THE IMPACT OF TECHNOLOGY USE AND ACCEPTANCE ON HEALTHCARE OUTCOMES AND PERFORMANCE FOR PATIENT ENCOUNTERS AND VISITS:AN EXTENSION OF THE UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY(UTAUT2)

by

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ABSTRACT

MAGBOR ATEM, The Impact of Technology Use and Acceptance on Healthcare Outcomes and Performance for Patient Encounters and Visits: An extension of the Unified Theory of Acceptance and Use of Technology (UTAUT2)
(Under the direction of DR. REGINALD SILVER)

Technology Usage has become an important topic because of disruptions in the healthcare space in recent years. Long wait times and service delivery times, reduced patient engagement and interaction on care plans, lack of access to just-in-time healthcare records, diverse IT infrastructure with little or no interoperability and frequent server downtimes are some of the critical issues that could leverage current technology solutions to engage with patients before, during and post encounter visits. This research extends the Unified Theory of Acceptance and Use of Technology, (the UTAUT2) model by examining the role of technology use in influencing patient outcomes and experience. The study also investigates how healthcare service modality (Brick& Mortar, Hospital at Home, Mobile/Telehealth) impacts the association between technology use and patient outcomes. Specifically looking at how different healthcare modality types can leverage modern technologies and disruption trends to improve patient satisfaction and patient engagement throughout the life cycle of a patient encounter visit. Our study model incorporates five constructs- Two Independent variables- Individual Behavioral Intention and Technology use, two moderators- Cloud based Electronic Medical Record (EMR) and Healthcare Service Modality and finally two dependent variables- Patient Satisfaction and Patient Engagement. Results from an online survey administered to patients who have experienced services from the different healthcare modalities was collected and analyzed to support the model. This study is an important innovative addition for the UTAUT2 model. It has practical implications for academia and industry by informing future research and operationalization strategies on trends that could be leveraged to significantly improve performance and outcomes in the healthcare industry.

Key Words – Healthcare Business Types, Technology Use, Cloud Enabled Patient Portal, Healthcare Service Delivery, Technology Acceptance Model (UTAUT2), Patient Satisfaction, Patient Engagement

DEDICATION

I dedicate this dissertation to my wonderful husband, my adorable three daughters, my mum and personal encouragement officer through whom I have learnt resilience, my two sisters and brothers in law and my five adorable nieces and counting! Your devotion and unconditional love, prayers and patience throughout this journey were truly a gift in achieving this milestone!

My Late Dad, Chief Akat Agbor Emmanuel who laid a strong foundation in investing his best to educate the girl child and believing in me!!! "Daddy, I made it !!!"

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LIST OF ABBREVIATIONS

BI	Individual Behavioral Intention
DIT	Diffusion of Innovation Theory
EHR	Electronic Healthcare Record (Patient Portals)
PaEn	Patient Engagement
PaSa	Patient Satisfaction
TPB	Theory of Planned Behavior
TU	Technology Use
UTAUT2	The Unified Theory of Acceptance and Use of Technology2

1 CHAPTER 1: INTRODUCTION

Technology Usage has become increasingly important in providing healthcare services, including boosting process efficiency and assisting in reaching patients in a very timely manner in recent years. Long wait and service delivery times, lack of access to just-in-time healthcare records, diverse IT infrastructure with little or no interoperability and frequent server downtimes are some of the critical issues that could leverage current cloud technology solutions and improve outcomes for healthcare businesses. Also, these issues limit the benefits of technology in healthcare and current innovative technology solutions could address these issues and improve outcomes for patients and healthcare providers. Interestingly, other industries have been able to successfully leverage these modern IT capabilities to improve performance and service delivery(Gao & Sunyaev, 2019; Venkatraman, Henderson, & Oldach, 1993)

There is a great need for innovative and interactive software like patient portals to enable engagement and interaction with customers for faster and better outcomes.(Gambetti & Graffigna, 2010). According to Gartner.com, customer engagement has great potential to accelerate the speed of delivery and significantly improve outcomes. (Gartner 2015). For example, the restaurant and retail industries in the USA especially, have embarked heavily on usage of cloud technologies including mobile and web applications (like door dash, grub hub, Instacart, just to name a few) to cater to customer needs before during and after meal delivery service whether for eating in or takeaway leading to successful customer experiences. The movie entertainment industry has also made tremendous impact in changing customer experiences with companies like Amazon Prime Movies, Netflix, Hulu, Vudu, Pureflix taking the lead and providing extensive varieties on the Internet via dynamic applications.

Recently, the education sector made a huge turnaround leveraging cloud technologies to deliver virtual learning experiences as a result of the COVID19 pandemic forcing all in-person learning to be transferred to online virtual delivery(Gibson, Rondeau, Eveleigh, & Tan, 2012; Sabi, Uzoka, Langmia, & Njeh, 2016). Just recently, the technology industry has seen large cloud technology giants like Oracle taking over one of the largest electronic medical records (EHR)company-Cerner (according to ehrintelligence.com) with the aim of increasing capabilities and transforming healthcare delivery with more data interoperability, faster and better information and analytics. Amazon.com also boasts its ability to work with providers and insurers to have patient medication delivered seamlessly through their Amazon Pharmacy prescription services. The opportunities for cloud technologies seem endless across industries and sectors and hence a good resource for healthcare businesses to leverage to significantly improve outcomes, service delivery and patient experience outcomes including patient satisfaction and patient engagement. The purpose of this research is to further expand on the Unified Theory of Acceptance and Use of Technology (UTAUT2) by examining the role of technology use as an intervention in influencing healthcare business outcomes, performance, and patient engagement. The research will focus specifically on how different healthcare business modalities can leverage modern technologies and innovative opportunities to improve performance and outcomes.

1.1 The Research Gap

Although the UTAUT2 model has been researched extensively, UTAUT2 has not been widely used in the literature to systematically study the benefits in healthcare settings (Venkatesh, Morris, Davis, & Davis, 2003). According to Nikolopoulos and Likothanassis (Nikolopoulos & Likothanassis, 2018), there is still a need to enhance knowledge of technology usage and adoption among healthcare IT resources. Despite the apparent maturity of the Technology adoption research stream, a comprehensive analysis of the moderating effects technology usage particularly relating to cloud among healthcare businesses and healthcare service delivery modalities have not yet been investigated. Moreover, while some studies have investigated factors influencing cloud technologies adoption in healthcare, there is no single study examining the variation effects of cloud-based technology usage in healthcare business types and service modality on patient experience outcomes particularly patient satisfaction and patient engagement. To fill this gap, this study builds on the theoretical foundation of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) by examining technology use in the healthcare industry, particularly looking at how new moderators like virtual healthcare service modality and cloud enabled patient applications moderate the relationship between technology use and patient satisfaction and technology use and patient engagement. The Unified Theory of acceptance and Use of Technology is a widely used model in information-systems research that seeks to explain how people embrace and use new technologies. UTAUT2 is a mediation moderation model since it contains both mediating and moderating variables. UTAUT2 suggests that behavioral intention is a direct antecedent of performance expectancy, effort expectancy, social influence, and facilitating factors, which in turn affects technology use behavior; for this study, we will solely focus on moderation and assess the impact of moderation on the association between Technology Use and Patient Satisfaction and Technology Use and Patient Engagement as an extension to UTAUT2 as they relate to healthcare outcomes. Hence the basis for this study.

The healthcare industry is currently facing challenges that include access to just-in time healthcare records, multiple IT infrastructure with little or no interoperability, several downtime periods with servers continuously being disrupted by challenges in the data centers. One of the most promising areas of information systems research is insight into healthcare adoption and use of information technology (O. Ali, Shrestha, Soar, & Wamba, 2018; Griebel et al., 2015). Cloud technologies systems provide dynamic features that can help solve these problems while both lowering costs and improving efficiency for these healthcare companies (O. Ali, Shrestha, Soar, & Wamba, 2018; Fichman, 2011; Griebel et al., 2015). With healthcare businesses currently evolving to more consumer-centric driven care models; that is from Brick and Mortar to hospital at home, Mobile and Virtual service delivery; there is a growing need for high-quality scalable IT technology that can allow healthcare practitioners to offer high-quality treatment services regardless of location (O. Ali et al., 2018; Fichman, 2011; Griebel et al., 2015). Cloud applications and technologies have been used to support healthcare to provide better access to patient records, reducing latencies, inconsistencies in data and reporting and for improving decision making (O. Ali et al., 2018). There is further potential for Cloud Enabled Patient Portal applications and technologies to enable healthcare businesses to increase sustainable performance, availability and outcomes while significantly reducing costs (O. Ali et al., 2018; Fichman, 2011).

Addressing Gaps in The Literature

To address this gap in the literature, we use the Unified Theory of Acceptance and Use of Technology (UTAUT2) adopted form (Venkatesh et al., 2003). UTAUT2 is an application of the Theory of Reasoned Action (TRA) to the topic of information security. According to UTAUT2, perceived utility and perceived ease of use determine an individual's intention to utilize a system, with this intention functioning as a mediator of actual system use. Perceived ease of use is frequently assumed to have a direct influence on perceived usefulness (Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Thong, & Xu, 2012). The Technology Acceptance framework demonstrates strong empirical support for technology adoption in general and can be extended or modified by introducing new moderating variables (Murkofsky & Alston, 2009; Yang & Yoo, 2004). In our case we seek to investigate the framework by introducing two moderating variables of cloud-based technology (EHR) usage and Healthcare service Modality (Brick and Mortar, Hospital at Home and Mobile/Telehealth); to develop research questions. My research seeks to investigate the impact of cloud enabled applications on technology use on health care outcomes (patient satisfaction and patient engagement). According to (Venkatesh et al., 2003), there still exists opportunities to find constructs in the knowledge area that can help predict behavioral intentions and usage decisions in organizations. This study builds on that foundation by adding the variations in healthcare service modality with a combination of traditional brick and mortar, hospital at home and Mobile or telehealth options. The study will also assess if modality plays a significant role in influencing the relationship between technology use and patient satisfaction or engagement throughout the encounter or visit.

1.2 Research Questions

The key research questions for this study are as follows:

1. What effect does technology usage have on the Healthcare Outcomes?
2. To what extent can cloud based technology use improve patient experience and engagement during the life cycle (pre, during and post) of the patient encounter?
3. How does Behavioral Intention influence Technology use for cloud enabled technologies (patient portals) for enhanced patient experience including engagement and satisfaction?
4. Is there a change in the level of patient satisfaction and engagement with use of cloud based or non-Cloud Enabled Patient Portals?
5. Does level of patient satisfaction and engagement change with technology use in different variations of healthcare modality?

To answer our research questions, we first need to conduct a thorough review of existing literature to understand the key concept of cloud technologies, healthcare service delivery modalities and how and why the UTAUT2 Model may be most appropriate for use in determining the impact of cloud technologies in healthcare businesses. Thus, we propose a model guided by the above research questions. (See model above)

The proposed conceptual model for this study will investigate the impact of cloud-enabled versus non-cloud-enabled patient portals on the relationship between Technology Use and Patient Satisfaction and Patient Engagement, as well as the impact of Virtual Healthcare service modality on the relationship between Technology Use and Patient Satisfaction on and Patient Engagement on the other hand (where Technology is the independent variable, Cloud based Electronic Medical Record (EHR) and Modality are the moderators and Patient Satisfaction and Patient Engagement are the dependent variables for the study). The data for this study will be collected through an online survey and will be analyzed to support the model.

This research is an important innovative contribution to the UTAUT2 model especially in the concept of the healthcare sector. Findings from the research will be useful for informing healthcare systems and healthcare software companies on important aspects that must be incorporated to improve delivery and outcomes. The results will also have practical implications for academia and industry by informing future research and operationalization strategies on possible trends that could be leveraged to significantly improve interoperability, serviced delivery, performance, and outcomes in the healthcare sector.

1.3 Research Contributions

This study's findings are expected to provide theoretical and practical contributions. This study adds to the literature on Technology Usage and Adaptation by proposing an empirically supported extension of the Unified Theory of Acceptance and Use of Technology (UTAUT2) model regarding healthcare businesses. We contribute to the growth of the theory by conceptualizing and testing the effect of cloud-based technology use as an intervention in improving patient experience and engagement across healthcare modalities.

Moreover, the outcomes of this study will be beneficial in providing a guide to evidence-based healthcare administration in their attempt to justify scalability of capacity for providing more customer centric healthcare services like where clients are able to effectively partner with providers in the entire healthcare delivery lifecycle. Quite frankly, policy makers can easily make more informed decisions and explore embedded opportunities based on information derived from extensive research and investigations in the literature.

Moreover, the model used in this study provides a significant contribution to behavioral studies specifically in the area of intention to use by proposing the moderating effect of new variables like service modality and cloud-based applications on client satisfaction and engagement.

1.4 Organization of Discussion

The rest of the paper covers the review of literature, conceptual framework and research propositions, the conceptual model, Data Collection and Analysis, Results, Discussion and Conclusion.

2 CHAPTER 2: LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Overview

This chapter aims to examine a wide collection of literature in the knowledge area. The review of existing literature facilitates the establishment of theoretical foundation and assists in identifying relevant and important gaps in the current research. This is important as it enables the researcher to analyze and gain an in-depth understanding of the main concepts and theories underpinning the subject.

This section also highlights how much research has been completed in this area, different theories used and the gaps or areas for further research opportunities and investigation. The chapter is thus organized into 4 parts: (1) A discussion of relevant theories underpinning the foundation of the study - primarily the unified theory of acceptance and use of technology(Venkatesh et al., 2003; Venkatesh et al.,2012), the Diffusion of Innovation theory (Rogers, 2003) and the Theory of Planned Behavior(Ajzen, 1991); (2) a detailed discussion of technology use trends and its importance in healthcare including factors affecting adoption of cloud based Platforms and EHR; (3) An extensive investigation into the business of healthcare - exploring major drivers for success in the healthcare industry, an exploration of the evolution of healthcare modalities and Patient Outcomes with a focus on patient satisfaction and patient engagement; (4) Synthesis.

2.2 Conceptual Framework

The proposed conceptual framework for this study (Figure 2.1) is to investigate the moderating effects of cloud-enabled technologies and virtual healthcare service modality on the relationship between technology use and patient satisfaction and patient engagement. This conceptual model focuses on five key variables. The proposed independent variable for this study is technology use in healthcare settings, which refers to the use of technology in healthcare settings, including electronic health records, telemedicine, and wearable devices. Although Technology appears to mediate the relationship between Behavioral intention and the two dependent variables (Patient Satisfaction and Patient Experience), the concept for this study focuses on the red box and tests only moderation since the mediation relationship (blue box has already been established in the literature (Venkatesh et al, 2003).

This framework contains two dependent variables. The first is patient satisfaction, which refers to the level of satisfaction that patients experience with the healthcare services they receive. The second dependent variable is patient engagement, which refers to a patient's level of involvement in their own healthcare, to the level of patient involvement in their own healthcare, including behaviors such as following treatment plans, asking questions, and participating in shared decision-making.

The moderating variables in this framework are cloud-enabled technologies and virtual healthcare service modality. Cloud-enabled technologies involve technologies that leverage cloud computing to provide healthcare services such as patient data storage and remote consultations. Virtual healthcare service modality refers to the use of technology to deliver healthcare services remotely, such as through telemedicine or remote monitoring.

According to the theoretical framework of this research, use of cloud-enabled technologies and virtual healthcare service modalities are hypothesized to have a positive moderating effect on the relationship between technology use and patient satisfaction and patient engagement. These technologies could improve patient outcomes by increasing access to healthcare services while providing more customer-centric care and significantly improving overall outcomes.

The relationship between Patient Satisfaction and Patient Engagement is another relationship in the proposed conceptual model we are interested in testing. Patient Satisfaction is influenced by a number of factors, including the quality of care, healthcare practitioners' communication skills, access to healthcare services, and overall healthcare experience On the other hand, Patient engagement can be influenced by factors such as health literacy, patient education, communication with healthcare providers, and access to healthcare information. The relationship between patient satisfaction and patient engagement can be viewed as a cyclical process. Patients who are actively involved in their healthcare are more likely to have appealing experiences with healthcare services, resulting in higher levels of satisfaction. Similarly, when patients feel satisfied with their healthcare experiences, they are more likely to continue being involved with their care, thus leading to better health outcomes and increased patient engagement.

Thus, in healthcare, patient satisfaction and patient engagement are interrelated and complimentary concepts. A satisfied patient is more likely to participate in their care, and a patient who participates in their care is more likely to have a pleasant healthcare experience and be satisfied with their care. While technology may play a mediating role in the relationship between the independent variable Behavioral Intention and the dependent variables (patient satisfaction and patient engagement), the various components of the model will be tested and hypothesized separately. This means that no mediation model will be proposed or tested in this study. The scope of this research will focus on the direct effects of Technology Use on patient satisfaction and engagement, as well as the moderating effects of cloud-enabled technologies and virtual healthcare service modalities on the relationship between technology use and patient satisfaction and engagement.

The relationship between Behavioral Intention and technology use is clearly documented in the technology literature. As a result, although this link reflects Behavioral Intention as an important antecedent, we will confirm it in our analysis, but the relationship (blue box) will be examined independently of the others (red box). Hence, we test this relationship as part of our model. Our proposed conceptual model is shown in Fig 2.1 below.

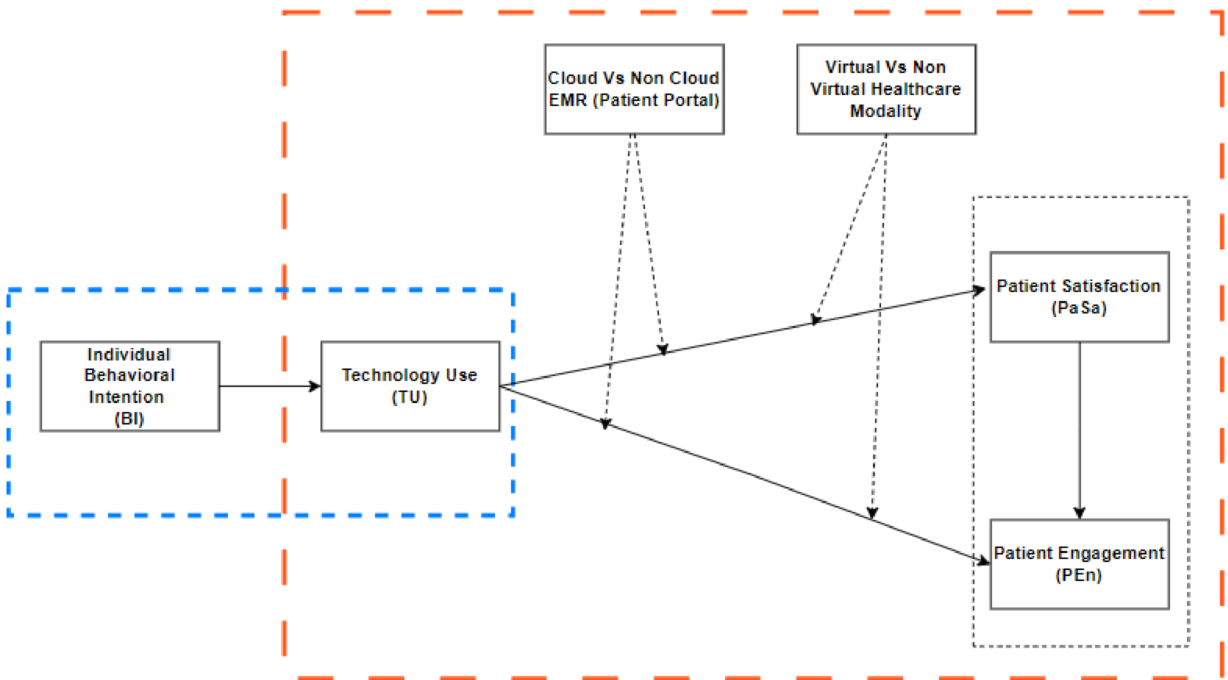

Figure 2.1: Proposed Conceptual Model of Moderating Effects of Cloud Vs Non-Cloud Based Patient Portals and Virtual Vs Non-Virtual Healthcare Service Modality on the relationship between Technology Use and Patient Satisfaction and Technology Use and Patient Engagement

2.3 Theoretical Basis

2.3.1 The evolution of Unified Theory of Acceptance and Use of Technology (UTAUT2)

Several theoretical models, primarily derived from psychological and sociological theories, have been developed to explain technology acceptance and use (Venkatesh et al. 2003). The Unified Theory of Acceptance and Use of Technology (UTAUT) model has analyzed the critical factors and possibilities related to predicting behavioral intention to use a technology and technology usage primarily in several organizational contexts but not investigated healthcare settings. Moreover, although some studies have investigated factors influencing technology use and adoption in healthcare, there is no single study examining the effects of healthcare businesses modalities (for example, Brick and Mortar versus Mobile and Telehealth) technology usage on the performance and behavioral intention to use new and innovative technologies (Nikolopoulos & Likothanassis, 2018; Silver, Subramaniam, & Stylianou, 2020).

The UTUAT literature demonstrates strong empirical support for technology adoption in general and can be extended or modified by introducing new moderating variables. Venkatesh et al.,2012 reaffirms the utility of the model in the technology acceptance and use research stream …. There have been many applications and replications of the entire model or part of the model in different organizational settings and industries that have contributed to fortifying its generalizability (e.g., Neufeld et al. 2007). According to Venkatesh et al (2012), there are three main approaches through which the UTAUT model can be extended or integrated. This is a gap in the literature presenting key dimensions through which the model can be extended. The first type of extension/ integration proposed, examines UTAUT in new contexts, such as new technologies (e.g., Cloud technologies, collaborative technology, health information systems; (Gibson, Rondeau, Eveleigh, & Tan, 2012; Nasir, 2005; Silver et al., 2020)), new user populations (e.g., Healthcare Business professionals, Healthcare Businesses; Yi et al. 2006(,Liu, Dong, Wei, & Tong, 2020; Silver et al., 2020)) and new cultural settings some of which have already been explored in the literature(e.g., African, Asian, Western; Gupta et al. 2008 (Alharbi, Atkins, & Stanier, 2017; Ali, Shrestha, Soar, & Wamba, 2018; Gupta, Seetharaman, & Raj, 2013). Another opportunity that the literature presents is the addition of new constructs (for example healthcare modality and access to cloud based versus non-cloud-based technology) in order to broaden the scope of UTAUT's logical concepts (e.g., (O. Ali et al., 2018). Even more interestingly, a third dimension of exploring this model is the inclusion of antecedents that could also affect the behavior of the UTAUT variables like habit and health literacy (Neufeld et al. 2007; Yi et al. 2006).

The Unified Theory of Acceptance and Use of Technology (UTAUT2) is an extension of the Unified Theory of Acceptance and Use of Technology (UTAUT) incorporating three additional constructs into UTAUT: hedonic motivation, price value and habit. Venkatesh et al (2012) also hypothesized individual differences like age, gender and experience to moderate the effects of the additional constructs to understand the effects on behavioral intention and technology use. In order to predict behavioral intentions to use technology and technology use particularly in organizational contexts, UTAUT has condensed the important elements and contingencies connected to the literature (Venkatesh et al, 2012). UTAUT2 extends to other contexts, such as consumer technologies, which is a hot topic in this line of research and given the influx of technology devices in recent years as a result of the pandemic, as opposed to the UTAUT theory, which was originally developed to explain employee technology acceptance and use. This acts as a strong foundation and the basis for our study. Also, in line with this the increase in consumer services as depicted by the consumer services research literature (Setophaga and Llamas, 2009). UTAUT2 specifically integrated key additional constructs as mentioned above and relationships to tailor the model to a consumer use context (Venkatesh et al, 2012). According to the literature, integrating hedonic motivation compliments the UTAUT's strongest predictor that emphasizes utility. Also, for understanding multiple consumer contexts, unlike workplace contexts, users are responsible for the costs and decisions (Chan et al, 2008; Brown and Venkatesh 2005). As such there is an opportunity to integrate a construct that provides some form of choice of service for consumers with respect to method of delivery like healthcare modalities (Venkatesh et al, 2012). Finally, recent research has questioned the significance of behavioral intention as a key predictor of technology usage and presented a new theoretical construct (i.e., habit) as another crucial predictor of technology use (e.g., Davis and Venkatesh 2004; Kim and Malhotra 2005; Kim et al. 2005;

Limayem et al. 2007). The incorporation of habit into UTAUT will supplement the theory's emphasis on intentionality as the overarching mechanism and major determinant of behavior. In fact, habit has been recognized as a valuable construct to integrate into the model providing meaningful explanations for behavioral intention patterns for consumers.

All these proposed variables are potential antecedents that could be integrated as predicting factors of UTAUT and UTAUT2 variables. These components of UTAUT will be beneficial in improving our understanding of how individual behavioral intention affects technology use of cloud vs non-cloud-based technology throughout the patient experience. The discussion for Technology use of Cloud based systems in different healthcare modalities suggests a very important dimension for extending the UTAUT2’s theoretical boundaries to new settings and environments. This is a great value-added benefit and case for including these dimensions to the model. Despite the apparent maturity of the Technology Acceptance research stream, a comprehensive analysis of the moderating effects of Cloud Enabled Patient Portal and healthcare modalities on the effect of technology use on patient experience and engagement is yet to be investigated(Nikolopoulos & Likothanassis, 2018). As a result, while the numerous studies contribute towards understanding the efficacy of UTAUT in various contexts, there is still a need for a systematic examination and theorizing of the relevant elements as it pertains to the Healthcare Business technology usage context.

Building on the UTAUT literature in the footsteps of Venkatesh et al, (2003) and Silver, Subramaniam and Stylianou, (2020); the objective of our work is to pay particular attention to the Healthcare Business use context, examining how healthcare service modalities and use of cloud-based technologies moderate the effect of technology use on patient satisfaction and engagement with the healthcare team throughout the continuum of care. This explains the context of this study and the goal to achieve meaningful use for the Healthcare industry and develop a new adaptable model. Compared to common theories related to the phenomena, in recent years, theories that focus on a specific context and identify key predictors and concepts have been regarded as essential for offering an in-depth understanding of a target or phenomenon and effectively extending theories. This also provides a justification of the approach for the study. There is evidence from the literature that new contexts can result in a variety of significant changes in theories, including rendering previously theorized relationships insignificant, changing the direction of relationships, changing the magnitude of relationships, and creating new relationships ((Alvesson & Kärreman, 2007; Anderson, Frogner, Johns, & Reinhardt, 2006; Tamilmani, Rana, Wamba, & Dwivedi, 2021). Each shift can disclose the deconstruction of hypotheses, resulting in the formation of new knowledge and opportunities (Alvesson & Kärreman, 2007). The approach taken by this study will add value to the body of knowledge in this field by looking at a different perspective like cloud-based systems used by clients in different healthcare modalities. In fact, Venkatesh et al. (2003) argues that there is still an opportunity to identify constructs that can add to the prediction of behavioral intentions and usage decisions in different types of organizational contexts like healthcare to the UTAUT2 model, which was originally developed to explain individual employee technology acceptance and use given the number of technology devices, applications, and services targeted at Healthcare Businesses (Venkatesh, Morris, Davis, & Davis, 2003). This not only posits another justification for the study but also practical implications as an expansion to what is known about the phenomenon and potentially influence generalizability and utility.

Against this framework, the investigation of the boundary conditions and expansions to UTAUT in a Healthcare Business setting provides a significant theoretical contribution. Posing potential constraints necessary for consideration in the study. In general, the context of technology acceptance, use and adoption, critics and proponents of models such as the technology acceptance model (TAM) have emphasized the need to broaden the universe of theoretical processes (Bagozzi 2007; Benbasat and Barki 2007; Venkatesh et al. 2007).

2.3.2 The Unified Theory of Acceptance and Use of Technology (UTAUT) and its Extension UTAUT2)

The UTAUT2 theory is an improved iteration of the Theory of Acceptance and Use of Technology UTAUT) which was originally developed by Venkatesh et al (2003) as a synthesis of prior technology acceptance and utilization research. The focus of UTAUT specified four key constructs (performance expectancy, effort expectancy, social influence and facilitating conditions) that are critical in understanding behavioral intention to use a technology and or/a technology use, which is critical for forming the basis of this study. As proposed by Venkatesh et al, 2003, Performance expectancy looked at the degree to which using a technology will provide benefits to consumers while performing certain activities. This provides a platform to begin our inquiry into the benefits of using technology as a facilitating mechanism for customer experiences from different healthcare modalities. With Effort expectancy, the second construct from UTAUT, the proponent suggests it reflects the degree of ease associated with consumers' use of technology. According to the Literature, consumers tend to be attracted to technology they perceive to be easy to use or confident of the support they will receive when navigating through new applications (Ashraf, Thongpapanl, & Auh, 2014; Venkatesh, Thong, & Xu, 2012). The literature also reports that repeated portal use, a form of healthcare technology use, has been shown to be prevalent among patients with chronic medical conditions(Ancker et al., 2011). Ghalandari et, Al (2012) define effort expectancy as the extent of convenience perceived for using a system (Ghalandari, 2012). This definition provides a good foundation for building our model for the healthcare industry as this is important in influencing patient engagement with the care process.

Social influence plays an interesting role in influencing the extent to which consumers perceive that significant other (e.g., family and friends) believe they should use a particular system. Studies that have explored technology use and acceptance theories have consistently identified social influence as a critical factor influencing behavioral intention to use technology.(Silver et al., 2020; Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Thong, & Xu, 2012)The literature reveals that social influence has the ability to significantly affect hedonic stimuli experiences. In healthcare several care experiences are received and given in company of other people (Raghunathan, 1992) . According to the UTAUT model, while social influence is an important antecedent for explaining individual behavioral intention, it could also be moderated by individual characteristics such as different combinations of age, gender and experience. Furthermore, Morris et al (2005) explain that the relationship between social influence and Individual behavioral intention can be viewed as a four way interaction effect including social influence, gender, age, experience on behavioral intention (Morris, Venkatesh, & Ackerman, 2005). UTAUT2 which is a revised theory from UTAUT integrates habit into the model to further explain the behavioral intention. Other schools of thought have debated the inclusion of habit as an antecedent affecting behavioral intention and called for further research and alternative theoretical mechanisms in predicting behavioral intention to use new technologies (Benbasat and Barki, 2007; Bagozzi 2007). Moreover, Some scholars demonstrate in their research that UTAUT predictors together with hedonic motivation , price value and habit play important roles in predicting continued use of information technology (Venkatesh et al., 2012).

Facilitating conditions, the fourth construct suggested by Venkatesh et al.,2003, refers to consumers' perceptions of the support that is available to them to effectively carry out an action. Thus, in their study, they project performance expectancy, effort expectancy and social influence to be highly predictive of behavioral intention.

2.3.3 The Theory of Planned Behavior

According to Taylor &Todd, 2022, the theory of planned behavior (TPB) (Ajzen 1985) extends the theory of Reasoned action originally proposed by Fishbein & Ajzen, 1975 to account for conditions where individuals do not have complete control over their behavior. In his 1991 Paper on Theory of Planned behavior, according to Ajzen, attitudes toward conduct, subjective norms, and perceived behavioral control can all be used to predict behavioral intentions with great accuracy. This research stream also suggests that behavior is often times related to appropriate sets of salient behavioral, control and normative beliefs. According to Ajzen, the central factor in the theory of planned behavior is the individual’s intention to perform a given behavior. Ajzen 2021 explains further that Intentions are assumed to capture the motivational factors that influence a behavior and are indications of how hard people are willing to engage or exert a particular behavior. In the context of technology acceptance, the success of technology usage is dependent on the individual ability to understand and utilize new technology. This concept also stems from the evolution of the Ajzen and Fishbein's Theory of Reasoned Action (Ajzen & Fishbein, 1980)used in predicting an individual’s intention to engage in a behavior at a specific time and place. The theory of planned behavior (Ajzen, 1991) also explains to a greater extent how individuals behave across different settings, scenarios, and situations. This gives us a solid foundation for understanding how to decipher our behavioral Intention to use patient portals in relation to our entire model.

2.3.4 The Diffusion of Innovation Theory

The diffusion of innovation theory explores how new ideas or technology expand through societies in different ways. According to Rogers (2005) diffusion is the process by which an innovation is communicated through certain channels over time among members of a social system (Rogers, 2003).

From these broad concepts, one key factor that enables us to use this theory part of our foundation for this research is that, firstly diffusion of innovation enables us to understand how alterations occur in structures and functions of a social system, in our case cloud enabled portals for healthcare service delivery. According to Balas and Chapman (2018), new scientific knowledge and innovation in the healthcare industry are frequently slow to disseminate (Balas & Chapman, 2018). They proceed to say that various defects and changes in innovation dissemination can provide valuable insights into what specific process components contribute to or fail to contribute to the adoption of innovation. There have been some discussions in the research explaining diffusion as a process through which an innovation is communicated and adopted through several channels of a particular social system over time (Merhi, Hone, & Tarhini, 2019) . The Literature provides a more enlightened explanation in that innovation is an idea, practice or object that is perceived as new by an individual or other unit of adoption (Al Aufa, Renindra, Putri, & Nurmansyah, 2020; Gibson, Rondeau, Eveleigh, & Tan, 2012). Innovation therefore could be explained in three dimensions. These include: - Innovation adoption process, Innovation adapter categories, Rate of Adoption.

The transformation of the healthcare delivery system over the years could be better explained based on the diffusion for innovation theory. Schulte (2009) posits that healthcare service delivery has changed dramatically over the years. From “sick houses” to brick-and-mortar buildings to mobile clinics and most recently virtual consults and telehealth (Shulte 2009).

The acceptance and adoption of e-health solutions including telehealth, virtual consults, e-prescriptions, etc. could be said to have diffused through an innovation decision process going from knowledge of the concept of capabilities of technology, to developing attitudes most informed by the preliminary results of the innovative technologies, to implementation, confirmation and finally a diffusion across the healthcare industry becoming the new norm.

The most recent covid-19 epidemic has also played an important role in hastening changes in the modality and accessibility of healthcare treatments (Nuryana, Pangarso, & Zain, 2021).Due to nature of the pandemic, healthcare systems were required to act quickly to incorporate virtual and telehealth technology in order to provide timely interventions for patients. The enormous success seen throughout the healthcare spectrum affected the rate of acceptance, implementation, and use of innovative delivery systems. Adoption of healthcare service delivery modalities, on the other hand, had a wider distribution of adopters, with many providers becoming early adopters in an attempt to save more lives, especially during the pandemic. Healthcare modalities and technology use can be considered to have diffused quite rapidly throughout the healthcare spectrum than traditionally.

Furthermore, (Sabi, Uzoka, Langmia, & Njeh, 2016) explain the rate of adoption to be measured by the length of time to adopt an innovation. They also explain further that innovations that have greater compatibility advantage have a more rapid rate of adoption which explains the rapid transformation of healthcare services delivery adopting several modalities in a rather short space of time.

Another stream of research suggests that the social structure of a system can affect the diffusion process. Social structure in this subject area can be seen as technological disruption and regulatory interventions. These are two critical composites of the healthcare social structure with extremely high influential power to influence the dynamics of healthcare delivery. Thus, facilitating transition from brick and mortar to telehealth, virtual consult, etc.

2.4 Behavioral Intention to Use

Effective implementation of any technology or information system depends on user acceptance (Davis, 1989). With the rapid advancement and increase of utilization of technologies to deliver so many different customer services, it has become increasingly important to understand how behavioral intention to use technology is influenced and how it affects user engagement and satisfaction. According to Chao 2019, people are most likely to utilize technologies for crucial services like mobile health, banking, and mobile learning. Venkatesh et al (2003) propose that the influence of effort expectancy and social influence on behavioral intention to use will be moderated by gender, age and experience (Venkatesh et al, 2003). They further project that behavioral intention to use a technology is associated with technology use. Although the UTAUT model and proposition for behavioral intention has been widely adopted in the research stream, there are still some schools of thought that suggest that increasing the number of external variables and moderators can enhance and better explain the model's ability to predict the acceptance and usage of technology especially as it relates to user engagement and satisfaction Gao 2019, Kabra et al, 2017, Venkatesh et al 2012).This is supported in further research by Lee et al (2019), where they included the trust variable in place of social influence and focused on operational usefulness for the performance expectancy factor(Lee et al, 2019). Furthermore, they argue that the modification would be very helpful in identifying, evaluating and understanding independent variables that influence user's intention to use a new technology-in their case blockchain. While there appears to be a wide adoption of the behavioral intention to use construct, there is still a gap in the research in the area of identifying moderating constructs that can add to the prediction of intention and behavior over and above what is already known and understood (Venkatesh et al, 2003; Venkatesh et al, 2012).Moreover, the literature suggests there may be some value in investigating moderators like organizational context-in our case healthcare modalities, user experience, user engagement and demographic characteristics which may significantly account for dynamic influences for technology usage in different settings (Venkatesh et al, 2003; Gao 2019; Lee et al, 2019).

2.5 The Technology Use Context

One of the most promising areas of information systems research is insight into healthcare adoption and usage of information technology (Ali et al., 2018; Griebel et al., 2015). Several theoretical models, mostly derived from psychological and sociological ideas, have been constructed to explain technology adoption and use (Venkatesh et al. 2003). The unified theory of technology acceptance and usage arose from a review and synthesis of theories/models of technology use (UTAUT; Venkatesh et al. 2003). The UTAUT model examined the important characteristics and possibilities for predicting behavioral intention to use a technology and technology utilization in numerous organizational contexts but did not research healthcare settings. Furthermore, while some studies have looked into factors influencing technology usage and adoption in healthcare, no single study has looked into the moderating effects of healthcare service modalities (for example, brick and mortar versus mobile and telehealth) on the relationship between technology use and patient satisfaction or engagement (Nikolopoulos & Likothanassis, 2018) The UTAUT2 paradigm provides strong empirical evidence for universal technology adoption and may be extended or modified by integrating new moderating variables. Murkofsky and Alston (2009); Yang and Yoo (2004) Many applications and replications of the full model or parts of the model in other organizational contexts and sectors have added to its generalizability.

According to Venkatesh et al., 2003, there is still an opportunity to identify constructs that can contribute to the prediction of behavioral intentions and usage decisions in various organizational contexts such as healthcare to the UTAUT model, which was originally developed to explain individual employee technology acceptance and use given the number of technology devices, applications, and services targeted at Healthcare Businesses). In light of this paradigm, the analysis of the boundary conditions and extensions to UTAUT in a Healthcare Business scenario makes an important theoretical contribution. In the context of technology adoption, critics and supporters of models such as the technology acceptance model (TAM) and UTAUT2 have underlined the importance of broadening the universe of theoretical processes (see Bagozzi 2007; Benbasat and Barki 2007; Venkatesh et al. 2007).

2.6 Current Market Trends for Cloud Technologies

According to info.flexera.com, to compete in today’s market environment, post pandemic, organizations must have the right cloud strategy in place. Several industries and businesses had already begun instituting some form of innovative technologies which have been accelerated drastically by the recent pandemic. According to flexera.com, in order to optimize use of cloud technologies and take advantage of some key benefits like agility, high scalability, high availability, reliability and highly secured capabilities the question is no longer “if” but “when” organizations will begin their cloud journey (info.flexera.com. 2022). Organizations must make strategic decisions about their cloud migration, cloud architecture, use of public clouds, efficient tooling, and cloud cost management if they want to stay competitive in this rapidly changing digital environment. (State of the Cloud Report, resources. flexera.com. 2022- Figure 2.2 and Figure 2.3).

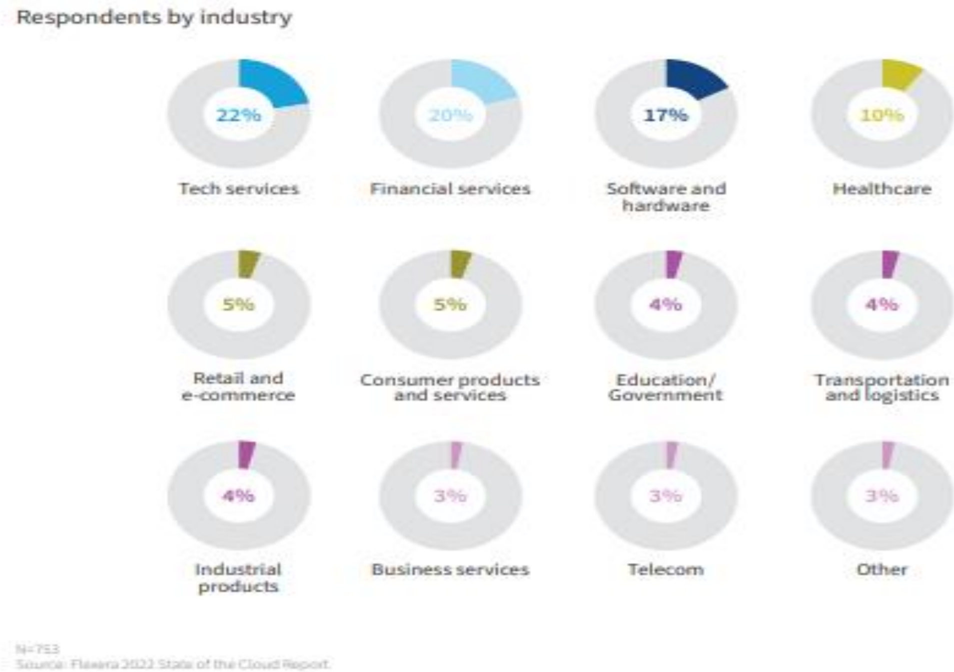

Figure 2.2: Current Market Trends for Businesses currently leveraging Cloud Technologies by Industry adopted from Flexera.com resources: State of the Cloud Report

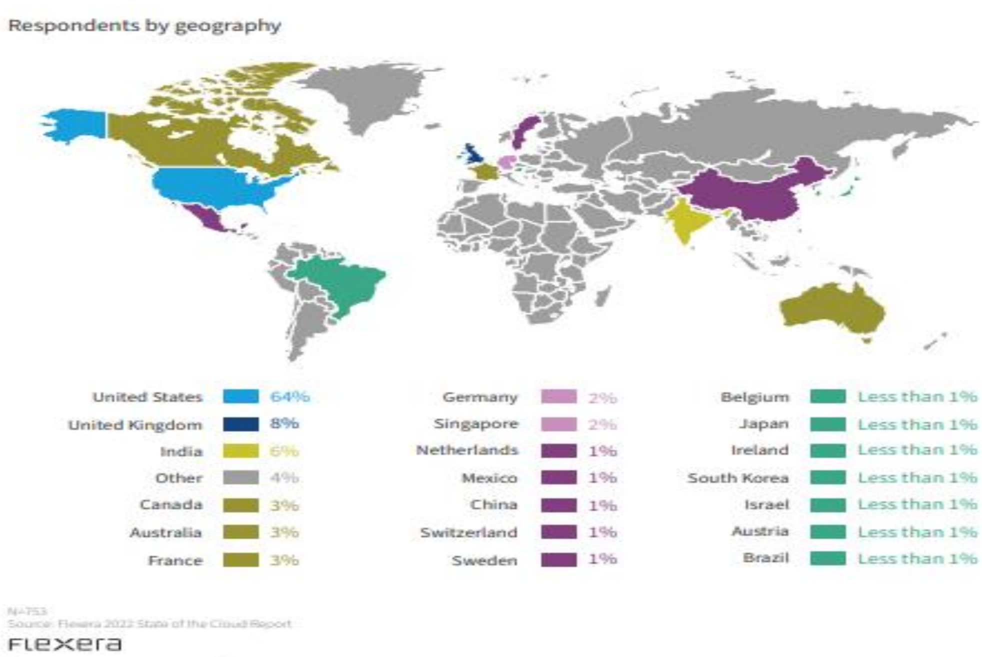

Figure 2.3: Current Market Trends for Businesses currently leveraging Cloud Technologies by geography adopted from Flexera.com resources: State of the Cloud Report

2.7 Cloud Adoption Across Industries

2.7.1 Restaurants and Retail

To understand how the restaurant industry has adopted cloud-based application capabilities to dynamically respond to the constantly changing needs of customers, we noted few trending applications currently being used in the USA. Applications like Door Dash, Instacart, Uber Eats, Chow Now, Grub Hub, Seamless, Hello Fresh and Caviar are constantly keeping customers engaged with interactive communication, discount offers, faster delivery options, etc. through the life cycle of the experience. Moreover, the capabilities of these applications continue to improve and change to maintain competitive advantage in this very aggressive market. Some important capabilities include text messaging to provide regular updates on the progress of the order preparation, who your server or driver is, when order leaves the shop, how it is being transported, when it is approaching your location and when your order arrives at your doorstep. Some of the applications even verify eligibility of vendor to ensure the security of product and service and customer information and experience.

Moreover, some major retailers are adopting cloud computing an AI to gain competitive advantage in the marketplace by leveraging consumer purchase behavior based on their interactions with the applications to gather and analyze data to gain insights into consumer preferences. This also helps boost sales and marketing efforts significantly (Tiwari, Bharadwaj, & Joshi, 2021; Yoo & Kim, 2018).

2.7.2 Education

The education sector has had a huge shift in the learning culture across the board from nursery and elementary education right up to higher education and professional institutions and educational levels. The recent pandemic encouraged a huge switch in the learning culture to incorporate hybrid and remote options of delivery. Tools such as Zoom, Google Meet, Microsoft Teams, Go to Meeting, Go To Webinar, Webex, etc. have now dominated the hybrid and Remote learning culture in most Educational Institutions. In fact, these tools have been continuously improved to include interactive tools, breakout rooms, white board demonstrations, reactions, screen sharing features to provide engaging interactions and a very collaborative experience. Recent years have seen quite a good number of educational platforms like Udemy, Edureka, Simplylearn, Ideal Lab Kids, etc. delivering complete academic experiences completely online. Also, cloud-based Learning management systems (LMS) have also enabled educational institutions to provide high quality access to their courses online regardless of student location. Some schools of thought argue that this has a significant reduction to the cost of education; (Sarrab, Al-Shih, & Rehman, 2013) while others still lay emphasis on the need for and importance of face to face academic interactions (Kendon, Harris, & Key, 2011).

2.7.3 Manufacturing

In recent years, manufacturers have also adopted to some extent some aspects of cloud applications to enable them to optimize their supply chain and manufacturing processes. With the high demand for automation, there is some pressure on manufacturers to engage in cloud technologies to enable them to provide more efficient processes and management of their supply chain processes. Also, based on the need to effectively manage inventory and backorder situations, it has become even more critical for manufacturers to engage in cloud-based solutions providing highly available, highly secured and interoperable applications.

2.7.4 Financial Sector

Based on a recent study by google cloud (cloud.google.com) where over 1300 leaders from financial services industry were surveyed across the United States, Canada, France, Germany, United Kingdom, Hong Kong, Japan, Singapore and Australia, 83% reported their organizations were already deploying some form of cloud technology (hybrid, single and multi-cloud technologies) as part of their primary computing infrastructures, while others indicated they were considering adopting a multi cloud strategy in the next 12 months (cloud.google.com, 2022). Moreover, the literature suggests that financial services institutions in North America are leading in cloud adoption as indicated in figure 2.4 below:

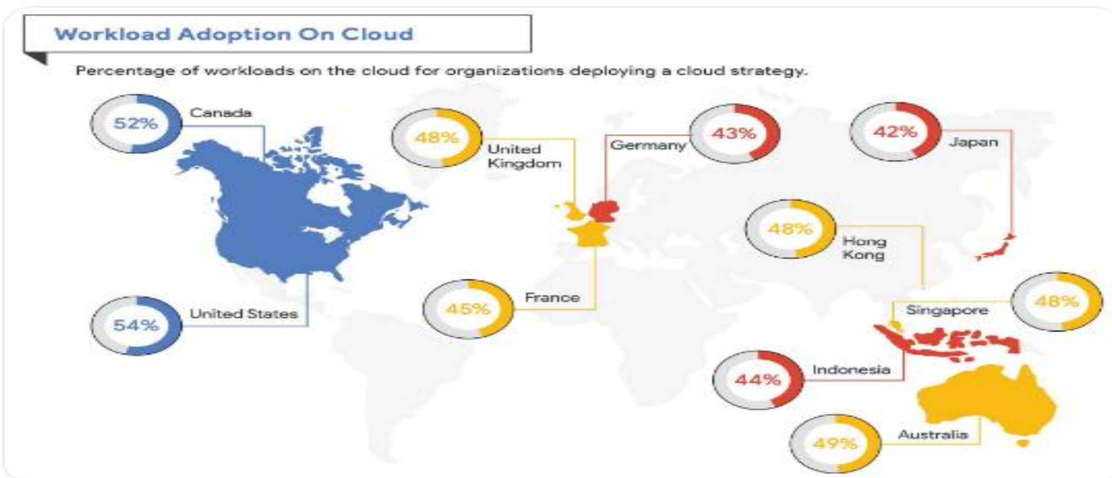

Figure 2.4: Financial Services institutions in North America leading in Cloud Adoption Source: *cloud.google.com, 2022*

Furthermore, the literature suggests that cloud adoption can help adapt to rapidly changing consumer behaviors and expectations, enhance operational resilience, support the creation of more engaging innovative new products and services, enhance financial services institutions' data security capabilities and improve on integration of legacy software infrastructure lacking interoperability thus improving overall financial services (*www.cloud.google.com*, 2022; (Gao & Sunyaev, 2019; Tak, Urgaonkar, & Sivasubramaniam, 2011).

The need for secure, cost-effective, and scalable IT infrastructure is driving a surge in cloud adoption across industries. Businesses can gain a competitive advantage in the marketplace, improve operational efficiency, and provide better service to their customers by leveraging the cloud.

According to Silver et al, 2020, patients who interact with healthcare technology like patient portals are usually motivated to use the technology as it gives them direct access to their provider and gives them some sort of control over their health record(Silver et al., 2020). In examining the delivery of different models of cloud computing, the literature reveals that actual use of cloud technologies is easily achieved when there is access and availability to cloud-based applications. (Gibson et al., 2012)

2.8 The Moderating Role of Cloud Enabled Patient Portal

2.8.1 Healthcare Business Context

According to Sawyer,2018 Healthcare is now strictly a business concept in the United States. Healthcare businesses organize physicians and patients into a framework where the partnership can be commercially regulated and payments strategically organized through third party for hospitals, clinics, health insurers, the pharmaceutical industry, and medical device manufacturers. (Sawyer, 2018). According to the NHS- One of the largest Healthcare employers in the world (Over 1.4 billion workers) and in the UK, (www.nhs.uk) healthcare Businesses span across three main sectors – Primary Care, Secondary Care and Tertiary Care sectors. The primary Care sector contains primary care physicians in doctor offices and clinics, while secondary care tends to be more hospital based including urgent and emergency care services and tertiary care more community based involving advanced care providers like pharmacists, dentists, etc. Interestingly although the US also captures a similar model except for an additional level -quad sector, our focus is rather on Healthcare Modalities that is Brick and Mortar, Virtual and Mobile healthcare business opposed to the sector.

2.8.2 The Evolution of Healthcare Modality and its moderating role

Over the last decade, the healthcare delivery system has been under intensive examination. According to Solloway (1982), one crucial feature of an effective healthcare delivery system is that it is intended to be productive and to strive for consistency with better and more tangible results. More intriguingly, several schools of thought have suggested that, rather than providing productive healthcare services, the US healthcare system is organized to emphasize profit, research, medical education, and training, with patient care remaining a secondary role. Ehrenreich, (1971). According to Shulte (2009), the healthcare system in the United States has developed and evolved considerably, as have other sectors of society. With a rise in healthcare innovation leveraging cloud technologies and Artificial Intelligence, advances in science and digital technology have considerably enhanced access to healthcare services and created more alternatives for healthcare delivery (Schulte, 2009; Griebel et al., 2015).

Despite the ever-changing nature of users, regulations, the healthcare industry environment, and natural factors, innovative options in healthcare have been steadily increasing, with cutting-edge technologies ranging from non-invasive surgeries to understanding sepsis and its association with infections and even death, to innovations in multiple organ transplant procedures, to name a few. In fact, the recent pandemic provided a great platform on which to test new and modern healthcare service delivery virtually which has also contributed in defining some important healthcare operations (Shulte 2009; O. Ali, Shrestha, Soar, & Wamba, 2018; Binsar, Kartono, Bandur, & Kosasih, 2022). Modern technology has enabled new pathways for providing high-value care and successful treatment strategies, such as Telemedicine with video conferencing and remote monitoring, Cloud enabled Electronic Medical Records allowing for easy access and just in time records, wearable technology such as fitness trackers and health monitors, and 3D printing in surgery, which have all significantly improved accuracy, treatment times, and risk of complications (O. Ali et al., 2018; Binsar et al., 2022; Griebel et al., 2015). Healthcare organizations have changed significantly from poor houses in the 18th century to the highly sophisticated organizations they are today (Shulte,2009). There is still however a lot of opportunity in examining technology usage to improve issues like lack of interoperability among disconnected systems, log wait times for services, long server downtimes which is one of the goals of this research.

As part of the meaningful use criteria, all patient portals and other forms of secure messaging between patients and physicians were reimbursed, according to HITECH 2009. To meet the meaningful use criteria for patient portals and secure messaging, providers had to show that they were using innovative technologies to engage with patients, such as by giving patients access to their health information, allowing patients to schedule appointments and request prescription refills online, and communicating with patients via secure messaging. Providers were also required to demonstrate that they used secure technologies to protect patient information and ensure the privacy and security of health information.

Overall, the ARRA 2009 meaningful use agenda aims to increase healthcare providers' adoption and use of HIT, with the goal of improving patient outcomes and lowering healthcare costs. HITECH compensates providers for the usage of patient portals and secure messaging. This triggered a significant shift in healthcare from paper-based records to digital ideas that, to some extent, facilitated access (www.nih.gov, 2009).

Cloud-based systems and technologies, the literature suggests great potential for interoperability with electronic medical records (EHR), Personal Health Records (PHR), Computerized Physician Order Entry, E-Prescriptions, home health monitoring systems, and other healthcare record keeping, or data exchanging systems used by healthcare organizations (Alharbi, Atkins, & Stanier, 2017; O. Ali et al., 2018; Gao & Sunyaev, 2019). When patients can obtain data more quickly and efficiently, it enhances patient satisfaction (Alharbi et al., 2017; A. Ali, Warren, & Mathiassen, 2017; Gao & Sunyaev, 2019).

Modern healthcare modalities such as brick-and-mortar, mobile, and virtual healthcare play an important role in improving diagnostic performance in healthcare systems for various applications such as prosthesis design, surgical implant design, diagnosis and prognosis, and abnormality detection in the treatment of various diseases (A. Ali et al., 2017; Ancker et al., 2011). Furthermore, Bajaj (2021) stresses real-time modifications in medicinal modalities and expresses the crucial necessity for these alternatives in today's healthcare delivery system (Bajaj et al., 2021; Esposito, De Santis, Tortora, Chang, & Choo, 2018).

2.8.3 From Traditional Brick and Mortar to Virtual and Mobile Healthcare Businesses

Although the acute brick and mortar facilities are the standard venue for treating acute serious illness and injuries, it has now become increasingly viable to provide high level of care via virtual telehealth applications and mobile models sometimes called hospital at home (Murkofsky & Alston, 2009). In fact, the recent pandemic and lock down triggered an unusual increase in the use of both virtual and hospital at home as more third-party payers and insurance plans embraced the opportunity and provided payment incentives. This has the added benefit of meeting the Meaningful Use requirements of the American Recovery and Reinvestment Act of 2009 (ARRA), which included the Health Information Technology for Economic and Clinical Health (HITECH)

Act, where such virtual portals are eligible for reimbursement as part of the criteria. Virtual and Mobile healthcare businesses have become an interesting trend attracting major online giants like amazon and eBay. According to Investopedia.com, Amazon is currently expanding its virtual healthcare service to all its US employees and other employers nationwide. More so, many hospital treatments can also be performed at home. When technically feasible, home care is usually less expensive and more convenient than hospital or nursing home care. Home care is preferred over emergency room care, hospitalization, or nursing home care due to new technologies and pharmaceutical advances, as well as a patient's desire to remain at home (Murkofsky & Alston, 2009).

2.9 Patient Experience

Patient Experience reflects all occurrences and events occurring independently and or collectively throughout the continuum of care. According to Wolfe et al. (2014), a focus on patient satisfaction and engagement is embedded within patient experience, where the patient is considered an important partner with the care team to ensure care is individualized and services are tailored to meet patient needs and expectations while providing them a platform to input their own experiences.

For our study, we will focus solely on patient satisfaction and Patient engagement as our main outcome variables. Moreover, the results of this study will be very instrumental in advancing the literature in this area as more studies have looked at satisfaction with technology by examining technology use. There have been no studies that have examined the use of technology and how it can be enhanced by cloud versus non cloud enablement to improve patient satisfaction with the continuum of care. Furthermore, extending the model by investigating the effects of engaging patients as partners (patient engagement) with the healthcare to collaborate and contribute with their care team via a cloud enabled patient portal adds significant value to our model and provides an interesting foundation for future research and practical implications. Next, we delve deeper into our main outcome variables -Patient satisfaction and Patient engagement.

2.9.1 Patient Satisfaction

Throughout the years, there have been several changes in the context of service delivery and the definition of the components that make up the entirety of patient satisfaction. Various models have attempted to define and interpret the idea of determining satisfaction through individual perceptions of the quality of healthcare delivered. Sitzia & Wood (1997) explained in their study that determinants of patient satisfaction could be examined in relation to the literature on expectations with a combination of demographic and psychosocial variables. In recent years patient satisfaction has become an important and commonly used indicator for measuring the quality of healthcare (Prakash, 2010).

With the shift to more customer-centric focus in the delivery of care, the patient is now the consumer and is now empowered to shop around until they can find healthcare services that satisfies their needs. In fact, this explains why most healthcare systems have begun to function more like a service industry. Third-party payers have also begun to recognize that patient satisfaction with healthcare service delivery is an important tool for their organization's success and are now closely monitoring patient satisfaction levels among their customers (Prakesh, 2010). To emphasize the importance of patient satisfaction, physician bonuses are now linked to patient evaluations of their personal interactions with the physicians in the United States (Prakesh, 2010). The healthcare industry has now come to terms with the changing dynamics of the market environment. Higher patient satisfaction is reportedly leading to huge benefits for healthcare service providers such as patient loyalty and retention, consistent profitability, increased staff morale, and reduced accreditation issues (for example, from the Joint Commission on Accreditation of Healthcare Organizations (JCAHO) and the National Accreditation Board for Hospitals (NABH) who now have a key strategic focus on quality service issues) for the healthcare industry in several ways.

2.9.2 Patient Engagement

According to Ancker et al, 2011, electronic portals provide a unique platform for patients to engage with their providers and access information from their electronic medical record at any time. In their study, they found good early rates of adoption and use of patient portals within the initial two years of the encounter visits for chronic patients (Ancker et al, 2011). Some schools of thought postulate that technologies that enhance the continuous flow of communication between healthcare provider and patient contribute a great deal towards health promotion and to an extent influences patient satisfaction.

Another interesting argument in the Literature examines the idea that it is possible for patient engagement to be influence by other external constructs like confidence in written and communication skills or trust in doctors or the healthcare system (Anker et al, 2019). Patient engagement could also be influenced by racial and economic disparities at all stages of access to the portal, activation of portal accounts and usage of portal accounts (Ancker et al, 2011).

Furthermore, Ghalandori (2012) broadens the argument by introducing the concept of convenience as perceived by the use of a technology for promoting patient engagement. Most patients are likely to be motivated to engage more with the patient portal due to the convenience of being able to receive healthcare services from the comfort of their home without having to do any travel or fill out many paper forms while waiting to be seen by their providers. We investigate this further via our research hypothesis.

2.10 Synthesis- The Relationship between Healthcare Technology Use and Patient Experience Outcomes (Patient Satisfaction and Patient Engagement)

Our study encompasses a comprehensive model which extends the UTAUT2 model in a unique way as it applies to the healthcare industry. First, we look at the relationship between behavioral intention to use patient portals (the main technology or application for the study). Prior studies have looked at different aspects of behavioral intention to use multiple technologies and platforms, for example banking applications, educational applications, just to name a few. Infact just recently the Covid-19 pandemic forced a shift in collaboration and meeting structures by creating a huge shift to virtual platforms for collaboration and meeting using tools like zoom, google meet, Microsoft teams, go to webinar, Webex amongst others. We have also previously discussed the antecedents that are responsible for influencing behavioral intention to use patient portals. This helps us set a good platform upon which to base our study as we examine other effects and relationships.

The technology use piece is the central pillar upon which our study is based. For our study, we are placing more emphasis on patient portals. A patient portal is a cloud-based application that allows secure confidential and efficient access to personal medical history and care records. Noblin et al (2014) explain that patient portals are necessary for streamlining processes related to routine patient communications given that patients can complete a lot of pre-visit processes like filling out forms, scheduling, educational material, requesting prescription refills or enquiries with billing. In other to understand the extent to the breadth and depth of technology use, it will be important to examine the patient experience outcome variables like patient satisfaction and patient engagement, which is the goal of our study. Our research looks at the breadth and depth of technology use, in addition to the actual technology (patient portal) under investigation. That is, the extent to which patients use different features of patient portals for their care activities, such as integrating the portal with wearables that monitor heart rate, steps taken, sleep patterns, and oxygen levels. We compare this to patients who do not use the technology quite often or maybe just for basic use like reading doctor notes or confirming appointments. Examining different components of technology use like ease of use of different features, frequency of use, benefits of certain features over others, quality of the look and feel of the portal will be critical in enabling us to recommend further opportunities for providers or vendors of the software. This will also provide opportunities for enhancement so as to facilitate communication between the healthcare service team and the patient.

The next component of our study is the evaluation of the effects of implementing a cloud based or cloud enabled patient portal versus non-cloud-based or non-cloud enabled patient portal. As per our discussion above, cloud-based applications have high availability meaning they can be accessed from anywhere and at any time. There is little or no down time and communication is just in time which enhances the provider- patient relationship. Lalow (2010) suggests that a patient portal is a secure web-based, self-service communication solution that is part of the practice website and provides online interaction between the practice and the patient. Other functionalities that such systems could have include the ability to store data regarding each encounter at the time of the encounter and could be used very well with either virtual or face to face consultations.

2.11 Research Model and Hypothesis Development

Based on the constructs and relationships depicted in the model above, we develop the following research hypothesis for this study.

Behavioral Intention and Technology Use

According to Gao 2019, consumers are more likely to be motivated to use new technology or portals for important services including mobile learning, banking, and health care.

Understanding the adoption and use of information technology in healthcare is one of the most promising areas of information systems research (Griebel et al.,2015; Ali et al. (2018). Our empirical analysis therefore seeks to determine the association between behavioral intention and technology use.

From the literature, there are several aspects of behavioral intention that we must examine to understand the key drivers of what influences a patient to use a patient portal. In line with Silver et al, (2020) understanding the differences in behavior by gender and age is critical as it will enable us to understand how to customize the features of the patient portal to appeal to the key target audiences. Moreover, the literature provides evidence of a positive association between behavioral intentions of patients to use a portal and their actual use (Reginald A. Silver, Subramaniam, & Stylianou, 2020). Silver et al (project that patients who have stronger intentions to use a portal are more likely to do so.

However, several factors can influence the relationship between behavioral intentions and actual use. Patients, for example, may have positive behavioral intentions but may face barriers such as a lack of access to technology, technical skills, or privacy and security concerns that prevent them from actual use of the portal.(Reginald A Silver, Subramaniam, & Stylianou, 2021) To overcome these barriers and improve the adoption and use of healthcare portals, healthcare providers can concentrate on increasing patients' awareness and education about the portal's benefits and functionalities, providing training and support to patients to help them use the portal effectively, and addressing their privacy and security concerns. Furthermore, healthcare providers can also concentrate on improving the usability and design of the portal to make it more user-friendly and accessible to patients. Addressing these factors could significantly increase patients' behavioral intentions and actual use of healthcare portals, resulting in better patient engagement, improved health outcomes, and more efficient healthcare delivery.

Internal perception versus external influences or subjective norms have also been advanced as the reason for consumers to change their behavioral intentions to use a technology. For the scope of this study, we will investigate consumers in the USA, but it may be a good idea to consider external influences like personal, cultural beliefs and values which are critical in influencing behavioral patterns. Once perception is influenced in a particular direction, it may be difficult to persuade or influence the consumer to perceive something differently to what their underlying beliefs or culture propose. This will be an even interesting factor to investigate for future research looking at behavioral intentions to use a patient portal across geographies and cultures.

Venkatesh et al (2003) also advance quite a number of interesting antecedents that could cause behavioral intention to vary in one way or another for instance the performance expectancy of the healthcare service via the portal, the perception of how much effort the customers perceive they will need to make their encounters successful, self -confidence and efficacy as well as the facilitating conditions that may exist like access to a computer or mobile phone through which they can connect to the patient portal. All these factors will enable us to explain in great detail the variance in behavioral intention to use a patient portal as it applies to cloud versus non-cloud-based technology. Thus, we propose that: Behavioral Intention (BI) to use a patient portal is positively associated with technology use. If a person plans to utilize a patient portal to access their health information or contact with their healthcare practitioner, they are more likely to engage with and use the technology. On the other hand, if a person has a stronger behavioral intention to utilize a patient portal, they are more likely to use it more frequently and efficiently. As a result, the individual is more likely to interact with the portal and profit from it, which leads to higher technology use.

I hypothesize that Behavioral Intention to use a patient portal is positively associated with Technology Use:

H1: Behavioral Intention (BI) to use a patient portal is positively associated with technology use.

2.11.1 Technology Use and Patient Satisfaction

Understanding the impact of technology use on levels of patient satisfaction and patient engagement may appear daunting at first, but it can be broken down to further understand the depth and breadth of how changes in this independent variable can influence our outcome variables. We begin by evaluating the breadth and depth of technology use. The extent to which the patient or consumer can use the technology or patient portal for a satisfactory interaction with their healthcare team depends on several factors which will be interesting to highlight here. Goa (2019) supports this stream of literature by explaining that consumers tend to be attracted to a technology they perceive to be easy to use or confident of the support and experience they will receive. As such, consumers may be more confident in exploring several features of the technology and not just the basic features recommended by their care team. Moreover, as they become confident in the usage of one feature and become satisfied with the responses from their care team for instance request for prescription refills or changes in appointments, it becomes easy to explore other features like analyzing lab results or chatting with their care provider on any particular healthcare issue. This has the potential to improve patient engagement and motivation to continue to engage with different clinicians involved in the continuum of care.

Silver, et al., (2020) also posit that facilitating conditions are critical in influencing how patients could use the technology. One way to think of facilitating conditions is to consider the aspect of accessibility to the technology. Another way to think about it is the underlying conditions of the patient whether or not they have any form of critical health conditions warranting them to use patient portals more frequently than if there was no underlying critical condition. With constant access to the patient portal, whether it be via access through a computer or mobile phone, it may be easier for a consumer or patient to utilize the technology more. Especially if they also have access to wearables that are easily integrated with their patient portals. To ascertain this fact, it will be interesting to look at frequency of use especially with respect to the above and if there are any differences with regards to control variables like gender, age, education and underlying critical health conditions. With health conditions, it will make sense to examine how frequency of use changes with different types of conditions. While this may be extensive, it could be a good area for further investigation with other use cases after we establish the basic underlying critical cases. Another important aspect we intend to consider as we investigate the technology use construct is the reliability and validity of the architecture. It will not make sense to have the wrong architecture in place as it will result in having the wrong features for our patient use cases. Moreover, if there is little or no support or helpdesk features in the portal, this could also affect the use of the technology and thereby negatively affect our patient experience outcomes. Venkatesh et al (2003), explain this further by stating that experience and performance expectancy are to a great degree influenced by the benefits of using a technology to perform certain activities. This could be greatly affected if the underlying infrastructure is inadequate or unreliable. In a sense this may also be a good case for trust issues and how patient engagement could be affected.

Technology Use and

Patient satisfaction has become a critical agenda item for every healthcare provider, with physician bonuses and system performance tied to patient satisfaction scores. It will be interesting to know how patients perceive the quality of their care when they have access to technology, and if their perception of value changes as technology becomes more available and accessible.

Another interest of our study is to investigate if patient satisfaction changes with availability or patient portals for follow-up and fast feedback lines up with the literature as discussed above. Patient portals are perceived to provide faster feedback loops and follow- up channels with easy chat functions while decreasing long wait times and overall length of stay with features like pre-visit forms and faster communication. With this, the patient can easily reach out to any member of their care team for a request, enquiry, fill out forms or even request availability for appointments without having to go through long phone calls. This is an interesting piece we are also interested in investigating to see if this will explain some of the variances in levels of satisfaction with the healthcare.

Moreover, a major element that has been observed to dramatically increase patient satisfaction is which draws our attention in this study is access to patient education that is made available and customized for each patient on their personal portals. By examining the variations in patient satisfaction with the healthcare service delivery via a patient portal, we will be able to advance the literature in this area as well as provide practical contributions for industry.

Furthermore, Anker et al (2011) reveal frequent technology use is prevalent among users with chronic medical conditions. Thus, if these patient segments are able to access a technology that will enable them effectively to monitor their health, it could positively affect their satisfaction levels. Ghalandori (2012) broadens the argument by introducing the concept of convenience as perceived by the use of a technology for managing patient experience outcomes, which increases interest in this study.

I hypothesize that Technology Use is positively associated with Patient Satisfaction:

H2 Technology use is positively associated with patient satisfaction.

Technology Use and Patient Engagement

Patients who use technology to manage their health are more likely to be interested in their healthcare, which could lead to improved and better health outcomes. In fact, the involvement of patients in their own care, such as taking an active role in making healthcare decisions and adhering to treatment plans, linked to improved health outcomes, enhanced satisfaction with healthcare, and to an extent lower healthcare expenses.

According to Silver, et al.,, 2020 there is a possibility of patients with health seeking behaviors to become more attracted to the healthcare service due to the continuous use of the patient portal. Quite frankly, the notion that patients can speak with their doctors, track their health data, and receive care remotely is quite appealing to patients in this technologically advanced society.

Dendere et al (2019) suggest in their study that patient portals may actually enhance patient engagement and satisfaction since it encourages patients to keep in continuous communication with their providers via a secured Electronic Medical Record platform. Overall, the relationship between technology use and patient engagement is complex and multifaceted. It is an important area of research that could have significant implications for improving healthcare outcomes and patient satisfaction. As a result, further investigation is required to better understand the relationship between technology use and patient involvement.

H3 Technology Use is positively associated with Patient Engagement

Cloud-enabled vs. Non-cloud-enabled Technology and Patient Satisfaction

Cloud based or enabled patient portals, have high availability, meaning the application can be accessed from anywhere at any time. This enables patients to connect and communicates with their healthcare team at any time they desire whether from home or abroad. These applications even have the ability to integrate with other health monitoring devices like wearables and other heart monitoring equipment creating the opportunity for providers to have access to patient's real time data.

Furthermore, cloud enabled patient portals are well designed to capture, store and transmit images providing capabilities for patients to send in images for infected areas, food portions, or any critical event or item they wish to enquire about.

High Scalability is also a very important feature of cloud enabled applications and patient portals. With High scalability, the patient portal is able to function seamlessly with a variance in traffic during peak and off-peak seasons. These capabilities, creates a seamless transition of messaging from the patient to their care team without any lags or delays or nee for waiting in line or on the phone queue. This is critical in boosting the entire patient experience, motivating them to engage more with their healthcare providers and take responsibility for some of the activities in managing the care process thus enhancing overall satisfaction.

Another important case for cloud enabled patient portal is the highly secured feature, meaning patient information and communication goes from the patient directly to their provider via the portal. There is little or no room for patient information floating around on paper forms and no external process or third-party interruptions. All cloud enabled applications or patient portals are mandated to comply with very high security requirements especially with the Health Insurance Portability and Accountability Act of 1996 (HIPAA).

I hypothesize that the presence of a cloud-enabled patient portal positively moderates the relationship between Technology Use and Patient Satisfaction:

H4 Cloud enabled patient portal positively moderates the relationship between technology use and patient satisfaction.

Cloud-enabled vs. Non-cloud-enabled Technology and Patient Engagement

The high availability of cloud enabled patient portals support the access to the technology from anywhere and at any time. Just like banking mobile applications, patients could be motivated to utilize patient portals more, engaging in activities and processes that will give them more control over the management of their care plans as well as the ability to carry out some basic functions instead of waiting for clinicians to complete.

Interestingly, some health monitoring apps even engage customers in a variety of exercises by providing education and corresponding follow-up interactive activities to improve their engagement and contribution to their care plans. We intend to uncover any underlying findings that may explain differences in engagement levels in relation to other control variables such as age, gender, education level, and critical health conditions based on our proposed research hypothesis.

According to Bhattarch (2017), Cloud Enabled Patient Portal has the potential to enhance the relationship between technology use and patient engagement. important benefits of cloud technologies like agility, high availability, high reliability, and scalability as demonstrated by flexera.com (2022), enhances the patient experience and engagement by using cloud-based tools. Perceived Performance expectancy of a Cloud Enabled Patient Portal refers to the degree to which the user perceives that the technology will help in carrying out functions important to the user (Venkatesh et al 2012). In line with the literature, performance expectancy of the Cloud Enabled

Patient Portal reflects the patient's perception of how well the technology will be able help to manage user's healthcare and overall experience (Silver et al, 2020; Thong et al, 2006).

I hypothesize that the presence of a cloud-enabled portal positively moderates the relationship between Tehcnology Use and Patient Engagement:

H5 Cloud enabled patient portal positively moderates the relationship between technology use and patient engagement.

Virtual Modality, Technology Use and Patient Satisfaction

With the recent COVId-19 pandemic, there has been a rise in healthcare providers offering different models of healthcare. For our study, we anticipate that choice of healthcare service delivery has the potential to enhance the use of patient portals which in turn increase patient satisfaction given that patients can begin their care encounter on the portal and end in the portal while choosing any mode of delivery (Virtual or in-person) as it appeals to them.

Recently, the quality of virtual care has been heightened to provide same services with the patients having more choice options. In fact, some systems have created a hybrid hospital at home where patients can be hospitalized in the comfort of their home surrounded by family and loved ones with clinicians regularly monitoring their portals and available on dispatch in case of any emergencies. This mode of care delivery has been significant especially during the recent pandemic where hospitals began experiencing bed shortages and had to create other opportunities to provide quality care to patients using different modes. It will be interesting to see if there are variances in the levels of satisfaction with patients who prefer virtual, or hybrid consults versus in-person.

Another interesting aspect we are looking to investigate is the level of satisfaction among different age groups, gender, mobility ability (on wheelchair or not) and even including employment status. We are interested in understanding if there will be a variation in the results of patients in these different categories. This will also help inform the healthcare industry on trends for further investigation especially if higher satisfaction levels are recorded for virtual consults versus non-virtual/in-person consults.

According to Venkatesh et al., (2012), there are benefits to using various healthcare modalities, particularly in terms of technology use and how it relates to patient outcomes. Griebel et al., 2015) expand on this theme by arguing that creating a variety of healthcare modalities provides patients with options, which may increase patient satisfaction.

I hypothesize that the use of a virtual healthcare modality positively moderates the relationship between Technology Use and Patient Satisfaction:

H6 Use of Virtual Healthcare Modality positively moderates the relationship between technology use and patient satisfaction.

Virtual Modality, Technology Use and Patient Engagement

Healthcare modalities give patients and consumers choice and convenience. This is a significant factor that has the potential to encourage patients to become more engaged with their healthcare team. Choice is important for patients because it indicates that they have more control over their care journey and can take on more responsibility. This could also include engaging with the variety of features and functionalities available to the patient via the portal, particularly with virtual rather than in-person options. We will investigate whether there have been any changes in levels of engagement with the healthcare team as a result of this.

Another aspect of this relationship we are interested in is that Patients can provide valuable contributions via the portal and own some processes with virtual healthcare modalities giving the patients more control. This is an interesting enquiry as it will provide some insight as to the extent to which patients are interested in engaging with the patient portal and software.

The UTAUT2 model provides a good foundation for determining the boundary conditions for healthcare modality (Venkatesh et al., ,2012). Given that consumers bear responsibility for the cost of services as well as the mode of delivery, it will be useful to investigate the impact of various healthcare modalities (virtual, brick and mortar, and mobile) on technology use and patient engagement (Davis and Venkatesh, 2004; Brown and Venkatesh, 2005; Nikolopoulos & Likothanassis, 2018).

The ARRA Act of 2009, which includes the HITECH Act, provides significant incentives for healthcare providers who are willing to develop a variety of platforms for providing care, engaging with patients, and encouraging collaboration in care. These incentives have the potential to significantly reduce the cost of providing care, resulting in a positive effect on cost for patients. Our hypothesis is intended to test whether the presence of healthcare modalities has a significant impact on the relationship between technology use and patient engagement.

I hypothesize that the use of a virtual healthcare modality positively moderates the relationship between Technology Use and Patient Engagement:

H7 Use of Virtual Healthcare Modality positively moderates the relationship between technology use and patient engagement.

The Relationship Between Patient Satisfaction and Patient Engagement

Based on the literature, it can be depicted that patients who are satisfied with their healthcare are more likely to engage more with the healthcare team thereby improving the overall patient experience. This is an interesting extension our study seeks to investigate with the aim of providing a significant and valuable contribution to the literature.

Another interesting observation to investigate will be the variance in strength of the relationship between patient satisfaction and patient engagement with respect to different modalities of healthcare delivery or cloud versus non-cloud-based patient portals. This could also point to some interesting areas of research that could help us learn more about how different types of consumers perceive healthcare service performance.

Moreover, patients who are engaged in completing their pre-visit information online in the portal are motivated by the reduced wait time they will have when they get to the facility thereby increasing satisfaction. According to Noblin et al., (2015) and Labow (2010), the more satisfied they are with their care, the more motivated they are to engage and collaborate with healthcare providers on the portal.

I hypothesize that there is a positive association between Patient Satisfaction and Patient Engagement:

H8 There is a positive association between Patient Satisfaction and Patient Engagement

3 CHAPTER 3: RESEARCH METHODOLOGY

Overview

This section includes a detailed description of the research design, participants, equipment, materials, variables, the rationale for why specific methods were chosen, how each research question was derived and investigated, how data was collected, the measures used, and how the data collected was analyzed. The goal for this section is to provide enough information to allow other researchers to replicate the experiment or study.

As previously stated, this study contains four primary aims comprised of seven hypotheses. The first is to establish a model of healthcare technology utilization and its implications on patient outcomes. The second goal is to investigate how cloud-based applications might affect patient experience and engagement across the care life cycle. The third goal is to determine how cloud-based technology and healthcare modalities affect the link between behavioral intention to utilize technology and patient outcomes. The fourth goal is to compare changes in patient experience and levels of patient engagement when using cloud-based technology against non-cloud-based technology.

3.1 Research Design and Methodology

The study adopted a quantitative research approach for assessing data acquired from a survey modified from previously validated scales from the literature (Hair et al., 2017; Venkatesh et al., 2017; Creswell, 2009; Pedhazur and Smelkin, 1991). Moreover, the unit of analysis for the model tested was individual-level, and the research was conducted across several internet communities and forums.

The framework had previously been used to analyze prominent IS theories like virtuality and knowledge in teams (Griffith et al, 2003) and UTAUT (Dwivedi et al., 2017, 2020; Rana et al., 2016; Rana et al.,, 2017; Venkatesh et al.,, 2003; Venkatesh et al.,, 2018; Williams et al.,, 2015), yielding thought-provoking results.

The study targeted current users of internet technologies in online communities with the help of Qualtrics to complete the assessment items in the designated online questionnaire collection. This was a voluntary decision for users of the online forums. Online surveys had the advantages of not being limited to a specific geological region, being cost-effective, and allowing users to respond instantly. (Chen et al.,, 2021). