offices this, on average, translates to a $7,500 drop in revenue per provider (Congressional Budget Office, 2008). These estimates of the disproportionate financial impact on smaller offices is especially relevant in behavioral health since most psychiatrists and psychologists report individual practice as their primary or secondary employment setting (Duffy et al., 2004). To accelerate adoption of EHRs, the American Recovery and Reinvestment Act (2009) provides incentives of up to $63,750 to eligible providers who meaningfully implement EHRs. However, of behavioral health providers, only those who are prescribers (i.e., psychiatrists, NP, PAs) are eligible for these incentives. These comprise, by far, the smallest proportion of behavioral health providers, therefore dampening the possible impact in behavioral health.

Limitations of the Study

There are a number of limitations to this study. First, the response rate for the second study, despite use of the Dillman method (2000), was calculated according to American Association for Public Opinion Research Response Rate 2 method as a fairly low 34% (American Association for Public Opinion Research, 2009). Although this rate is similar to other organizational response rates of 35%, it may indicate a non-representative sample. The sample was not significantly different from the population on gender, age, practice setting, and many professional licensure categories. This similarity may assuage some concerns, but there remain concerns that the sample does not represent the population on other dimensions. Second, all providers in this study practice in

Nebraska. It is possible that Nebraska behavioral health providers may be different from providers in other states, making the findings from this study non-generalizable to the larger population of behavioral health providers across the United States. However, there are no studies that have been found that would suggest that Nebraska providers differ significantly from other providers. Third, some variables that would have been of interest were not collected. For example, it is known that smaller medical practices lag in adoption of EHRs (SK&A, 2010). It would have been illuminating to have been able to relate size of practice to the cluster results. In future research, size of primary practice should be included. Finally, these studies focused on beliefs about EHRs, but do not take the next step in assessing the value of these beliefs in predicting behavioral intention and actual behavior. A relationship would be expected, based on TRA, but these studies did not take this next step. Currently there are no operational behavioral health information networks that would enable timely research on actual usage. A behavioral health information network is expected to debut in southeast Nebraska in March 2011. However, to have waited for implementation and then to later have tied stable usage patterns to the data in the studies would have extended the time frame of this work. It was determined that the present studies provided a useful and satisfactory scope of work and that usage data would be a part of further research undertaken, but not part of this dissertation.

Future Research

This study focused on behavioral health provider beliefs as a first step to predicting their adoption and use of EHRs. Beliefs have repeatedly been shown to be useful predictors. However, there are other aspects, beyond individual beliefs, that will likely play a role in the diffusion of EHRs, and may be fruitful areas for future research. Three main areas include: (a) those related to an individual's use decision, but unrelated to the innovation, (b) those related to whether the individual will have the opportunity to adopt based on decision making at the organizational level, and (c) the temporal dimension of acceptance decisions.

First, variables unrelated to EHRs may play a role in the adoption decision. For example, Markus (1983) explains resistance using a variant of interaction theory. This theory views political constructs, not based on user beliefs about an innovation, but rather in terms of interactions between an information systems implementation and its context. That is, if a user will determine whether or not to use a system based upon whether it supports their position of power. If they think it will negatively impact their power, they will resist. Joshi's (1991) equity implementation model (EIM) uses equity theory to describe how users assess net outcomes in social comparison when determining whether to adopt a new information system: users will resist changes in information systems if they perceive inequalities. Martinko, Henry, and Zumd (1996) propose attributional explanations for technology acceptance, based on how individuals attribute past information technology success and failures. Other issues, not directly explored by the current study may also ultimately impact adoption; for example, physicians who value close patient relationships have been found to have less positive attitudes about EMRs (Aydin et al., 1994; Dansky et al., 1999).

