SCALING INNOVATIONS IN HEALTHCARE

“A multi-method analysis of facilitators and barriers of innovation adoption in hospitals”

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ABSTRACT

This research paper examines the innovation adoption of technology, specifically Artificial Intelligence (AI) implementations in hospitals by exploring the capabilities that enables AI innovations using the dynamic capabilities (sensing, seizing and reconfiguring) framework and clinicians' intentions to use AI innovations for patient care by applying the technology adoption/acceptance framework Unified Theory of Acceptance and Use of Technology (UTAUT) utilizing qualitative case study analysis and quantitative survey methodology respectively. This multi-disciplinary research has considerable relevance to both healthcare business leaders and clinical practitioners by identifying the key factors that drives the decisions to adopt innovations to improve healthcare organizations' competitiveness to enhance patient care as well as to reduce overall healthcare costs. The main findings are:

(1) On an organizational level, healthcare organizations with strong and versatile dynamic capabilities, who build on their existing knowledge and capabilities are better able to integrate the innovations into their internal operations and existing services. The identified barriers provide a clear sense of organizational barriers and resistance points for innovation adoption

(2) On an individual level, the impact of quality of care and organization leadership support are the key factors that facilitates the adoption of innovation among the clinicians.

(3) Current trends and key impact areas of AI technology in the healthcare industry are identified

Key words: Innovation, Innovation Adoption, Dynamic Capabilities, Healthcare, Artificial Intelligence, AI, Technology, Strategic Management

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CHAPTER 1

INTRODUCTION

The US healthcare system has undergone heavy institutional change in the past few decades. Healthcare leaders are confronted with a nexus of healthcare forces that is transforming the industry by introducing new models of care delivery and value-based payments. Fundamental to this transformation is the relationship between healthcare and patient, as the health ecosystem changes swiftly from provider centric to patient/customer centric. The changing healthcare marketplace, transformational new healthcare model, and uncertainties in future healthcare reform make it critical that healthcare organizations build new capabilities and explore innovative strategies to survive and thrive in these difficult economic times amidst a volatile healthcare environment.

Innovation is seen as a key means by which healthcare organizations can accomplish this transformation. Although most hospitals have sensed the market forces and decided to invest in innovation, only some are succeeding in developing the capabilities that are required to seize this opportunity.

The processes of generating and adopting innovation are distinct phenomena that are facilitated in different organizational conditions. The Innovation Generating Organization (IGO) depends heavily on its technological knowledge and market capabilities to develop and commercialize innovations; in contrast, the innovation-adopting organization (IAO) relies more on its managerial and organizational capabilities to select and assimilate innovations (Damanpour & Wischnevsky, 2006). Organizational innovation adoption has received increased attention in the IS, medicine, and management literatures over the past two decades. The general topic of adoption of innovation has inspired much research and many theoretical frameworks seek to describe the dynamic process of the implementation of innovations. Little is known, however, about factors related to decisions to adopt innovations and how the likelihood of adoption of innovations can be increased (Rye & Kimberly, 2007).

Around the world, every health care systems struggle with rising costs and uneven quality of care despite the hard work of well-intentioned, well-trained clinicians. The US healthcare system is the costliest in the world, accounting for 17% of the gross domestic product (GDP) estimated at $3.4 trillion with a projected increase to nearly 20% by 2020.

Artificial intelligence (AI) research within medicine is also growing rapidly. The rise of artificial intelligence (AI) in the era of big data could assist clinicians in shortening processing times and improving the quality of patient care in clinical practice. Clinicians diagnose diseases based on personal medical histories, individual biomarkers, and their physical examinations of individual patients. In contrast, AI can diagnose diseases based on complex algorithms using hundreds of biomarkers, imaging results from millions of patients, aggregated published clinical research from PubMed, and thousands of physician's notes from electronic health records (EHRs) (Krittanawong, 2018).

In recent years, AI projects in healthcare have attracted more investment than AI projects in any other sector of the global economy. As artificial intelligence reshapes the contours of the healthcare industry, innovation adopting healthcare organizations (IAO) are increasingly investing in AI applications like Predictive Analytics, Chatbots/Virtual Assistants, and Predictive Health Trackers at the point of care (POC) in the areas of clinical diagnoses and treatments. This surging interest in AI and related concepts, such as predictive analytics, suggests that AI is primed not only to influence specific areas of medical care, but also to help inform healthcare leaders through enhanced intelligence, such as demonstrating how to build capacity and outperform the competition in a rapidly changing environment. Industry analysts estimate that the AI health market is poised to reach $6.6 billion by 2021, and by 2026 it could can potentially save the U.S. healthcare economy $150 billion in annual savings (Accenture report).

There is a general consensus that organizational factors can both facilitate and inhibit the implementation and adoption of technological innovation in healthcare, particularly those innovations that are likely to have a major discernible impact on care processes (Cresswell & Sheikh, 2013).

The adoption of innovation is intended to contribute to the organization's effectiveness and competitiveness by changing the adopting organization so that it can adapt to new conditions in its external environment. The adopting organization aims to match the organization's strategic requirements with capabilities and potentials of the innovations available in the market. The adoption process emphasizes the integration of the innovation into the organization (Damanpour & Wischnevsky, 2006). Two types of organizational adoption decisions can be identified, i.e. the decision made by an organization and the decision made by key stakeholders within an organization (Frambach & Schillewaert, 2002).

The central focus of this paper is to explore and understand the connections at both organizational and individual levels on innovation adoption in healthcare organizations. This paper is organized as depicted in Figure 1 below.

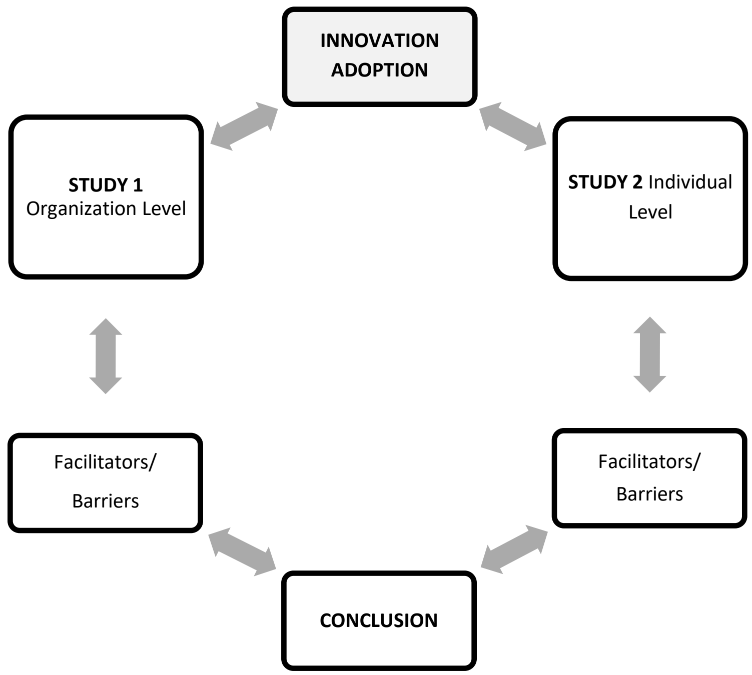

Figure 1. Organization of the Dissertation

In the first study, I explore the capabilities that drives the adoption of AI technology innovations in hospitals at the organizational level. I am using qualitative case study methodology and leveraging dynamic capabilities (DC) theoretical to address the question "How dynamic capabilities enable AI technology adoption in hospitals?" This exploration leads to a new, inductively developed operational model that describes heterogeneity of dynamic capabilities in a healthcare setting.

In the second study, I examine clinicians' intentions to use AI innovations for patient care at an individual level within organizations by applying the technology adoption/acceptance framework Unified Theory of Acceptance and Use of Technology (UTAUT) using a quantitative survey methodology for physicians/nurses to address the question "What are the key factors that influence clinicians' decision to adopt AI technology innovations?" I have applied the UTAUT model in a healthcare context and identified healthcare specific constructs and confirmed support for several of the hypotheses.

Based on the results of the two studies, I put forward several ideas for additional research to exploring the manifestations of dynamic capabilities in other industry contexts to enhance the understanding of their commonalities in organization structures and business practices. I conclude the paper with implications for healthcare leaders and clinicians concerning the key factors that act as facilitators and barriers to innovations adoption in hospitals to improve healthcare organizations' competitiveness and to enhance patient care as well as to reduce overall healthcare costs.

The following chapters begin with a review of the literature with the specific focus on how manifestations of dynamic capabilities practices impact innovation adoption in healthcare organizations and the determinants of the innovation adoption by individuals within an organization. Chapter 3 describes Study 1, an exploratory cross case study inductive analysis, where I present five in-depth case studies to demonstrate how the manifestations of dynamic capabilities acts as drivers to enable innovation adoption and also identify the barriers to innovation adoption on an organizational level. I also review of my contribution to theory and management practices and recommendations for future research. Chapter 4 describes Study 2, overviewing quantitative survey results to determine the significant factors leading to the innovation adoption on an individual "clinicians" level. I also review my contribution to theory and management practices and recommendations for future research.

CHAPTER 2

LITERATURE REVIEW

In this section, I review relevant literature in the areas of Innovation & Innovation Adoption, Dynamic Capabilities, Artificial Intelligence (AI) and The Unified Theory of Acceptance and Use of Technology (UTAUT), and their relevance of application to this study.

Innovation and Innovation Adoption

The largely accepted definition of innovation among researchers in the field of innovation is "the intentional introduction and application within a role, group, or organization, of ideas, processes, products or procedures, new to the relevant unit of adoption, designed to significantly benefit the individual, the group, or wider society" (West, 1990). This encapsulate three key dimensions of innovation: (1) novelty, (2) an application component, and (3) an intended benefit (Lansisalmi, et al., 2006).

In other words, innovation can be considered the successful implementation of a novel idea in a way that creates compelling value for some or all of the stakeholders (Varkey, et al., 2008).

Innovation in healthcare must be managed similarly, but not identically, to innovation in any field. Innovations in healthcare organizations are typically new services, new ways of working and/or new technologies.

"Healthcare innovation can be defined as the introduction of a new concept, idea, service, process, or product aimed at improving treatment, diagnosis, education, outreach, prevention and research, and with the long term goals of improving quality, safety, outcomes, efficiency and costs" (Omachonu et al., 2010).

The adoption of innovative technologies intended to contribute to the organization's effectiveness and competitiveness by changing the adopting organization so that it can adapt to new conditions in its external environment. The adopting organization aims to match the organization's strategic requirements with capabilities and potentials of the innovations available in the market. The adoption process emphasizes the integration of the innovation into the organization (Damanpour & Wischnevsky, 2006).

Artificial Intelligence (AI) and Healthcare Applications

AI has been defined as an area of study in computer science concerned with "the development of computers to engage in human-like thought processes such as learning, reasoning and self correction" (Dilsizian & Siegel, 2014). This includes machine learning, deep learning, and reasoning systems which are either memory or logic based.

Computer science advances and ultra-fast computing speeds find artificial intelligence (AI) broadly benefitting modern society—forecasting weather, recognizing faces, detecting fraud, and deciphering genomics. Machines (computers) learn to detect patterns not decipherable using biostatistics by processing massive datasets (big data) through layered mathematical models (algorithms). AI is being successfully applied for image analysis in radiology, pathology, and dermatology, with diagnostic speed exceeding, and accuracy paralleling, medical experts. While diagnostic confidence never reaches 100%, combining machines plus clinicians reliably enhances system performance. AI may optimize the care trajectory of chronic disease patients, suggest precision therapies for complex illnesses, reduce medical errors, and improve subject enrollment into clinical trials (Miller & Brown, 2018). By leveraging natural language processing, an AI tool can compile and connect decades of accumulated diverse electronic medical records (EMR) data like history, physical, laboratory, imaging, medications to predict future illness trajectories and medical outcomes.

Dynamic Capabilities

Dynamic capabilities are a special class of capabilities concerned with change and innovation. Dynamic capabilities help explain how organizations enhance and sustain performance in rapidly changing environments by creating, extending, or modifying their resource base through investment and other managerial interventions. Dynamic capabilities have also been conceptualized as flexibility and adaptability of resources and routines (Evans et al., 2017). Teece (2007) introduced a framework categorizing a firm's dynamic capabilities in three groups, related to sensing opportunities and threats, seizing opportunities, and reconfiguring the firm's asset base.

Sensing

Sensing involves scanning, searching, and understanding customer needs, latent demand, technological possibilities, local and non-local markets, and the probable supplier and competitor responses (Agwunobi & Osborne, 2016).

Successful sensing enables an organization to focus on where it will be tomorrow, rather than on where it is today. But sensing is not easy, as it is difficult to spot emerging trends. One example of innovation adoption by sensing capability of hospitals was the rapid ascendency of “hospitalists”—doctors who work exclusively in the hospital managing patients for primary care physicians and specialists. During their emergence in the mid-1990s, the hospitalist movement faced significant resistance and skepticism from physicians based on the discontinuity of patient care inherent in the model. However, this novel concept became the fastest-growing medical specialty in the history of U.S. medicine, and soon it was a fixture of most of hospitals with more than 200 beds.

Seizing

The organization’s ability to sense a market opportunity does not mean that it can seize it effectively. The managerial skills needed to sense are quite different from those needed to seize and those needed to reconfigure. To seize opportunities effectively, enterprises must have the ability to make high-quality investment decisions; they must have or create the right business model; and they must maintain and improve technological competences and complementary assets (Teece, 2007). The challenge hospitals face includes their hierarchical structures which slow decision making and lead to bidirectional loss of information.

Reconfiguration Capability

Reconfiguration capability is defined as the capacity of firms to effectuate strategic moves. Even when well-established firms are aware of a need to change to cope with the shifting business environment, it is often difficult to respond effectively. The reconfiguration capability requires that change in operational capabilities is performed in a rapid manner, preventing them from becoming core rigidities (Eisenhardt & Martin, 2000).

Given the changes in the hospital business environment over the last decade, the dynamic capabilities framework, long considered to be particularly relevant for multinational enterprises and other firms in volatile environments is now also relevant and needed for hospitals. Not only does it provide a template for understanding where to focus efforts to create lasting competitive advantage, it illuminates the specific causes of the mismatch between hospitals' archetypal capabilities/leadership skills and the demands of an evolving business environment characterized by increased competition and uncertainty.

While prior research recognizes the importance of dynamic capabilities in innovation on a conceptual level, very little research has empirically identified the role of dynamic capabilities related to innovation adoption in healthcare industry.

The Unified Theory of Acceptance and Use of Technology (UTAUT)

Information Systems (IS) research has long studied how and why individuals adopt new information technologies. One stream of IS research focuses on individual acceptance of technology by using intention as a dependent variable (Venkatesh et al., 2003).

The UTAUT was developed from eight theories, which include the Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivational Model (MM), Theory of Planned Behavior (TPB), Combined TAMTPB (C-TAM-TPB), Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT) and Social Cognitive Theory (SCT) (Venkatesh et al., 2003).

Dynamic Capabilities and Artificial Intelligence (AI) Innovation Adoption in Healthcare

According to a 2017 study released by HIMSS Analytics, although just a small portion of the healthcare field is using AI now, its application is poised to increase tremendously in next three to five years.

AI has been promising intelligent machines and computer programs for at least 50 years but has been delivering on that promise only incrementally. However, the current wave of AI interest is different. AI has gotten a lot smarter really fast in the past 10 years or so. The technology is just stronger now and therefore more promising (Radick, 2017).

CHAPTER 3

STUDY 1: INNOVATION ADOPTION (ORGANIZATION LEVEL)

This chapter describes the research framing, design, methods and data.

Framing

Based on the literature review presented in CHAPTER 2, I use the dynamic capability framework (sensing, seizing and reconfiguration) introduced by (Teece, 2007) to explore the capabilities that enables AI innovation adoption in hospitals by addressing the first research question. The advantage of this framework is that it explicitly introduces a bundle of practices or microfoundations that constitute each category of dynamic capabilities. The term "practices" refers to general-level, shared organizational activities (Jantunen et al., 2012). Applying this framework to healthcare context, I bundled two of the main categories of practices together as sensing capabilities, two categories as seizing capabilities, and three categories as reconfiguring capabilities. Table 1 summarizes this categorization.

This categorization of sensing, seizing and reconfiguring capabilities and the practices they consist of is utilized as the analysis framework in the empirical part of the study as depicted in Figure 1.

Table 1.
Categorization of Dynamic Capabilities (Adopted from Jantunen et al., 2012).

Category	Function	Practices of Dynamic Capabilities	Reference
SENSING	Scanning the environment and identifying new business opportunities	Internal R&D	The search activities that are relevant to 'sensing' include information about what's going on in the business ecosystem. With respect to technologies, R&D activity can itself be thought of as a form of 'search' for new products and processes (Teece, 2007).
		Supplier/Complementor Innovation	In fast-paced environments, with a large percentage of new product introductions coming from external sources, search/exploration activity should not just be local. Enterprises must search the core as well as to the periphery of their business ecosystem. Search must embrace potential collaborators—customers, suppliers, complementors—that are active in innovative activity (Teece, 2007).
SEIZING	Ability to make high-quality investment decisions; create the right business model; maintain and improve technological competences and complementary assets	Decision-making protocols	Addressing opportunities involves maintaining and improving technological competences and complementary assets and then, when the opportunity is ripe, investing heavily in the particular technologies and designs most likely to achieve marketplace acceptance (Teece, 2007).
		Leadership practices promoting commitment and new ways of allocating resources	The leadership practices promoting commitment and new ways of allocating resources, belong to the set of the firm's seizing capabilities (Teece, 2007).
RECONFIGURING	Reconfiguring resources and business processes in order to come up with new productive assets	Knowledge management & Learning	A learning capability is defined as the capacity to acquire, assimilate, and exploit new knowledge that enables informed decision making. Learning is argued as being a very important process, which through experimentation and repetitions leads to better and swifter problem resolution (Teece et al., 1997).
		Process/Protocols to synchronize the work	Coordinating capability is defined as the ability to orchestrate and deploy tasks and resources and synchronize activities with involved stakeholders. By strengthening their coordination capability, firms can easily identify complementarities and synergies, reduce task redundancies, and promote effective collaboration (Mikalef and Pateli, 2017).

		Data assimilation	An integrating capability concerns the evaluation of firm and partner resources and capabilities and the capacity to embed and exploit them in new or revamped operational capabilities. The capacity to integrate dispersed resources is viewed as the foundation of dynamic capabilities (Teece, 2007).

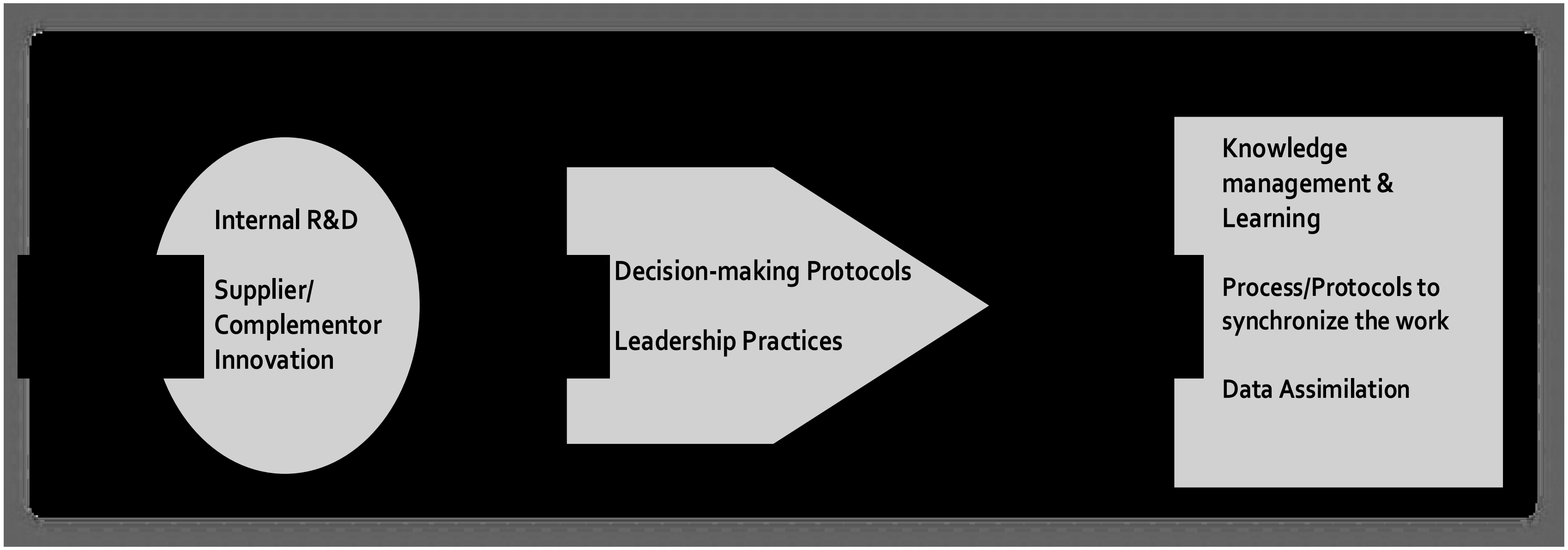

Figure 2. Practices Comprising Dynamic Capabilities (Analysis Framework for Healthcare Context).

Adopted from microfoundations of dynamic capabilities (Teece, 2007)

Research Design and Methods

Case Selection

Applying a case study method to investigate dynamic capability building processes in the context of collaboration is not new in the literature. The case study method is particularly suitable for practice-oriented fields and addresses "how or why" social phenomenon operates (Yin, 2014). Given the objective to explore the relationship between dynamic capabilities and innovations adoption, I chose a multiple-case study as the research design. As multiple-case studies retain only relationships that are replicated across most or all of the cases, the resulting conceptual frameworks or hypotheses are often more parsimonious, robust and generalizable compared to single-case studies. Multiple-case studies apply replication logic; in other words, each case is treated as "an independent experiment" that stands on its own as an analytical unit (Eisenhardt & Graebner, 2007; Yin, 2014).

Following the suggestions put forward by (Rouse & Daellenbach, 1999), I controlled for the industry context by taking the case companies from the same healthcare industry (specifically hospitals). Given the objective to link firm-level dynamic capabilities with innovation adoption, this research design covers the level of analysis at the organization level.

The research method for this paper is to build an exploratory cross-case comparison study between academic and community hospitals using semi-structured interviews with healthcare leaders/administrators and clinicians in order to explore, discover, and identify how dynamic capabilities (sensing, seizing and reconfiguring) enables innovation adoption (specifically AI technology innovations).

The operating environment of healthcare is undergoing a paradigm shift from an illness model to a wellness model, and hospitals face external pressure to respond through innovation and adaptation. Thus, I see the context appropriate for research on dynamic capabilities. Additionally, the chosen case hospitals possess highly advanced digital patient record environment, Electronic Medical Record Adoption Model (EMRAM) stage 6 or 7, and they have all taken a proactive approach to technological change, having either implemented or begun implementing AI technology in their organization. The similarity of the cases provided an appropriate foundation for comparing their dynamic capabilities.

Data Collection

Given my aim to pinpoint how dynamic capabilities are manifested in practice and to assess their similarity, it is critical that the analysis is based on data that can capture the nuances in the case companies. As such, I chose to collect qualitative data in the form of semi-structured interviews. Further, because of the paper's focus on the renewing hospitals' capabilities driven by technological change, the interviews focused on the development of recent AI related innovation implementations and related processes and practices.

The semi-structured interviews were administered through a set of open-ended questions. I prepared an interview guide listing the main interview themes, varying the wording and the order of the questions to allow me to follow the lead of the interviewees. The interviews were informal and narrative in nature, the aim being to tap into authentic and contextualized experiences (Eriksson & Kovalainen, 2008). The focus was on the particular innovation(s) related to AI technology. The main emphasis was on the current situation as, I wanted to gain an understanding of the actual processes deployed and the actions taken in their implementation, and of how the organization had adjusted its practices accordingly. I conducted 10 interviews in total. The interviews were conducted on the interviewees' company premises from summer through the winter of 2018, the interviews lasted, on an average, 45 minutes. All interviews were recorded and transcribed with the permission of the interviewees. The details of the interviewees in each case is presented in Table 2.

Table 2.
***Interviewees*.**

Case	Type	EMRAM Stage (HIMSS Analytics)	Interviewees	Title/Role/Reference
Hospital Arcee	Community Hospital	6	1	Chief Information Officer (CIO)
Hospital Prime	Academic Hospital	6	4	Head of Innovation Center/Physician Executive/Respondent 1
				Chief Information Officer (CIO)/Respondent 2
				Chief Administrative Officer (CAO)/Respondent 3
				Head of Clinical Innovations /Physician Executive/Respondent 4
Hospital Cliffjumper	Academic Hospital	6	1	Medical Director /Physician Executive
Hospital Carrera	Academic Hospital	6	1	Chief Information Officer (CIO)
Hospital LightBright	Community Hospital	7	3	Chief Medical Information Officer/Physician Executive/Respondent 1
				Head of Innovation Center/Respondent 2
				Medical Director /Physician Executive//Respondent 3

Data Analysis

I conducted the analyses in three consecutive phases. In Phase I, I conducted a thematic analysis for each case company data in order to categorize the different types of dynamic capabilities. To enable a thorough comparison of cases, I adopted a deductive approach and used the classification presented in Table 1 as our main coding frame. After this round of analysis, I was able to describe the dynamic capabilities of each case. In Phase II, I examined the data on the individual cases to explore the manifestation of each category of dynamic capabilities, one by one. In Phase III, I analyzed the data related to the barriers question to identify various themes. The different phases of the data analysis are summarized in Table 3.

Table 3.
Phases of Case Analysis.

Analysis Phase	Analytical goal	The analytical process used and the outcome
Phase I	Categorize the different types of dynamic capabilities	Thematic analysis. Deductive coding of the different types of capabilities according to the research framework (Table 1) in order to break down and reconstruct the data in the individual dynamic capabilities
Phase II	Assess the manifestations of different types of dynamic capabilities across the case companies	Cross-case comparison resulting in a detailed description of similar structures and case-specific patterns in the manifestations of dynamic capabilities
Phase III	Evaluate the barriers of innovation adoption	Cross-case comparison resulting in a summary of barriers related to the adoption of all innovations and AI specific innovations

Gibbert et al. (2008) discuss the validity and reliability criteria in case study research within the field of management and strategy research. The present study meets the criteria as follows: Internal validity is supported by careful literature review and deriving the conceptual categorization from the current literature. This framework was used as the starting point for designing the interview guide for data collection phase.

Construct validity, i.e. the quality of conceptualization and operationalization of the relevant concepts, was supported with data triangulation (interviews and secondary data and explanation of the data analysis process). Following Yin (2009), I also maintained a chain of evidence from the case study protocol through different rounds of data analysis to conclusions. The qualitative analysis software NVivo was used as a tool in the analysis to help maintain the linkage between interview transcripts, direct quotes, interviewees and different categories of analysis codes. Hence, the analysis process could be jointly reviewed and revised later if necessary. The cross-case analysis together with careful case selection and context description support external validity (Eisenhardt, 1989). To ensure reliability, a case study protocol was designed (case selection, interviewee selection, interview guide, data analysis process). Taken together, I believe this study to meet the main criteria for reliability and validity.

Findings

In this section, I present the findings of the individual case analyses and compare them across cases.

Sensing Capabilities

The sensing capabilities are embedded in Hospital Prime's culture. The respondents from this organization mentioned that, as an academic hospital,

> We are a research-intensive place; new discoveries are happening in our laboratories all the time because we have got a huge faculty and residents and an enormous engine that fuels that kind of discovery.

The current AI implementation focus areas are Radiology, Radiation oncology and identification of sepsis. The type of AI applications are "chatbots" for cancer treatment follow up and scheduling patient appointments.

Hospital Arcee is a community hospital and they focus on clinical process and product/service innovations with a special emphasis on technologies by partnering with external vendors.

Their current AI implementation is to support clinical decision making with a key focus on cardiac diseases. The respondent stated that,

> We have partnered with a technology vendor to build algorithms for cardiac risk score. These algorithms help detect cardiovascular diseases from several patterns that are particular to our patient population.

As an academic hospital, Hospital Cliffjumper has a long and distinguished tradition of research that has spanned nearly a century. They are working on an AI implementation, to build a predictive model to support clinical decision-making. He respondent commented that,

> We are building an enterprise-class stream computing cluster platform to analyze thousands of vital sign readings in near-real time, enabling it to use proven predictive models to support clinical decision-making.

Hospital Carrera is an academic hospital playing a leading role in its revitalization of the local community that has a partnership with leading cancer centers in the region. They leverage

AI tools for clinical decision making in the areas of cancer, radiology and stroke. Interestingly they are looking into cyber security applications. The respondent from this hospital mentioned that

> We have a flavor of AI in security in our security platform to understand where the threat is. We are using AI for threat intelligence.

Hospital Lightbright is built on their foundation as a community health system and become an innovative population health leader that creates superior quality and value for the patients and communities they serve. Their focus is on clinical process and product/service innovations with a special emphasis on technologies by partnering with external vendors and other academic institutions. The key focus for them is to improve cancer diagnoses through using artificial intelligence. The respondent commented that,

> We have established a partnership with an academic health system and a technology vendor to improve cancer diagnoses through using artificial intelligence by participating in clinical trials for various cancers, including trials for kidney, breast and skin cancers.

Seizing Capabilities

Hospital Arcee's leadership made steadfast commitment to embrace advanced technologies early on to support its core organizational mission of making quality healthcare accessible to all and to empower provision of patient-centered clinical information across all of its hospitals. The respondent mentioned that,

> Being at the forefront of healthcare delivery in the region, an advanced health information system provides the underpinnings for decision-making and is critical to the journey of healing.

Hospital Prime made significant executive commitments and investments to recombining their people, processes and technology assets. The respondents commented that,

> We have created a new project management intake process to channelize the ideas coming out of the innovation center or out of a data sciences team. Then it flows to IT team for technology assessment. and for proof of concept development. Then nursing and physician informatics community are involved for validating the proof of concept solutions.
>
> We have installed an enterprise-wide EMR system , a technological platform to work collaboratively with our hub and spoke sites that is centrally managed. It's one platform that we can innovate off of one system that we can put a recommendation for, care clinical alerts, best clinical practices all in one system.

They have a separate organization structure "innovation center" to promote research, development and innovation. The respondent described the role of their innovation center as,

> Our innovation center comprises various accelerator programs and acts as an innovation funnel. All the new technology innovation initiatives are channelized through the innovation center.

Hospital Cliffjumper's established a health informatics group to work collaboratively with various stakeholders by leveraging their technical assets especially their enterprise-wide EMR system. The respondent commented that,

> Our health informatics department collaborates closely with regulatory, compliance, legal, and IT groups to establish governance that promotes research. This group consists of a unique combination of clinical practitioners, principal investigators, clinical database specialists, and informatics programmers to deliver actionable clinical data to researchers and to provide tools for efficient data management.

Hospital Carrera defined a process at the institution leadership level to funnel the new technology initiatives. The respondent explained their process as,

> We have a process for clinicians to come out with robust use cases and it is vetted through a technology committee that comprises IT leadership and clinical leadership

Hospital Lightbright's leadership established a new structure "Connected Care and Innovation center" to generate and create new connected care programs and innovative ideas.

The respondent commented that,

> We provide creative space and support to multidisciplinary stakeholders to work collaboratively to foster the development, beta testing, implementation of innovative ideas, processes and technologies and to scale it across the network of our hospitals in the region.

Reconfiguring Capabilities

Hospital Arcee primarily rely on vendor educational programs related to AI technologies.

The responded commented that,

> We use pilot programs and software prototypes to educate the clinicians.

The respondent explained that, they use focus groups to coordinate with various stakeholders - clinicians, technologists and vendors.

> It takes a lot of analysis by our cardiologists and data scientists to come up with several models of correlation. They have to then apply their clinical intelligence on these correlations. Before an algorithm for machine learning is considered usable, it has to be perfect. Then it has to go through several rounds of testing, verification, validation to ensure that the result matches with the actual practice.

After reaching the EMRAM Stage 6, a higher lever for electronification of the patient clinical data, Hospital Arcee have started to evaluate their data for care delivery process improvements. The responded mentioned that,

> We are working the technology vendor on an AI-powered Cardio API platform, which would enable our patients to come to the hospital and be able to find their heart risk score without a detailed health check-up.

Hospital Prime use micro videos as a main mode of communication for their clinical community. The respondents commented that,

> We use micro video snippets to explain new features that are introduced to the clinicians like here are some new things you can do in EMR, here's a faster way to

> discharge a patient, here's a better way to communicate with your colleagues.
>
> We use vendor conferences to learn about the new technologies and the best practices for implementations. Pilots and software protypes are extensively used for engaging the clinicians to increase the adoption of new innovations.
>
> We form a multi-disciplinary team is formed that consists of stakeholders from various departments - Innovation center, data sciences, IT and clinical community. The innovation center and data sciences team crystallize the idea to come up with prototypes and they look for proof of concept and once there's some level of a proof for validity to their thought process, then they engage IT to try to scale it.

Hospital Prime leverages their enterprise wide EMR system as a repository for all of their patient clinical data by integrating it with other sub systems and AI tools. The respondent mentioned that,

> We have an AI tool that integrates with our enterprise wide EMR (electronic medical records) system to find complex patterns in big data, both clinical data and research data, to gain insights that might be missed using traditional statistical approaches.

Hospital Cliffjumper follow a formal process defined by the innovation center more from an IT leadership standpoint. For the most the clinicians use informal processes. The responded commented that,

> As a clinician, I have been here long enough, and I know the IT leadership well enough. I could just go straight to them and say, you know, I got this idea, and this needs to be done or we got to look at this.

Hospital Cliffjumper leverage their historical data in their enterprise wide EMR by integrating it with other sub systems to perform BIG data analytics and build AI tools. The responded mentioned that,

> We have created a data warehouse to enable it to use historical data to develop and refine its models, and gradually transition from retrospective to real-time analysis.

Hospital Carrera utilizes a well-established change management approach. The respondent commented that,

> We have a change management process that becomes a very integral part of introducing any technology.

Hospital Lightbright have an enterprise level decision making group. The respondent commented that,

> There is a decision-making group on an enterprise level that consists of multi-disciplinary clinical and operational leaders who review the strategic and operational goals for new technology initiatives.
>
> As an EMRAM Stage 7 hospital, Hospital Lightbright is at the highest stage that represents an advanced electronic patient record, paperless environment and capability for community healthcare information exchange. The respondent commented that, We are working with our technology vendors to build a data warehouse to integrate the data from various systems to drive decisions support off of those registries of at risk or high risk populations and drive decision support right at the point of care.

All the case hospitals have implemented a centralized electronic medical records (EMR) and leveraging their BIG DATA assets for predictive analytics.

Barriers

A common theme was noted in all the cases from the answers related to barriers question in disseminating innovations in hospitals. All respondents mentioned that the barriers to innovations in their organizations are legal/regulatory constraints, reimbursement challenges and resources contention issues. The other themes emerged during the interviews are summarized in Table 4.

Table 4.
Summary of Barriers to AI Innovation Adoption

THEME	DESCRIPTION
1. Change	"This is a sea change for clinicians the way they operate and they are uncomfortable with machine-enabled clinical decisions"
2. Job Security/Fear	"Though artificial intelligence is an emerging area in healthcare industry, there is potential to make workflows more efficient with machine learning and automation"
3. Liability	"You're actually doubling and tripling the liability, legal liability, even one vendor defaults"
4. AI Terminology & Understanding	"AI - Artificial Intelligence or Augmented Intelligence? - a lot of people mix up AI, machine learning and predictive analytics"
5. Overhype of Benefits	"Most of the vendor solutions are chasing the problems and we need to make sure the selected solution fits the clinicians workflow to increase the adoption."
6. Trust in Technology	"Clinicians see this as a "black box" problem, the inability of systems to explain how they arrived at a decision"
7. Technology Maturity	"AI technology is maturing but their applications in healthcare is not yet, but will get there soon"
8. Technology Cost	"The technology's not becoming affordable unfortunately, and hence we are losing the benefit of technology of what it can do"

	9. Data Cleanliness	"We need to do a better job on our data cleanliness. The moment you clean your data, its ability to be analyzed and worked upon increases a lot"
	10. Risk Sharing	"Willingness of the vendor to share risk"
	11. Risk Tolerance	"With innovation comes risk and some of these concepts will work and some of them won't"
	12. Resource Limitations	" Our clinicians are so pressed for time and they're still recovering from adopting the EMR"

Discussion

Overall, I noticed similar structural changes as well as management and co-specialization practices, across all the cases. The common patterns in the relationship between the composition of dynamic capabilities portfolio and innovation adoption is interesting.

The empirical findings of this study confirm the different manifestations of dynamic capabilities. First, I noted that all of the different forms of dynamic capabilities (two different practices of sensing, two of seizing and three of reconfiguring capabilities) were represented in all the five case companies. I have utilized dynamic capabilities model defined by (Teece, 2007) to examine the empirical components of dynamic capabilities. Thus, this study contributes to the dynamic capabilities view from conceptual work towards empirical operationalization.

Second, the empirical findings indicate that different forms of dynamic capabilities differ in terms of the commonalities and idiosyncratic features between cases. Manifestations of sensing and seizing capabilities seemed to be largely similar across the case companies. The academic hospitals leverage more of their internal R&D efforts to identify the new opportunities whereas the community hospitals work with the external technology vendors to consummate new innovations. All the case hospitals leadership have made significant commitment and investments in technology advancements. They all followed a multi-disciplinary team practices to synchronize the work between various departments. On the other hand, the data analysis suggests that there are more commonalities in the manifestation of sensing and seizing capabilities than of reconfiguring capabilities. It seemed that while the outcomes of reconfiguring capabilities are sometimes apparently very similar, the actual internal processes leading to them vary case by case. For data integration capabilities , some case hospitals created their own data warehouse for analytics, but others worked with their vendors for data integration efforts. Regarding learning capability, some case hospitals have taken the approach of “learning by experimentation” by creating innovation labs and others used “learning by doing” by creating prototypes and pilot programs. The implication is that reconfiguring activity as such does not depend as much on the context in which it functions. It seems that sensing and seizing are, to a large extent, dependent on firm-specific factors such as the firm's existing type of structure (academic or community hospital). Therefore, the practices comprising sensing and seizing capabilities are likely to be similar across firms within a single industry, while practices comprising reconfiguring capabilities likely differ more between firms. As such, I argue that a prerequisite for hospitals to survive and prosper is a relatively strong ability to discover and develop new opportunities; in other words, strong sensing and seizing capabilities.

The organizations studied have the awareness of AI innovations and AI appears on their organization’s innovation strategy/agenda. For community hospitals, the AI applications inspiration comes outside of the organization and for academic hospitals the inspiration springs from both outside and inside of the organization. The management team is captivated by industry or functional use cases and has made significant investments to explore the potential of AI benefits primarily in the clinical areas. These organizations are very active in the experimentation of AI-driven innovations and the leadership is actively involved in promoting and facilitating the adoption of AI innovations in their institutions.

Contributions

The dynamic capabilities research stream identifies two diverging schools of thought regarding assumptions about firms' degree of heterogeneity in their dynamic capabilities. According to (Teece et al., 1997), dynamic capabilities are essentially firm specific and unique. In contrast, Eisenhardt and Martin (2000) asserted that though idiosyncratic, dynamic capabilities exhibit commonalities or "best practices" across firms.

This study contributes to the literature with regard to theory by showing that dynamic capabilities have both commonalities and idiosyncratic features across the firms in the same industry. The inductively developed operational model in this study that is used to explore heterogeneity of dynamic capabilities in a healthcare setting is a progression in the field of dynamic capabilities from conceptual work towards empirical operationalization.

From a managerial point of view, this study has important implications. The findings shed light on manifestations of dynamic capabilities in actual business processes and practices in a healthcare setting. This illustrates to the practicing managers that the healthcare organizations with strong and versatile dynamic capabilities that build on their existing knowledge are better able to integrate the innovations into their internal operations and existing services. Managers should not be falsely comforted by the current situation of their firm capabilities but pay attention to the identified barriers of innovation adoption in their respective organizations and act on it to scale innovations in their organizations.

Limitations and Future Research Recommendations

There are some limitations associated with this study, some of which point to promising directions for future research endeavors. First, the data comes from five cases representing the healthcare provider industry, and care should thus be taken in generalizing the findings to other contexts. Future studies could explore the linkages between dynamic capabilities and innovation adoption by expanding the organization types to include for-profit hospitals and in other contexts. Second, the cases may have idiosyncratic characteristics. The selected case companies were all considered innovative and involved in AI implementations, which may have an impact on their capabilities. The suggested relationships need to be validated against other cases and methods to see if these inductive insights survive the empirical test. Nevertheless, the study opens up avenues for future research. For example, longitudinal studies on innovation adoption and capabilities and their coevolution would be valuable. It would also be interesting to find out how sensing, seizing and reconfiguring capabilities are manifested in other industries, and how they differ from those identified in this study. To conclude, I consider the interrelationship between a firm's capabilities and its innovation activities a very complex and promising research area.

CHAPTER 4

STUDY 2: INNOVATION ADOPTION (INDIVIDUAL LEVEL)

Framing

This study applies the Unified Theory of Acceptance and Use of Technology (UTAUT) to clinicians' (physicians/nurses) adoption of AI (Artificial Intelligence) technology. UTAUT integrates eight theories of individual acceptance into one comprehensive model designed to assist in understanding what factors either facilitate or hinder technology adoption and use. As AI technologies become prevalent in healthcare industry, the UTAUT model provides a useful lens through which to view what is currently taking place in the healthcare industry regarding AI adoption. This research has considerable relevance to both the healthcare and IS communities, as UTAUT offers valuable practical insight to the healthcare industry in identifying the key factors that drives the decisions to adopt AI technology as well as what prescriptions may facilitate future adoption, while offering the IS community the opportunity to strengthen existing theory through an illustration of its application.

Conceptual Model and Hypothesis

The UTAUT model was developed from eight theories, which include the Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivational Model (MM), Theory of Planned Behavior (TPB), Combined TAMTPB (C-TAM-TPB), Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT) and Social Cognitive Theory (SCT) (Venkatesh et al., 2003). The UTAUT model constructs are described in Table 5.

Table 5.

UTAUT Model Construct Definitions (Venkatesh et al., 2003).

CONSTRUCT	DEFINITION
Performance Expectancy	The degrees to which an individual believes that using the system will help him or her attain gains in job performance
Effort Expectancy	The degree of ease associated with the use of the system
Social Influence	The degree to which an individual perceives that important other believe he or her should use the new system
Facilitating Conditions	The degree to which an individual believes that an organization and technical infrastructure exist to support use of the system
Behavior Intention	An individual users' behavior intention to using the technology

One of the implications drawn from Venkatesh et al.'s (2003) UTAUT study was the importance of analyzing contextual factors when developing implementation strategies. The medical informatics literature contains a large body of research pertaining to technology adoption and use. Based on my literature review, I mapped the UTAUT constructs to relevant themes in a healthcare context.

In the following paragraphs, I will discuss these themes within the context of the UTAUT constructs in which we categorized them and offer several hypotheses designed to guide this research. Figure 3 shows our conceptual mapping and outlines our research hypotheses.

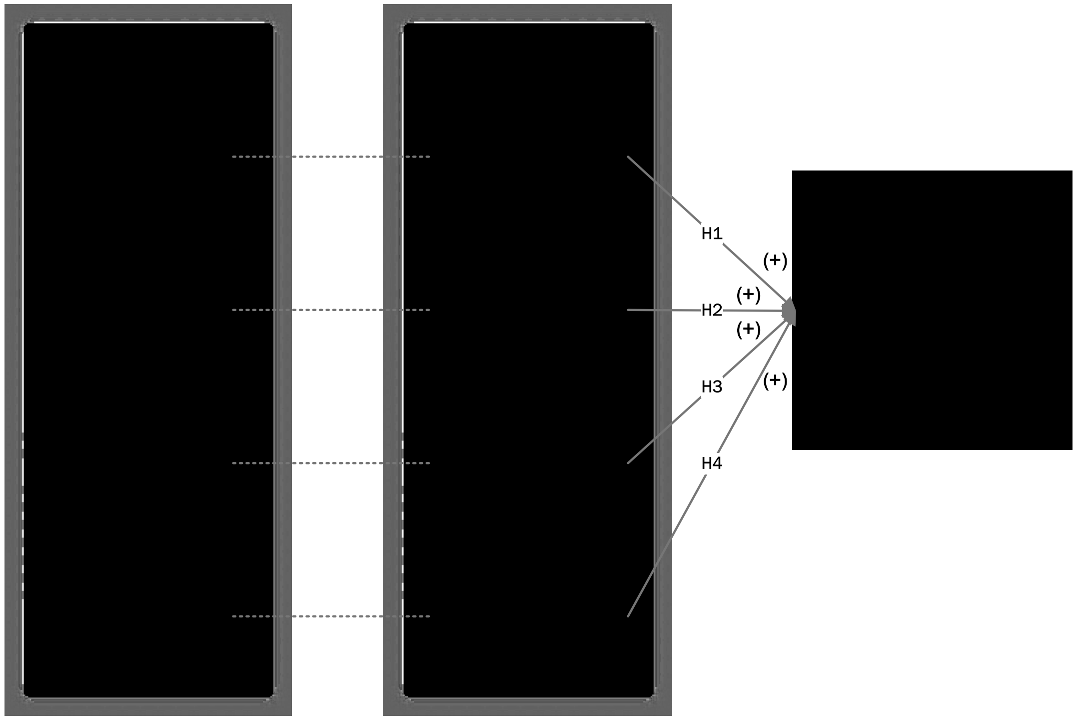

Figure 3. Unified Theory of Acceptance and Use of Technology (UTAUT) Conceptual Model (Healthcare Context)

Performance Expectancy

Performance expectancy is defined as “the degree to which a person believes that using a particular system would enhance his or her job performance”, which is derived from perceived usefulness proposed in the original TAM (Fan et al., 2018).

Venkatesh et al. (2003) demonstrated that performance expectancy had a direct influence on behavioral intention towards adopting a target technology.

Healthcare technology helps to improve the quality and performance of treatments (Calman et al., 2007). So, I map the construct Performance Expectancy to Quality of Care in a healthcare context.

The rise of artificial intelligence (AI) in the era of big data could assist clinicians in shortening processing times and improving the quality of patient care in clinical practice. Clinicians diagnose diseases based on personal medical histories, individual biomarkers, and their physical examinations of individual patients. In contrast, AI can diagnose diseases based on a complex algorithm using hundreds of biomarkers, imaging results from millions of patients, aggregated published clinical research from PubMed, and thousands of physician's notes from electronic health records (EHRs) (Krittanawong, 2018).

Based on the discussions above, we argue that the mechanisms related to performance expectance and behavior intention is also true in the context of AI Technology. Consequently, the following hypothesis H1 is suggested:

H1: Quality of Care has a positive influence on behavioral intention to use AI Technology.

Effort Expectancy

Effort expectancy is defined as “the degree of ease associated with the use of the system”, which is derived from perceived ease of use proposed in the original TAM (Venkatesh et al., 2003).

In organizational settings, employees assess time and effort in forming views about the overall effort associated with the acceptance and use of technologies (Venkatesh et al., 2012).

A clinician’s effort expectancy is shaped by his or her perceptions of the ease of use associated with a system. I suggest that clinicians’ effort expectancy is shaped not only by the ease of use of the technology, but also by the effort required to incorporate technology into existing work processes.

The easier to operate a new technology i.e. when the clinicians perceive that the technology is less complex, the more active they are to use it. Therefore, I map the construct effort expectancy to the complexity of AI technology, and I expect that it is important for the clinicians to perceive ease of use when using AI technology. Consequently, the following hypothesis H2 is suggested:

H2: Technical Complexity has a positive influence on behavioral intention to use AI technology.

Social Influence

Social influence is defined as "the degree to which an individual perceives that important others believe he or she should use the new system". Individuals are more or less influenced by others, especially those who are closer and important to them, such as relatives, friends, superiors, etc. (Venkatesh et al., 2003).

From health organizations' perspective, the clinicians may take more consideration on the top management support (Fan et al., 2018).

Good support from management may facilitate healthcare professional adoption of technology (Gagnon et al., 2016). So, we map the construct social influence to leadership support in a healthcare context.

Thus, I believe that clinicians' intention to use AI technology would be impacted by important persons in their social circles mainly the leaders of their organization. Consequently, the following hypothesis H3 is suggested:

H3: Leadership support has a positive influence on behavioral intention to use AI

Technology.

Facilitating Conditions

Facilitating Conditions are circumstances that an individual believes exist to support his/her activities, such as the infrastructure or environment (Phichitchaisopa & Naenna, 2013). Specifically, in UTAUT, facilitating conditions is hypothesized to influence technology use directly based on the idea that in an organizational environment, facilitating conditions can serve as the proxy for actual behavioral control and influence behavior directly because of many aspects of facilitating conditions, such as training and support provided (Venkatesh et al., 2012).

Prior research has distinguished between operational (or ordinary) and dynamic capabilities (Winter, 2003; Helfat et al., 2007). An operational capability enables the firm to perform an activity on an on-going basis using more or less the same techniques on the same scale to support existing products and services for the same customer population. Such a capability is ordinary in the sense of maintaining the status quo (that is not out of the ordinary; (Winter, 2003) refer to these as zero order capabilities.

In contrast, a dynamic capability is one that enables a firm to alter how it currently makes it living by altering their operational capabilities or features of the external environment or ecosystem (Helfat & Winter, 2011). (Teece, 1997) defined dynamic capabilities as “the firm’s ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments in which there is deep uncertainty.”

AI technology is still in a fairly early stage of implementation in the healthcare sector, and organizations are working on building new operating capabilities to adopt AI technologies.

Therefore, I map the construct facilitating conditions to dynamic capabilities in a healthcare context and argue that clinicians who has access to a favorable set of facilitating conditions is more likely to have a higher intention to use a technology. Thus, I hypothesize:

H4: Dynamic Capabilities act as facilitating conditions that has a positive influence on behavioral intention to use AI Technology.

Research Design and Methods

Instrument Design

I have conducted a survey among clinicians (physicians and nurses) in healthcare organizations to inspect the five determinants of healthcare technology acceptance: performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention; no modulators included. The questionnaire was divided into two parts: demographic respondent profiles and affected factor items. First, the demographic questions ask for age, and employment experience. Next, affected factors the five latent constructs were scale items for examining the determinants.

Table 6 summarizes the operational definitions of construct items. Each item was measured using a five-point Likert type scale with anchors ranging from “strongly agree” (1) to “strongly disagree” (5).

Table 6.

Construct Measurement Items.

CONSTRUCT	ITEM CODE	QUESTION (modified)	SOURCE
Performance Expectancy **(Quality of Care)**	PE1	AI technology enhances the efficiency of my service	Healthcare technology enhances the efficiency of your service (Phichitchaisopa and Naenna, 2013)
	PE2	AI technology enhances accessibility and communication with my patient/customer	Healthcare technology enhances accessibility and communication with your patient/customer (Phichitchaisopa and Naenna, 2013)
Effort Expectancy **(Technical Complexity)**	EE1	I would find the AI technology easy to use	I would find the system easy to use (Venkatesh et al., 2003)
	EE2	My interaction with the AI technology would be clear and understandable	My interaction with the system would be clear and understandable (Venkatesh et al., 2003)
Social Influence **(Leadership Support)**	SI1	People who influence my behavior think that I should use the AI technology	People who influence my behavior think that I should use the system (Venkatesh et al., 2003)
	SI2	People who are important to me think that I should use the AI technology	People who are important to be think that I should use the system (Venkatesh et al., 2003)
	SI3	The senior management of this business has been helpful in the use of AI technology	The senior management of this business has been helpful in the use of the system (Venkatesh et al., 2003)
	SI4	In general, the organization has supported the use of the AI technology	In general, the organization has supported the use of the system (Venkatesh et al., 2003)
Facilitating Conditions **(Dynamic Capabilities)**	FC1	My organization pays attention to bring in new AI technology	Your healthcare pays attention to bring in new technology (Phichitchaisopa and Naenna, 2013)
	FC2	My organization provides training for using the new AI technology	Your healthcare provides the training for employee whenever there is important on the system/technology (Phichitchaisopa and Naenna, 2013)

Intention to Use	USE1	I intend to use AI technology in my patient care and management when it becomes available in my department or hospital	[ITU1] I intend to use telemedicine technology in my patient care and management when it becomes available in my department or hospital (Hu et al., 1999)
	USE2	I intend to use AI technology to provide health-care services to patients as often as needed	[ITU2] I intend to use telemedicine technology to provide health-care services to patients as often as needed (Hu et al., 1999)
	USE3	I intend NOT to use AI technology in my patient care and management routinely	[ITU3] I intend NOT to use telemedicine technology in my patient care and management routinely (Hu et al., 1999)
	USE4	Whenever possible, I intend NOT to use AI technology in my patient care and management	[ITU4] Whenever possible, I intend NOT to use telemedicine technology in my patient care and management (Hu et al., 1999)
	USE5	To the extent possible, I would use AI to do different things, clinical or nonclinical	[ITU5] To the extent possible, I would use telemedicine to do different things, clinical or nonclinical (Hu et al., 1999)
	USE6	To the extent possible, I would use AI in my patient care and management frequently	[ITU6] To the extent possible, I would use telemedicine in my patient care and management frequently (Hu et al., 1999)

Subject and Sampling

The subjects for this study are clinicians (physicians and nurses) working in healthcare organizations in Pennsylvania and New Jersey. This study was approved by Temple university IRB board. The recruitment of care providers to participate in the surveys was made possible by my industry associations and professional networking; no materials were used to recruit respondents, and the list of possible participants was obtained from private contacts.

The online survey created using Qualtrics tool was posted for about ten weeks from November 2018 to January 2019. The survey questions are listed in APPENDIX B. The Qualtrics online survey web link was sent out via email to private contacts using two methods: (1) directly sending the survey link to known contacts of physicians and nurses, and (2) sending the survey link to heads of physician groups and nursing groups so that they could forward it to individuals in their organization via email distribution lists. In total, I reached out to about 250 clinicians and received 103 responses. After removing 19 incomplete questionnaires, the 84 completed questionnaires yielded a total response rate comprising 40% of the primary population. Table 7 shows the demographic age profile of the survey respondents. The demographic profile shows that the majority of the respondents are “Generation X” about 45% are between 38 and 53 years old.

Table 7.
Demographic Age Profile.

Age bracket	%	Count	Generation*
18 - 37 years	20%	17	Millennials
38 - 53 years	46%	38	Generation X
54 - 72 years	35%	29	Boomers

* Definition from Pew Research center: http://www.pewresearch.org/fact-tank/2018/03/01/defining-generations-where-millennials-end-and-post-millennials-begin/

Data Analysis and Results

Partial least squares (PLS) is a second-generation structural equation modeling (SEM) technique that is used to evaluate causal relationship between latent constructs. Compared to other structural equation modeling (SEM) techniques, like AMOS and LISREL, PLS has advantages when analyzing sample of small size (Wu et al., 2011). In this study, I examined a sample of 84 clinicians, the size of which may not be large enough for AMOS or LISREL technique. The constructs used in the model are reflective latent constructs i.e. the causality goes from the construct to the indicators. PLS is suitable for validating predictive models that uses reflective latent constructs (Chin, 1998). Therefore, for this study I applied PLS (SmartPLS V 3.2.7) to analyzing the proposed research model as depicted in Figure 3. The PLS supports two measurement models: (1) the assessment of the measurement model, and (2) the assessment of the structural model.

As criteria for reflective models, the study first evaluated the measurement model based on validity and reliability coefficients of Cronbach's Alpha (CA), Composite Reliability (CR), Average Variance Estimates (AVE), Discriminant Validity and Heterotrait-Monotrait (HTMT). This was followed by examining the significance of the structural model based on, hypothesized relationship testing, Effect size (f2), Predictive relevance (Q2), and Importance–Performance Map Analysis (IPMA).

Assessment of the Measurement Model

The first stage in PLS analysis is measurement model evaluation that is used to examine the reliability and validity of each construct (Anderson & Gerbing, 1988), which reveals whether the items developed in questionnaire are able to comprehensively and validly measure constructs in AI technology adoption model for healthcare professionals. This is an essential prerequisite to validate the model based on questionnaire design as explained in Table 6.

Assessment of reflective models involves determining (1) indicator reliability (squared standardized outer loadings), (2) internal consistency reliability (composite reliability), (3) convergent validity (average variance extracted, AVE), and (4) discriminant validity (Fornell-Larcker criterion, cross-loadings) (Henseler et al., 2009; Hair et al., 2011). Table 8 exhibits the indexes of reliability and convergent validity for the scale items.

Table 8.
Measurement Model Results.

	Items	Loadings[a]	AVE[b]	CR[c]	Cronbach Alpha[d]
Quality of Care	PE1	0.945	0.888	0.941	0.874
	PE2	0.940			
Technical Complexity	EE1	0.958	0.899	0.947	0.888
	EE2	0.938			
Leadership Support	SI1	0.969	0.939	0.969	0.935
	SI2	0.969			
Dynamic Capabilities	FC1	0.927	0.909	0.952	0.908
	FC2	0.980			
Intention to use AI	USE1	0.882	0.665	0.908	0.873
	USE2	0.888			
	USE4A	0.714			
	USE5	0.805			
	USE6	0.776			

a. All Item Loadings > 0.7 indicates Indicator Reliability (Hulland, 1999)
b. All Average Variance Extracted (AVE) > 0.5 indicates Convergent Reliability (Bagozzi & Yi, 1988; Fornell & Larcker, 1981)
c. All Composite Reliability (CR) > 0.7 indicates Internal Consistency (Gefen, et al., 2000)
d. All Cronbach's alpha > 0.7 indicates Indicator Reliability (Nunnally, 1978)

Indicator Reliability

In PLS, individual item reliability is assessed by examining the loadings (or simple correlations) of the measures with their respective construct. A rule of thumb employed by many researchers is to accept items with loadings of 0.7 or more, which implies that there is more shared variance between the construct and its measure than error variance (Hulland, 1999).

During my iteration #1 of testing shown in Figure 4, the loading values for two items were <0.7. So, I removed the items SI4 (0.697) indicator of “Leadership Support” construct and USE3A(0.624) indicator of “Intention to Use” construct. During the iteration #2 of testing shown in Figure 5, I found the loading value of the item SI3 became < 0.7. So, I removed the item SI4 (0.604) indicator of “Leadership Support” construct. After removing the three items, we ran the final iteration of indicator testing shown in Figure 6, and all the indicators items values were loaded > 0.7 as shown in Table 8. We used this model as our final model to perform further assessments.

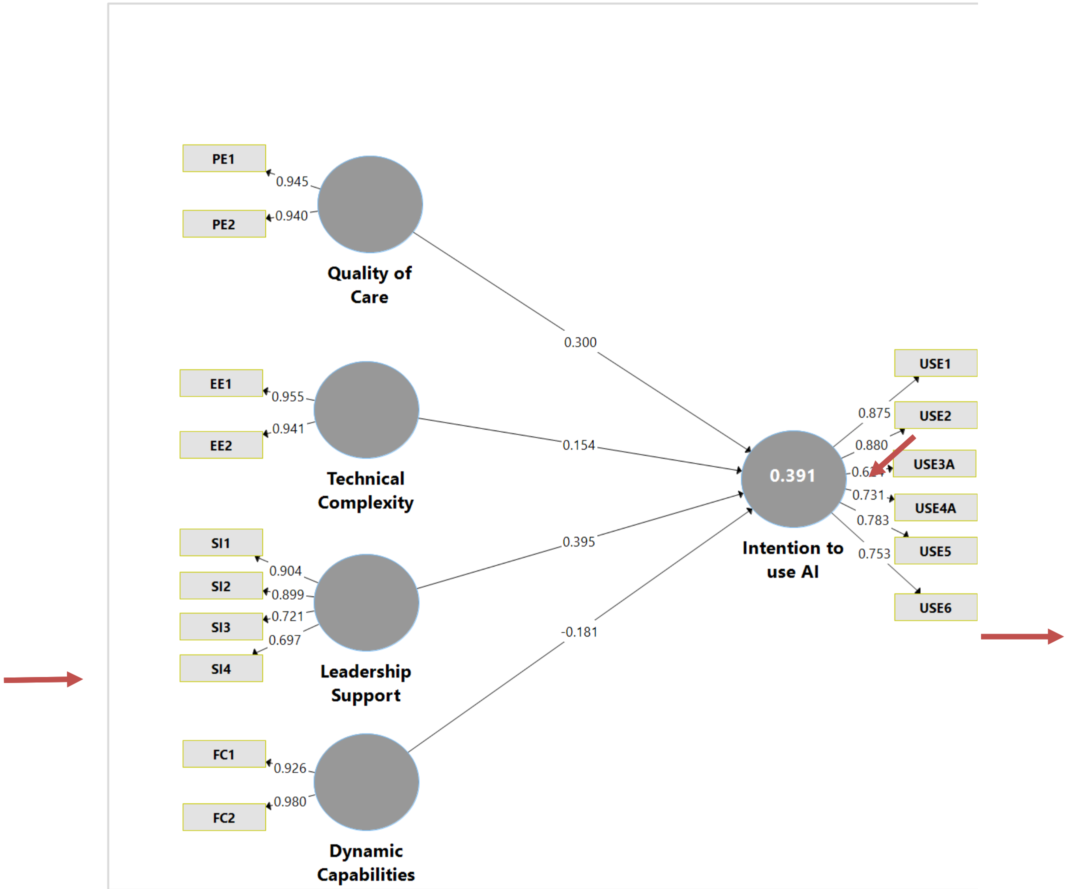

Figure 4. Indicator Reliability Testing #1.

*The loading values for Items SI4 (0.697) and USE3A (0.624) < 0.7

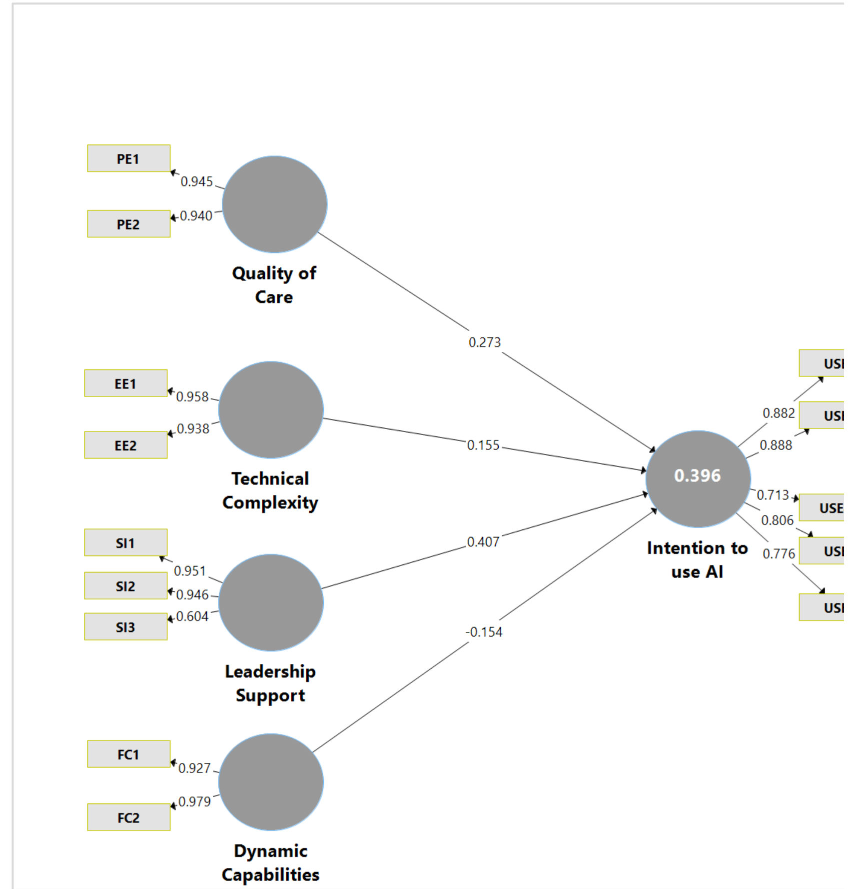

Figure 5. Indicator Reliability Testing #2.

*The loading values for Item SI3 (0.604) < 0.7

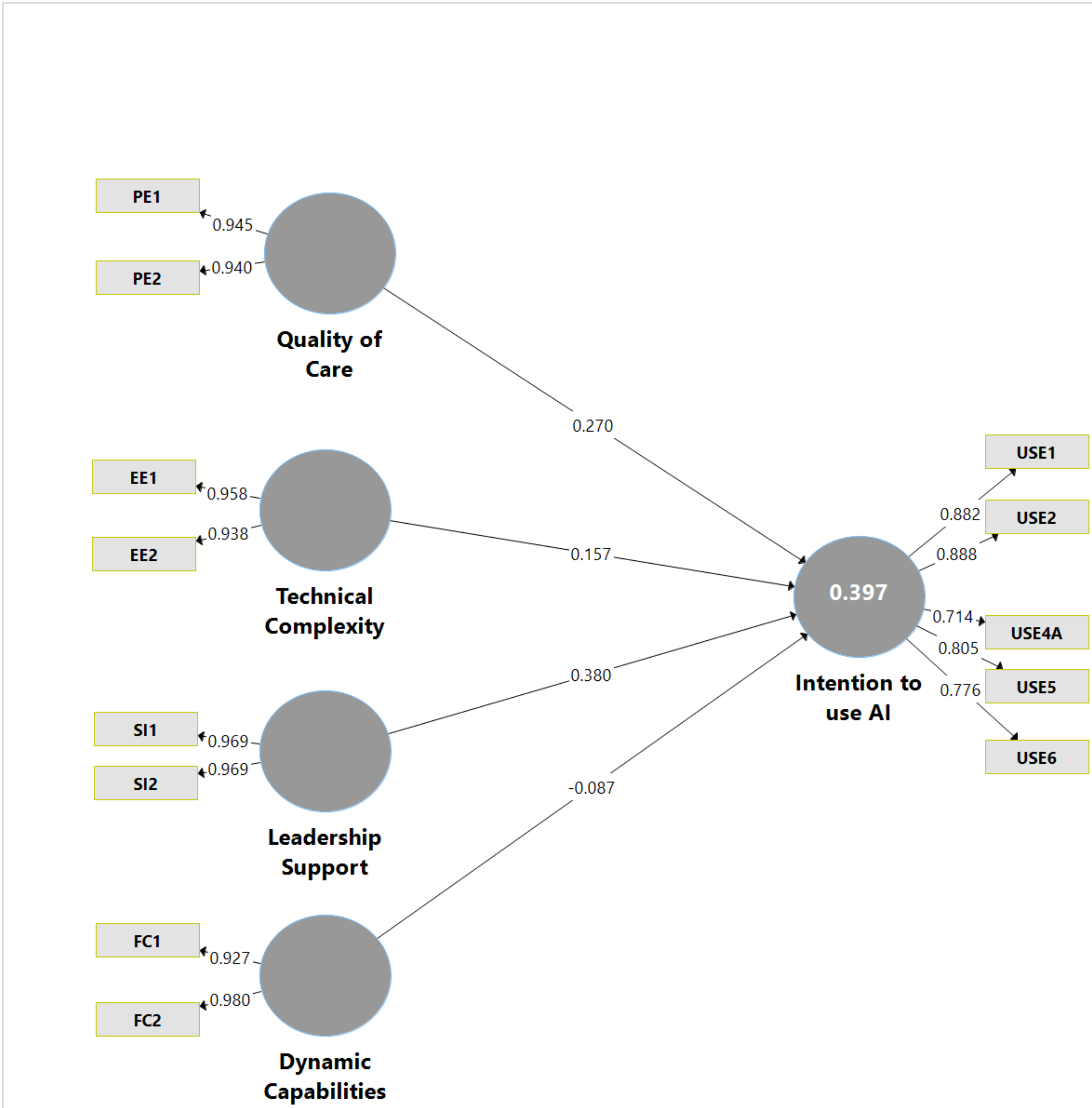

Figure 6. Indicator Reliability Final.

*The loading values for all indicator items were > 0.7

Internal Consistency Reliability

Prior assessments of reporting practices revealed that Cronbach's alpha is the most common measure of internal consistency reliability (Shah & Goldstein 2006; Shook et al., 2004). However, Cronbach's alpha is limited by the assumption that all indicators are equally reliable (tau-equivalence), and efforts to maximize it can seriously compromise reliability (Raykov, 2007). In contrast, composite reliability does not assume tau-equivalence, making it more suitable for PLS-SEM, which prioritizes indicators according to their individual reliability (Hair et., 2012). In this study, we calculated both Cronbach's alpha and Composite reliability (CR). All Composite Reliability (CR) > 0.7 indicates internal consistency (Gefen, et al., 2000) and Cronbach's alpha > 0.7 indicates indicator reliability (Nunnally, 1978). Table 8 shows that Cronbach's alpha and composite reliability (CR) value of all constructs exceed 0.7, which indicates a high degree of reliability.

Convergent Validity

When multiple measures are used for an individual construct, the researcher should be concerned not only with individual measurement item reliability, but also with the extent to which the measures demonstrate convergent validity.

The convergent validity is commonly assessed by the criteria average variance extracted (AVE) and the average variance extracted (AVE) for each construct should be higher than 0.5 (Wu et al. 2011). As shown in Table 8, the AVE of each construct is above the suggested value 0.5 and this demonstrates a high level of convergent validity.

Discriminant Validity

The discriminant validity is assessed by a rule of thumb that the square root of AVE for each construct is supposed to be higher than its correlations with other constructs (Fornell, 1982; Fornell & Larcker 1981).

Table 9 shows Indicator Item Cross Loadings and all are in the acceptable range.

Table 10 shows that in no case was any correlation between the constructs greater than the squared root of the AVE (the principal diagonal element).

Table 11 shows that the HTMT values are well below the threshold value 0.9.

Overall, the assessment of the measurement model showed the study's construct measures possessed the required reliability and validity.

Table 9.
Indicator Item Cross Loadings (Discriminant Validity).

	Dynamic Capabilities	Intention to use AI	Leadership Support	Quality of Care	Technical Complexity
EE1	0.315	0.483	0.474	0.568	**0.958**
EE2	0.311	0.403	0.416	0.583	**0.938**
FC1	**0.927**	0.130	0.327	0.308	0.303
FC2	**0.980**	0.243	0.356	0.437	0.325
PE1	0.414	0.481	0.494	**0.945**	0.612
PE2	0.353	0.460	0.347	**0.940**	0.528
SI1	0.328	0.529	**0.969**	0.432	0.480
SI2	0.370	0.525	**0.969**	0.436	0.434
USE1	0.276	**0.882**	0.463	0.48	0.460
USE2	0.255	**0.888**	0.553	0.454	0.462
USE4A	0.205	**0.714**	0.407	0.364	0.303
USE5	0.064	**0.805**	0.363	0.372	0.378
USE6	0.021	**0.776**	0.406	0.349	0.287

* Cross Loadings > 0.7 is acceptable (Chin, 2010)

Table 10.
Discriminant Validity (Fornell-Larcker Criterion).

	Dynamic Capabilities	Intention to use AI	Leadership Support	Quality of Care	Technical Complexity
Dynamic Capabilities	**0.953**				
Intention to use AI	0.211	**0.816**			
Leadership Support	0.360	0.544	**0.969**		
Quality of Care	0.408	0.500	0.448	**0.943**	
Technical Complexity	0.330	0.471	0.472	0.606	**0.948**

*The diagonals are the square root of the AVE of the latent variables and indicates the highest in any column or row

Table 11.
Discriminant Validity (HTMT).

	Dynamic Capabilitie s	Intention to use AI	Leadership Support	Quality of Care	Technical Complexit y
Dynamic Capabilities					
Intention to use AI	0.240				
Leadership Support	0.814	0.552			
Quality of Care	0.436	0.595	0.587		
Technical Complexity	0.365	0.537	0.590	0.687	

*The threshold value is < 0.9 (Gold et al., 2001)

Assessment of the Structural Model

The structural model evaluation is the second stage in PLS analysis for testing hypothesis. The structural model presents information about the path significance and an indication of the model's predictive power R-Square (R2). R2 is coefficient of determination that represents the amount of variance in the latent endogenous constructs that is explained by all of the other exogenous constructs linked to it and expressed as a percentage (Chin, 1998). The R2 ranges from 0 to 1 with higher values indicating higher levels of predictive accuracy. The PLS structural model can also be assessed by their effect size (f2). The effect size evaluates if the omitted construct has a substantive impact on endogenous construct which is also known as the effect size of the exogenous latent variable on the model. The assessment of this effect size follows (Cohen, 1988) guidelines which are 0.02, 0.15 and 0.35 for small, medium and large effects respectively.

Blindfolding is a sample re-use technique to calculate predictive relevance (q2). It allows calculating Stone-Geisser's Q^2 value (Stone, 1974; Geisser, 1974), which represents an evaluation criterion for the cross-validated predictive relevance of the PLS path model.

Bootstrapping

The bootstrapping method estimates the spread, shape, and bias of the sampling distribution of the population from which the sample under study is drawn from. The observed samples are treated as if represents the population. Bootstrapping creates a large, pre-specified number of samples and every time sampling happens in bootstrap the same number of cases as the original sample will be analyzed. The path significance levels (t-values) are estimated by the bootstrapping method (Chin, 1998).

Bootstrapping analysis is used to evaluate the direct effects of all the hypothesized relationships that are represented by statistical testing of the hypothesis. The hypothesis is supported if $t_{0.05} > 1.96$ (Peng & Lai, 2012). To assess the path significance and relevance of the structural model relationships I ran the Bootstrapping. Figure 7 shows the Smart PLS 3.0 results for the proposed structural model, with path coefficients and t-values. The thicker lines between the constructs represent more significance.

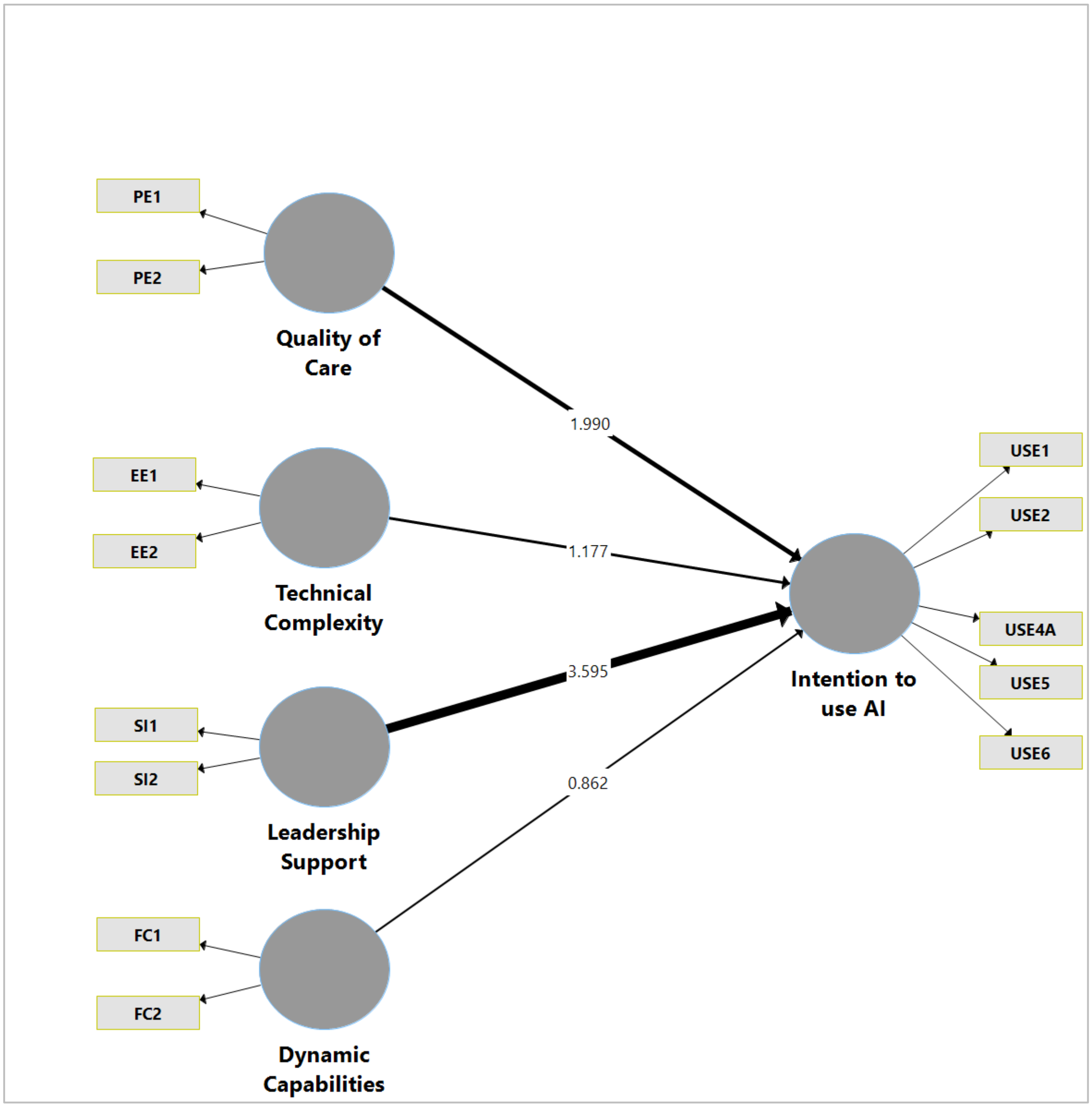

Figure 7. The SmartPLS 3.0 bootstrapping results for the hypothesized paths.

The results of the structural model and the direct relationships of hypothesis testing are presented in Table 12. The PLS results indicate that the research model is structurally sound as it offers adequate predictive performance. Of the four predictor constructs, leadership support had the strongest direct effect on intention to use AI technology, followed by quality of care. The model explains 39% of the variation in behavioral intention to use AI technology. Hypothesis (H1), the path coefficient between quality of care and intention to use AI technology, was 0.27, $p < 0.05$, indicating that quality of care had a positive and significant influence on intention to use AI technology. Hypothesis (H2), the path coefficient between technical complexity and intention to use AI technology, was 0.15, $p > 0.05$, which indicated that technical complexity did not have a positive and significant influence on intention to use AI technology. Hypothesis (H3), the path coefficient between leadership support and intention to use AI technology was 0.38, $p < 0.05$, indicating that leadership support had a positive and significant influence on intention to use AI technology. Hypothesis (H4), the path coefficient between dynamic capabilities and intention to use AI technology was -0.08, $p > 0.05$, which indicated that dynamic capabilities did not have a positive and significant influence on intention to use AI technology.

Examining the individual effect sizes of predictors (f^2) provides further information about the unique and separate contributions of each of the constructs. According to (Chin, 2010), $\mathbf{f^2}$ of 0.02, 0.15 and 0.35 can be viewed as a gauge for whether a predicting construct has a small, medium, or large effect at the structural level. With respect to Intention to use AI technology, Leadership Support (Social Influence) had the largest effect size (0.16) classified as “medium” according to the categories proposed by (Chin, 2010). Quality of Care (Performance Expectancy), Technical Complexity (Effort expectancy), and Dynamic Capabilities (Facilitating

Conditions) all had less of an effect with sizes in the “small” category. This indicates that the majority of the variance was accounted for by the combined effect of these four constructs rather than their separate, independent contributions.

Table 12.
Structural Model Results (Direct Relationships of Hypothesis Testing).

Hypothesis	Relationship	Std Beta	Std Error	t-value	p value	Decision	f^2	q^2	95% CI LL	95% CI UL
H1	Quality of Care -> Intention to use AI	0.270	0.136	1.99*	0.023	Supported	0.0663	0.0283	0.042	0.493
H2	Technical Complexity -> Intention to use AI	0.157	0.134	1.177	0.120	Not Supported	0.0232	0.0090	-0.054	0.389
H3	Leadership Support -> Intention to use AI	0.380	0.106	3.595**	0.000	Supported	0.1658	0.0746	0.203	0.546
H4	Dynamic Capabilities -> Intention to use AI	-0.087	0.101	0.862	0.194	Not Supported	0.0083	0.0051	-0.241	0.09

- Path significance: * $p < 0.05$, ** $p < 0.01$
- Marked coefficients (*) are significant at $p < 0.05$ ($t > 1.96$)
- R^2 (0.397)
- Effect size (f^2) impact indicators according to (Cohen, 1998); f^2 values: 0.35 (large), 0.15 (medium), and 0.02 (small)
- Q^2 (0.223)
- Predictive Relevance (q^2) of Predictor Exogenous Latent variables according to (Henseler et al., 2009); q^2 values: 0.35 (large) 0.15 (medium), and 0.02 (small)

Overall the results of measurement model analysis indicated that measures of all constructs demonstrated values for reliability and validity meeting existing criteria and thus indicating that they were psychometrically acceptable measures for this structural model. The structural model analytic results indicated that more than half of the variance in intention to use (IT acceptance) and over one quarter of the variance in IT use was explained by these measures. Given that there are a large number of factors that could impact both IT acceptance and IT use, the variance explained by our research model is substantial.

Discussion

The objective of this research is to identify the factors that predict the clinicians' intention to use AI technology in healthcare by applying an extant theoretical model. As a result, the focus of the study was the prediction of the intention to use AI technology by employing an adaptation of the UTAUT model. It is hypothesized that intention to use AI technology is a function of the perception that AI technology is useful (quality of care), that it exhibits ease of use (technology complexity), that important others and leadership believed that he/she should use AI technology (leadership support) and the perception that organization dynamic capabilities facilitates use AI technology.

The analysis shows that consistent with hypothesis 1 (H1), quality of care, or the degree to which a user believes AI technology will improve performance, has a positive effect on intention to use an AI technology. The results are consistent with previous studies (Venkatesh et al., 2003; Chang et al., 2007; Yi et al., 2006).

Prior studies indicate that clinicians perceive quality of care can be improved via the use of healthcare information systems (Nielsen et al.,2000; Overhage et al.,2001; Leung et al., 2003).

Secondly, interesting finding is the non-significant influence of technical complexity on intention to use an AI technology (H2), which is contrary to what was posited in the original UTAUT.

Prior studies completed in the health sector suggest that effort expectancy is not applicable in the health professional context (Hu et al.,1999; Schaper & Pervan, 2007).

Drawing upon the research (Venkatesh et al., 2013), the effort expectancy construct is significant only during the first time period of the technology use and become nonsignificant over the periods of extended and sustained usage.

About 60% of the survey participants in this study, answered that currently they are using AI technology in their organizations. Since they are already using AI technology, they might have integrated their workflows and optimized the process issues after the implementation. This is in line with prior studies that effort-oriented constructs are expected to be more salient in the early stages of new behavior, when process issues represent hurdles (Davis et al,. 1989; Szajna 1996; Venkatesh 1999). A plausible explanation for the unsupported prediction might be due to survey sample composition.

Thirdly, confirming the hypothesis (H3), the results showed that leadership support had the strongest effect on intention to use AI technology of all the main determinants. The finding in this aspect is inconsistent with the viewpoint noting that some healthcare professionals specifically physicians may have less need to rely on social influence when making decisions about accepting or rejecting technology perhaps due to their high level of autonomy (Aggelidis & Chatzoglou, 2009; Schaper & Pervan, 2007; Walter & Lopez, 2008). This study reveals that leadership support in relation to enhancing the use of AI technology does matter for the clinicians sampled in the study.

Finally, another interesting finding is the nonsignificant influence of dynamic capabilities on intention to use AI technology in this study (H4), which is consistent with prior studies. Prior studies revealed that facilitating conditions significantly predicted technology use but did not predict intention to use IT (Holden & Karsh, 2010; Johns, 2006; Klein, 2007b; Lapointe & Rivard, 2006; Raitoharju, 2005). When both performance expectancy and effort expectancy constructs are present, facilitating conditions becomes nonsignificant in predicting intention to use technology (Venkatesh et al., 2003).

Based on the data analysis from Study 1, the following comments from respondents validates that the AI technology is being widely adopted in hospitals.

> "Though artificial intelligence is an emerging area in healthcare industry, there is potential to make workflows more efficient with machine learning and automation."
>
> "AI technology is maturing but their applications in healthcare is not yet but will get there soon."
>
> "AI will assist in revolutionizing healthcare. It is going to be a definitive tool that clinicians can use for furthering clinical excellence and augmenting their clinical expertise. It will also expedite the speed of diagnosis."

Therefore, I argue that the perception of organization dynamic capabilities facilitates use of AI technology does not matter for the healthcare professionals sampled in the study as they all see that AI technology use and adoption is inevitable.

Contributions

From a theoretical point of view, this is a comprehensive study to understand the clinicians' intention to adopt AI technology with a focus on the unique features in healthcare context. I looked deep into the decision making process on an individual level to adopt a new technology. While many studies have discussed healthcare professional adoption of various applications, only few have focused on the application of artificial intelligence technology, a potential area to assist clinicians in the areas of diagnosis and treatment, reduce costs, improve quality of care, and easily integrate with patients (Krittanawong, 2017). As this study attempts to explain the clinician's behavior to apply AI technology in their daily work, my work extends the research by introducing a new adoption object.

By theorizing about how a simplified UTAUT without any moderators, to fit the context of AI technology adoption among clinicians, this study contributes significantly to both healthcare IT and UTAUT research.

From a managerial point of view, in order to encourage the clinicians to adopt AI technology, the hospital management should focus on:

(1) emphasize the usefulness and performance improvement of the technology to utilize AI technology solutions to performing their job.

(2) provide the right organizational and technical infrastructure to support the use of the implemented AI technology solutions.

(3) this study illustrates to the practicing managers the current trends and key impact areas of AI technology applications (diagnostic interpretation, clinical decision-making support, task automation, and medical education/research). Figure 8 summarizes the survey results and the key impact areas of AI technology with their aggregate rankings on a 1-5 scale. AI

applications in the areas of diagnostic interpretation is ranked highest (4.43) followed by task automation (4.26) then medical education/research (4.21), and clinical decision-making support (4.16).

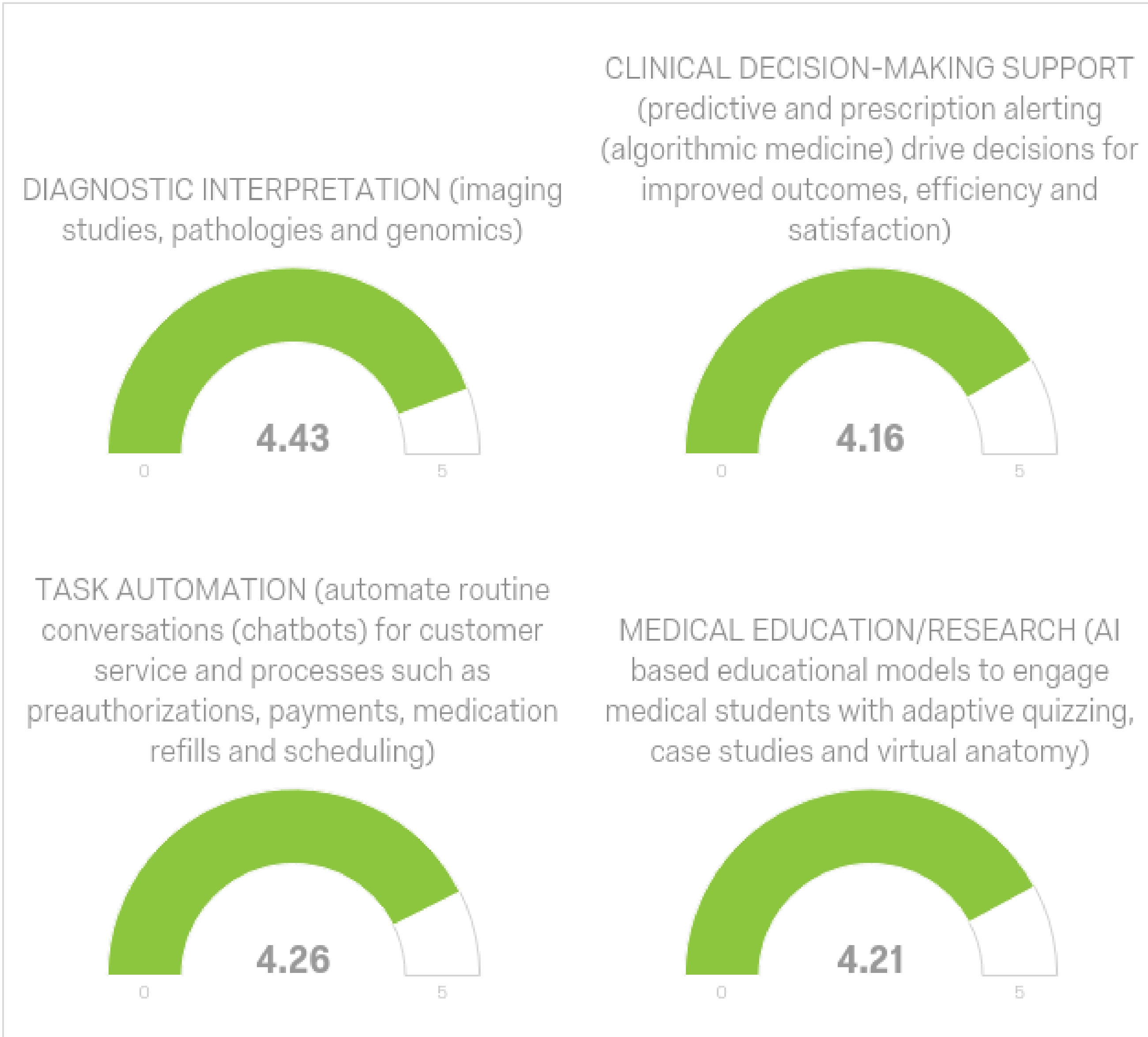

Figure 8. High Impact Areas of AI in Healthcare.

Limitations and Future Research Recommendations

Some ideas for future research emerge from the limitations of this study. Although the sample used in this study is relevant, this could be considered small. According to (Cohen, 1988) increases in sample size increase statistical power, thus probability of detecting the phenomenon under test increases. This is very significant in case of UTAUT model testing (Venkatesh & Zhang, 2011). Future research should address this limitation by conducting studies using larger samples.

Next, our study included both physicians and nurses, but other health professionals are involved in critical support roles like para-medics and physiotherapists. Studying their reactions and the interplay between the viewpoints of physicians, nurses and other healthcare professionals and the consequent impact on the use by all the user groups is an important next step in this line of inquiry.

CHAPTER 4

CONCLUSION

This dissertation is an exploration and examination of the facilitators and barriers to innovation adoption at both organizational and individual levels in healthcare organizations.

In the first study, I explored the capabilities that drive the adoption of Artificial Intelligence (AI) technology innovations in hospitals at the organizational level by using dynamic capabilities (DC) framework using qualitative case study methodology to address the question, “How dynamic capabilities enable AI technology adoption in hospitals?” This led to a new, inductively developed operational model that can be used to describe heterogeneity of dynamic capabilities in a healthcare setting. Further, this study illustrated that the practicing managers in healthcare organizations with strong and versatile dynamic capabilities, who build on their existing knowledge and capabilities are better able to integrate the innovations into their internal operations and existing services. The managers should also take the identified barriers of innovation adoption into account in their respective organizations and act on it to adopt innovations in their organizations.

In the second study, I examined clinicians’ (physicians/nurses) intentions to use AI innovations for patient care at the individual level within organizations by applying the Unified Theory of Acceptance and Use of Technology (UTAUT), utilizing a quantitative survey methodology to address the question “What are the key factors that influence clinicians' decision to adopt AI technology innovations?” The findings suggest that the impact of quality of care and leadership are key factors facilitating the adoption of technology innovations among clinicians.

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APPENDIX A

QUESTIONNAIRE FOR STUDY ONE

QUESTION (modified)	**SOURCE (Mikalef & Pateli, 2017)**
Are you doing any AI implementation in your organization? If so, What are the areas? How do you identify the need of new AI applications? Who drives the AI implementation decision in your organization?	[SNS_1] Scanning the environment and identifying new business opportunities
Coordinating: How do you synchronize the work with other functional units or business partners during the AI implementation?	[CRD_3] Ensuring that the output of work is synchronized with the work of other functional units or business partners
Learning: Who are the end users of AI? How do you educate implementation team and the end users regarding AI adoption benefits?	[LRN_3] Assimilate new information and knowledge
Integrating: Do your business partners have access to AI data and other resources real time? Do you share data and other resources with AI vendors?	[INT_1] Easily accessing data and other valuable resources in real time from business partners
Do you have an established AI implementation process/procedures/protocols? Did you change any of your old processes to facilitate the AI implementation?	[RCF_4] Reconfiguring our business processes in order to come up with new productive assets
What are the barriers to disseminating AI innovations in your organization?	

APPENDIX B

SURVEY QUESTIONS FOR STUDY TWO

Artificial Intelligence (AI) Innovations in Healthcare

Q1 The objective of this study is to understand the key factors that drives Artificial Intelligence (AI) technology innovations adoption among clinical care providers in health care organizations. The answers and comments you provide will be kept strictly confidential and anonymous. Clicking the "Yes" button below indicates your consent to participate in this survey.

- ○ Yes
- ○ No

Q2 What is your age bracket?

- ○ Under 18 years
- ○ 18 - 37 years
- ○ 38 - 53 years
- ○ 54 - 72 years
- ○ > 72 years

Q3 I am a

- ○ Physician
- ○ Nurse/Nurse Practitioner

Q4 Number of years in Clinical Practice:

- ◯ < 5 years
- ◯ 6 - 10 years
- ◯ > 10 years

Q5 In which country do you currently reside?

- ◯ United States of America
- ◯ India
- ◯ United Kingdom of Great Britain

Q6 Do you currently use any Artificial Intelligence (AI) application(s)?

Some AI application examples in health care are:

- Image analysis in radiology, pathology, and dermatology
- Robots assisting the human experts in surgery
- Virtual health assistants to monitor patient's condition and follow up with treatments
- Digital medical consultation based on personal medical history and common medical knowledge

- ◯ Yes
- ◯ No

Q7 Please indicate the extent to which you agree with the following statements:

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
AI technology enhances the efficiency of my service	○	○	○	○	○
AI technology enhances accessibility and communication with my patient/customer	○	○	○	○	○

Q8 Please indicate the extent to which you agree with the following statements:

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
I would find the AI technology easy to use	○	○	○	○	○
My interaction with the AI technology would be clear and understandable	○	○	○	○	○

Q9 Please indicate the extent to which you agree with the following statements:

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
People who influence my behavior think that I should use the AI technology	○	○	○	○	○
People who are important to me think that I should use the AI technology	○	○	○	○	○
The senior management of this organization has been helpful in the use of AI technology	○	○	○	○	○
In general, the organization has supported the use of the AI technology	○	○	○	○	○

Q10 Please indicate the extent to which you agree with the following statements:

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
My organization pays attention to bring in new AI technology	○	○	○	○	○
My organization provides training for using the new AI technology	○	○	○	○	○

Q11 Please indicate the extent to which you agree with the following statements:

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
I intend to use AI technology in my patient care and management when it becomes available in my organization	○	○	○	○	○
I intend to use AI technology to provide health-care services to patients as often as needed	○	○	○	○	○
I intend NOT to use AI technology in my patient care and management routinely	○	○	○	○	○
Whenever possible, I intend NOT to use AI technology in my patient care and management	○	○	○	○	○
To the extent possible, I would use AI to do different things, clinical or nonclinical	○	○	○	○	○
To the extent possible, I would use AI in my patient care and management frequently	○	○	○	○	○

Q12 What areas do you think where AI innovations can make an impact? Please rate the following areas from 1 - 5.

	Low Impact 1	2	3	4	High Impact 5
DIAGNOSTIC INTERPRETATION (imaging studies, pathologies and genomics)	1	2	3	4	5
CLINICAL DECISION-MAKING SUPPORT (predictive and prescription alerting (algorithmic medicine) drive decisions for improved outcomes, efficiency and satisfaction)	1	2	3	4	5
TASK AUTOMATION (automate routine conversations (chatbots) for customer service and processes such as preauthorizations, payments, medication refills and scheduling)	1	2	3	4	5
MEDICAL EDUCATION/RESEARCH (AI based educational models to engage medical students with adaptive quizzing, case studies and virtual anatomy)	1	2	3	4	5