The second area relates to the unit of decision making about EHR adoption. Although the majority of psychiatrists and psychologists report individual practice as their primary or secondary employment setting (Duffy et al., 2004), many behavioral health providers work in larger settings, also. Rogers (1995) acknowledges that the decision to adopt an innovation is more complicated in organizational settings. Studies have suggested that characteristics endogenous to the organization as well as those exogenous may impact innovation receptivity. For example, More (1984) identified 12 structural characteristics that impact organizational adoption. Stefflre (1985) suggested that the magnitude of the decision, the expected timeframe, the problems to be solved, and the stakeholder positions may dictate decision making such that large organizations are more likely to focus on short-term, internal issues, for whom a solution is minimally dissatisfactory to stakeholders. Exogenous factors, such as market structure may also play a role in receptivity to innovation, such that industries with limited price intensity, supplier incentives, and vertical links to buyers are important in achieving adoption (Gatignon & Robertson, 1989). Bradley and Stewart (2002) found that factors internal to the organization were the most influential inhibitors to innovation adoption, while external factors were the key drivers. A number of researchers have concluded that organizational resistance to innovation is a particularly under-researched area (Bao, 2009; Bradley & Stewart, 2002). Future research should expand the focus from the individual unit of analysis to include multi-level models.

Third, absent from the present study is the temporal dimension of innovation acceptance. The present study identified two clusters of providers (i.e., Positives and

Negatives) without regard to temporal concerns. It is not known how time may impact these groups. For example, this study is unable to assess whether providers in the Negatives cluster are postponers, rejectors, or opponents, to use the non-adopter terminologies suggested by Kleijnen et al. (2009). Although stability over time is generally a desirable trait in market segments (Fonesca & Cardoso, 2007), it has been shown to be fairly elusive (Calatone & Sawyer, 1978; Yuspeh & Fein, 1982). In some cases membership in a segment and size of segments may be expected to change, particularly in the case of benefit-segmented populations (Calatone & Sawyer, 1978). Shifts may occur as individuals experience changes in the benefits desired or problems anticipated. In the case of the present study, it would be reasonable to expect that as individuals have increased positive exposure to EHRs, they may shift from emphasizing barriers to emphasizing benefits. This would be consistent with research indicating that physicians who have experience with EMRs tend to rate benefits more highly and barriers as less of a problem, than do those providers who do not have experience (Gans et al., 2005; Scheck McAlearney et al., 2004; Wright et al., 2010).

Rogers (1995) acknowledged that time is an important element in diffusion and that there are five phases in the innovation decision process: (a) knowledge, (b) persuasion, (c) decision, (d) implementation, and (e) confirmation. This process is an information-seeking and information-process activity that decreases uncertainty about the innovation. The process may lead to adoption or rejection, either of which may be reversed at other points in the process (e.g., a user rejects an innovation prior to adoption but later changes his/her mind and decides to adopt, a user adopts an innovation but later decides to discontinue its use). In a collective case study of physicians' perspectives during an EMR implementation, Lapointe and Rivard (2006) found that initial support or neutrality was transformed into resistance due to communication miscalculations by administrators in responding to concerns during the implementation.

Ajzen and Fishbein (1973) also acknowledge that individuals' beliefs change over time as they consider new information. Change primarily occurs through new information as it relates to behavioral and normative beliefs. They suggest that changes may be accomplished by stressing the normative component in cooperative endeavors (i.e., that others important to the individual believe it is a good idea). TAM anticipates change primarily happening as individuals process new information that requires adjustments in their perceptions of usefulness and ease of use (Davis, 1989). The new information that users process may be positive or negative, of course. A new study raises concerns that physicians currently exchanging data electronically are having negative experiences: Over half of the patient data exchanges have suffered from accuracy, completeness or timeliness issues (U.S. Department of Health and Human Services, Agency for Healthcare Research and Quality, 2010).

Recommendations

The present research suggests five key recommendations in promoting the adoption of EHRs by behavioral health providers:

1. *Usability*. According to TAM, an individual's perception of a system's usability is the single most direct predictor of acceptance. Systems should be designed and marketed to emphasize how they contribute to enhancing

providers' ability to do their job. Based on the results of the present study, the primary usability interest behavioral health providers have relates to improved client care and communication with other providers, and secondarily, to improved workflow and control. Specific aspects that might be incorporated into products and then promoted would be the ability of providers to have improved access to client medical/physical health records, improved coordination of care among all providers, more complete information to help with diagnoses and treatment planning, improved ability to track medication history, improved ability to control who has access to client information, improved office work flow for practices, and improved billing accuracy for practices.

2. *Ease of Use*. Although ease of use is not directly related to acceptance, it may be directly related to rejection decisions. Systems should be designed and marketed to emphasize that they are easy to use. Based on the results of this study, aspects of ease of use most important to behavioral health providers are EHRs that: may be implemented and maintained without technological expertise, are not time consuming to implement and do not require extra work on a daily basis, are not too costly to implement, will not disrupt work flow, will not require time-consuming training to use, and do not require use of an overly-templated behavioral health record.
3. *Privacy and Confidentiality*. Privacy and confidentiality of client information is a special issue in behavioral health EHR adoption. Both in

the first and second study, providers evidenced concerns about how they could ensure privacy and confidentiality of client information. In the banking sector, the banks that have been most successful in attracting their customers to on-line banking have been those who have stressed the safety and security of their services (Lee et al., 2009). In a similar vein, providers must be assured of the safety and security of EHRs. Providers should be given clear information about how EHRs will protect client information, in comparison to current paper-based systems. EHRs have additional functions of which providers should be made aware. For example, EHRs provide a means to definitively document every individual who has accessed any part of a client record. This is inconceivable in paper-based systems. Providers should be given concise information about the security systems and practices that protect information, and also a clear understanding of the vulnerabilities.

4. *Cost*. The cost to implement systems is, undoubtedly, a significant hurdle for some providers. Based on this study, two possibilities are apparent. First, federal agencies should consider extending incentives to include behavioral health providers. Incentives for medical providers appear to have accelerated EHR adoption (Mosquera, 2011; SK&A, 2010). Inclusion of behavioral health could do the same for behavioral health providers and would result in more complete patient records for all providers. Second, small offices face particular challenges in

implementing EHRs. Until recently, having an EHR meant purchasing and locating a server and software onsite. As the Internet has grown more prevalent and robust, EHRs are increasingly available through *software as service* arrangements (sometimes referred to as software on demand). In these arrangements, providers access the EHR through the Internet and pay the vendor to maintain all software and hardware located at an offsite location. Software as service arrangements are widely regarded as having lower total cost of ownership, particularly for small offices because they benefit from economies of scale.

5. *Marketing*. Market segmentation provides valuable information about potential users. Marketing research has found considerable evidence of the benefits of targeting messages to the most receptive audiences. In the present study, it is clear that the Positives cluster comprises the most receptive audience. Targeting the most receptive audience ensures that initial messages are directed at those most likely to take positive action. Messages to providers in the Positives cluster should reinforce how EHRs will improve care and communication among providers, will not be a cost and time burdens, will result in improved workflow and control, and will not exacerbate access and vulnerability. Addressing perceived barriers to an innovation can be critical to acceptance (Lee, Morrin, & Lee, 2009). In the case of providers in the Negatives cluster, it would be important to specifically address perceived barriers, particularly the fear of added cost

> and time burdens, and access and vulnerability concerns. The barriers should be addressed along with providing persuasive information about the possible benefits, including improved workflow and control, and improved care and communication.

Successful widespread implementation of EHRs across the U.S. has the potential to improve safety and quality of care and reduce healthcare costs (Hillestad et al., 2005). The inclusion of behavioral health information is desired and needed for providers to have complete information (Institute of Medicine, 2006). Behavioral health providers, however, are trailing medical providers in EHR adoption. Most providers in this study had positive views about EHRs. Perhaps the ultimate question is whether EHRs will result in improvements in quality and safety for patients without sacrificing the confidentiality of information.

INSTITUTIONAL REVIEW BOARD APPROVAL

The research has been approved by the University of Nebraska-Lincoln Institutional Review Board through two expedited reviews:

Study 1: #2009019432EP; Project ID: 9432; Received January 12, 2009

Study 2: # 20100210260EP; Project ID: 10260; Received February 4, 2010

APPENDIX A: STUDY 1 SEMI-STRUCTURED INTERVIEW PROTOCOL

Overview

In this document, plain text is spoken, italics are notes for the interviewer. This script will be used for face-to-face interviews with providers who have scheduled an appointment for an audio-taped interview with a University of Nebraska Public Policy Center researcher. A consent form will be sent to the interviewee prior to the interview along with the Exchanging Patient Data Electronically *Survey. The letter of consent should be signed and if not returned earlier, collected at the interview along with the Survey.*

The primary questions we will be asking in this interview are as follows:

1. *What do you think would be the benefits of a system that allows providers to electronically exchange patient behavioral health information with other providers?*
2. *What do you think would be the barriers in developing a system that allows providers to electronically exchange patient behavioral health information with other providers?*
3. *What is the likelihood that you and others in your primary practice would use an electronic sharing system if it were developed?*
4. *Do you have any other comments about sharing patient behavioral health information?*

Introduction

Hello. My name is (-------------) and I am with the University of Nebraska Public Policy Center. We are working with the Southeast Nebraska Behavioral Health Information Network (SNBHIN) on a project that will enable behavioral healthcare providers to electronically share patient's health information.

I appreciate you taking the time to talk with me today about your views on electronically sharing patient behavioral health information. This interview will take about 30 minutes.

[If provider has returned consent and demographics, skip to the next section (background).]

Before we get started, I have a couple of forms for you to complete.

1. Letter of Consent Form. I'd like to have you take a few minutes to read and then sign this consent form that details our research study.

2. Exchanging Patient Data Electronically Survey. We are interested in collecting some background information from you.

Background to Study

[Before beginning, look over their survey and ask questions about anything out of the ordinary. Also, ask all participants the following questions as you review their survey.]

1. In the survey, we asked you some questions about your primary place of practice. Do you work at more than one practice? Yes No

[If "no", skip the next questions and begin with "As noted in the letter of consent…"]

[If "yes," ask these questions]

2. Other than the practice you listed in your survey, what additional practice or practices do you work at?

3. Do you exchange health information differently at that/those other practice(s)? If so, how do you do it differently?

As noted in the letter of consent, we would like to audio-record this interview. The audio file and transcripts will be maintained securely by the University of Nebraska Public Policy Center and will remain confidential. No information will be released in a way that would identify interviewees. I'll tell you when I turn the recorder on and off. Is it all right if I turn the recorder on now?

As you may know, the Southeast Nebraska Behavioral Health Information Network is developing an exchange which will allow patient records to be transferred electronically. We are interested in learning what you think about the prospect of exchanging patient health information electronically with other healthcare providers.

> By "patient health information," we mean **clinical information such as: patient's name, date of birth, social security or insurance identification number, guardianship, diagnosis, treatment information, previous and current medications, compliance with the regimen, efficacy of past prescriptions, coordination with the primary care providers, patient involvement in other community services, history, symptoms or presenting problems, and the level of risk of harm to self or others.**

Much has been written about exchanging patient health data, but very few of those studies talk about the benefits and barriers of exchanging data from the perspective of behavioral health providers. Your insights will be very helpful as we study the benefits and barriers to implementing an effective exchange system.

1. **What do you think would be the benefits of a system that allows providers to electronically exchange patient behavioral health information with other health care providers?**

   Note that "other health care providers" are not restricted to other behavioral health care providers—they could include primary care physicians and any other health care providers.

   "Benefits" may include such issues as: improved access to medical record information, improved workflow, improved charge capture, reduced medication errors, improved care coordination…

   a. When you think about exchanging patient data electronically as opposed to other methods, can you identify any specific benefits for **providers and their organizations**?

   b. Are there specific benefits to **patients** if providers are able to electronically exchange their behavioral health information?

   c. Are there specific benefits to **the behavioral or primary health system of care** if providers are able to electronically exchange patient behavioral health information?

   d. Are the benefits for the exchange of behavioral health **different** than you'd expect for the electronic exchange of general health information?

2. **What do you think would be the barriers in developing a system that allows providers to electronically exchange patient behavioral health information with other health care providers?**

   Note that "other health care providers" are not restricted to other behavioral health care providers—they could include primary care physicians and any other health care providers.

   "Barriers" may include such issues as: lack of capital, disruption to workflow, training/productivity concerns, inability to select appropriate product, inability to integrate with practice management system, concerns about privacy and confidentiality, lack of IT support or knowledge…

a. Are there specific barriers **providers or their organizations** experience in adopting a system for electronically exchanging patient behavioral health information?

b. Are there specific **patient-related** barriers that would inhibit providers from adopting a system for electronically exchanging patient behavioral health information?

c. Are there specific barriers within the **behavioral or primary health system of care** that would inhibit providers from adopting a system for electronically exchanging patient behavioral health information?

d. Are the barriers for the exchange of *behavioral* health information **different** than you'd expect for the electronic exchange of *general* health information?

3. **Who in your organization would you rely on to be part of the decision-making process regarding <u>adopting and implementing</u> an electronic system for behavioral health information?**

   *NOTE: We are looking for **roles**, not people's names!*
   If a name is mentioned: What is that person's role, job title, or job description?

4. **What is the likelihood that you and others in your primary practice or organization would use an electronic sharing system if it were developed?**

   a. If an electronic exchange system was provided by your practice or organization, would **<u>you</u>** use it?

   ☐ Yes
   Why:

   ☐ No
   Why not:

b. If an electronic exchange system was provided by your practice or organization, do you think **other providers** in your practice use it?

☐ Yes
Why:

☐ No
Why not:

c. What would **improve** the likelihood that **you** would be willing to adopt an electronic patient information exchange?

d. What would **improve** the likelihood that **others at your practice** or organization would be willing to adopt an electronic patient information exchange?

5. **On a scale of 1-10, 1 being non-acceptance/resistance and 10 being total acceptance/ high desire for adoption. What do you think the level of acceptance towards adopting the electronic sharing of behavioral health records is among other providers in your organization? (This includes psychiatrists, nurses, medical records staff, etc.)**

6. **Do you have any other comments about sharing patient behavioral health information?**

a. Do you have any other questions or comments for me?

Closing Questions

Finally, for descriptive purposes, we would like to be able to report the approximate sizes of the practices that were involved in these interviews. Would you or someone at your facility be able to tell us:

a. Approximately how many **behavioral healthcare providers work at this facility**?

(Please estimate the number of fulltime equivalents, including: psychiatrists, psychologists, advanced practice nurses, mental health practitioners, licensed independent mental health practitioners, professional counselors, alcohol/drug counselors, compulsive gambling counselors, marriage & family therapists, master social workers, psychiatric nurses)

__________________ full-time equivalent behavioral healthcare providers

b. Approximately how many **medical records staff** work at this facility?
(Please estimate the number of fulltime equivalents)

__________________ full-time equivalent medical records staff

I will turn off the recorder now. Thank you for your help with this project.
Thank you again for your help.

APPENDIX B: STUDY 1 SOCIO-DEMOGRAPHIC QUESTIONNAIRE

Dear Behavioral Healthcare Provider,
We appreciate you taking time to fill out this brief survey about your experience with information technology for our research study on how behavioral heath providers view the electronic exchange of patient information. Your individual responses will be kept confidential and all information that would let someone identify you will be kept private. Please follow the survey instructions below.

SURVEY INSTRUCTIONS

- Answer all the questions by checking the box to the left of your answer. You may also leave written comments to clarify your answer.

- You are sometimes told to skip over some questions in this survey. When this happens you will see an arrow with a note that tells you what question to answer next, like this:

  - ☐ Yes
  - ☐ No ➲ If No, Go to Question 12

- When you have completed this information technology survey, please return it with the Letter of Consent to the University of Nebraska Public Policy Center.

TECHNOLOGY USE

1. Do you use a computer at **work** (your primary practice)?
   - ☐ Yes
   - ☐ No ➲ (If No, go to question 4)

2. How often do you use a computer at **work**?
   - ☐ Multiple times a day
   - ☐ Once a day
   - ☐ Weekly
   - ☐ Monthly
   - ☐ Never

3. How often is a computer readily accessible to you as you provide patient care?
   - ☐ Always
   - ☐ Usually
   - ☐ Rarely
   - ☐ Never

4. Do you have a computer at **home**?
   - ☐ Yes
   - ☐ No ➲ (If No, go to question 6.)

5. How often do you use a computer at **home**?
   - ☐ Multiple times a day
   - ☐ Once a day
   - ☐ Weekly
   - ☐ Monthly
   - ☐ Never

6. What types of software programs do **you** regularly use at **work or home?** *(Check all that apply.)*
   - ☐ Electronic medical records
   - ☐ Practice management software
   - ☐ Billing software
   - ☐ Patient scheduling
   - ☐ E-prescribing
   - ☐ Lab results
   - ☐ Clinical decision support tools
   - ☐ Word processing
   - ☐ Spreadsheets
   - ☐ Adobe Acrobat (pdf) software
   - ☐ Databases
   - ☐ PowerPoint
   - ☐ E-mail
   - ☐ Internet browsers
   - ☐ I do not use software programs regularly
   - ☐ Other, please specify ____________________________

EXCHANGING PATIENT INFORMATION

We are interested in how **you** and **others** at your **primary practice** currently exchange patient health information with other healthcare providers.

> *Patient health information* might include clinical information such as: patient's name, date of birth, social security or insurance identification number, guardianship, diagnosis, treatment information, previous and current medications, compliance with the regimen, efficacy of past prescriptions, coordination with the primary care providers, patient involvement in other community services, history, symptoms or presenting problems, and the level of risk of harm to self or others.

7. At your **primary practice**, how do **you** exchange patient information with providers at other facilities? *(Check all that apply.)*

- ☐ Phone
- ☐ FAX
- ☐ Send paper files or letters through US Mail
- ☐ Send through e-mail
- ☐ Send through an electronic medical records system
- ☐ Someone else does this for me. (*Please describe.*)

  ____

- ☐ Other methods. *(Please describe.)*

  ____

8. How do **other behavioral healthcare providers** exchange patient information with providers at other facilities when working at your **primary practice**? *(Check all that apply.)*
   - ☐ Phone
   - ☐ FAX
   - ☐ Send paper files or letters through US Mail
   - ☐ Send through e-mail
   - ☐ Send through an electronic medical records system
   - ☐ Someone else does it. *(Please describe.)*

     ____

   - ☐ Other methods. *(Please describe.)*

     ____

PRACTICE AND PROFESSIONAL INFORMATION

9. Which of the following <u>best</u> describes your **primary practice setting**? *(Check one.)*

   - ☐ Administrative Agency
   - ☐ Agency Staff
   - ☐ Alcohol/Detox/Halfway House
   - ☐ Ambulatory Care Clinic
   - ☐ Clinic (Free-standing)
   - ☐ Clinic (hospital)
   - ☐ Correctional Facility
   - ☐ County Institution
   - ☐ Group Health Plan

☐ Hospital (Non-Federal)
☐ In-Home
☐ Indian Health Services
☐ Insurance Company
☐ Long-Term Care Facility
☐ Military Facility
☐ Non-Profit Facility
☐ Occupational Health
☐ Public Health
☐ Research
☐ Regional Center
☐ School/University
☐ State Institution
☐ Student Health
☐ Urgent Care
☐ VA Facility

10. What is the name of your **primary practice**?

    ____

11. How many patients do **you** see at your **primary practice** each week (give range)?

    Between _____ and _____ # of Patients each week

12. How would you best describe your practice arrangement at your **primary practice**? *(Check one.)*
    ☐ Hourly Employee
    ☐ Contract Employee
    ☐ Locum Tenens
    ☐ Physician Network
    ☐ Salaried – Academic
    ☐ Salaried – Federal Government
    ☐ Salaried – Group Health Plan
    ☐ Salaried – Hospital (Non-Federal)
    ☐ Salaried – Federal Government
    ☐ Salaried – Military
    ☐ Salaried – State/County Government
    ☐ Self-employed – Partnership or Group
    ☐ Self-employed – Solo Practice
    ☐ Volunteer
    ☐ Other ______________________________

13. Are you employed full-time or part-time?

- ☐ Full-time
- ☐ Part-time

14. What is your age?
    - ☐ 21-30 years of age
    - ☐ 31-40 years of age
    - ☐ 41- 50 years of age
    - ☐ 51- 60 years of age
    - ☐ Over 61 years of age

15. What is your gender?
    - ☐ Female
    - ☐ Male

16. What is your highest educational degree?
    - ☐ Associate
    - ☐ Bachelors
    - ☐ Masters, please specify area ___________
    - ☐ PhD, please specify area ______________
    - ☐ PsyD
    - ☐ EdD
    - ☐ MD
    - ☐ Nursing, please specify area ___________
    - ☐ Other, please specify _________________

17. In what year did you obtain your highest educational degree? ___________

*** If you have additional comments about this study or about the electronic exchange of patient records for behavioral health patients, please include them in the space below or you may submit them in a separate envelope.*

Should you have any further questions or concerns about this survey or your interview time, please contact Elizabeth Willborn at (402) 472-0108 or ewillborn@nebraska.edu.

Thank you for promptly returning the following materials to us in the provided envelope before your scheduled interview.

1. This completed ***Information Technology Survey***
2. The enclosed ***Letter of Consent***

APPENDIX C: STUDY 2 SURVEY OF BEHAVIORAL HEALTH PROVIDERS

Thank you for your willingness to participate in this study!
Researchers at the University of Nebraska Public Policy Center are studying behavioral health providers' perspectives about **electronically sharing client information with providers at other organizations** (in comparison to sharing through other methods you may currently use such as fax, phone, or mail).
There is a national push toward electronic health records, but not much is known about how behavioral health providers view using electronic systems for sharing client information (diagnoses, assessments/tests, medications, treatment plans, progress notes) with providers at other organizations.
By returning this survey, you are agreeing to participate in this study (more information about the study is attached). This survey will take approximately 10 minutes. Your responses will be kept confidential.

1. Imagine a system that enables you to **electronically share client information** with medical and behavioral health providers at other organizations, who have the appropriate release of information.

From your perspective, such an electronic sharing system would:

Strongly Disagree	Disagree	Neither Disagree Nor Agree	Agree	Strongly Agree	
1	2	3	4	5	Improve your practice's billing accuracy
1	2	3	4	5	Provide more complete information to help with your diagnoses and treatment
1	2	3	4	5	Improve coordination of care among all providers working with the same
1	2	3	4	5	Result in extra work for you on a daily basis
1	2	3	4	5	Compromise your professional ethics
1	2	3	4	5	Disrupt your own work flow
1	2	3	4	5	Be impractical because behavioral health information cannot be captured
1	2	3	4	5	Improve your access to client medical/physical health records
1	2	3	4	5	Lead to more complete client information

Strongly Disagree	Disagree	Neither Disagree Nor Agree	Agree	Strongly Agree	
1	2	3	4	5	Reduce duplicating client evaluations, assessments, or tests that have already
1	2	3	4	5	Require more training than you have time for
1	2	3	4	5	Streamline your access to client information/records
1	2	3	4	5	Increase the time your practice spends on transcriptions
1	2	3	4	5	Improve your communication with other providers
1	2	3	4	5	Be resisted by some providers
1	2	3	4	5	Be difficult because your practice lacks the technological expertise to
1	2	3	4	5	Save costs for your practice in the long run
1	2	3	4	5	Improve your clients' safety
1	2	3	4	5	Improve your ability to track medication history
1	2	3	4	5	Increase your legal vulnerability
1	2	3	4	5	Negatively influence treatment plans
1	2	3	4	5	Disrupt your relationships with your clients
1	2	3	4	5	Improve your practice's office work flow
1	2	3	4	5	Be difficult for you due to your apprehensions about computer
1	2	3	4	5	Create more time for client care
1	2	3	4	5	Be misused by third party payers
1	2	3	4	5	Cost your practice too much to implement
1	2	3	4	5	Be resisted by clients

Strongly Disagree	Disagree	Neither Disagree Nor Agree	Agree	Strongly Agree	
1	2	3	4	5	Reduce the time you spend on paperwork
1	2	3	4	5	Result in more data entry errors in client records
1	2	3	4	5	Force you to use an overly templated behavioral health record
1	2	3	4	5	Improve your clients' satisfaction with the admissions process
1	2	3	4	5	Improve privacy and security of confidential client information
1	2	3	4	5	Be time consuming for your practice to implement
1	2	3	4	5	Make you become too reliant on technology that could crash
1	2	3	4	5	Improve the quality of care your clients receive
1	2	3	4	5	Improve your ability to control who has access to your clients' information
1	2	3	4	5	Be resisted by staff at your practice

2. Rate your level of agreement with the following statements. *(Circle the appropriate number)*

Strongly Disagree	Disagree	Neither Disagree Nor Agree	Agree	Strongly Agree	
1	2	3	4	5	I find working with computer software programs very easy
1	2	3	4	5	I am very confident in my abilities to make use of computer software
1	2	3	4	5	I find it difficult to get computer software programs to do what I want
1	2	3	4	5	I usually find it easy to learn how to use a new software program

1	2	3	4	5	I seem to waste a lot of time struggling with computer software programs
1	2	3	4	5	As far as computer software programs go, I don't consider myself to be very
1	2	3	4	5	Computer software programs help me to save a lot of time
1	2	3	4	5	I find working with computer software programs very frustrating

3. Do you now, or have you ever, used electronic behavioral health records for diagnoses, treatment plans, medications, or progress notes? *(Check one box)*

   ☐ Yes
   ☐ No. *If you checked "No," skip to question #5.*

4. If you answered "Yes" to question #3, rate your overall satisfaction with the electronic behavioral health records system you have used. *(Circle the appropriate number.)*

Very Dissatisfied	**Dissatisfied**	**Neutral**	**Satisfied**	**Very satisfied**
1	2	3	4	5

5. Have you provided behavioral healthcare to clients during the past 12 months? *(Check one box)*

   ☐ Yes
   ☐ No. *If you checked "No," skip to question #7.*

6. How do you currently share client behavioral health information with providers at other organizations? *(Check all that apply)*

   ☐ Fax
   ☐ Phone
   ☐ Mail
   ☐ E-mail
   ☐ Electronic behavioral health records system
   ☐ Rely on others to do it for me
   ☐ Other: *(Please describe)*
   ____

7. Overall, rate your support for creating a system that would enable providers to electronically share client information in a secure manner. *(Circle the appropriate number)*

Not Supportive	Somewhat Not Supportive	Neutral	Somewhat Supportive	Very Supportive
1	2	3	4	5

8. Please provide any additional comments you may have about the survey or about electronically sharing behavioral health client information.

Thank you for your time in responding to this survey of Nebraska's behavioral health professionals. Return your survey in the **enclosed stamped envelope** to:

University of Nebraska Public Policy Center
215 Centennial Mall South, Suite 401
Lincoln NE 68588-0228

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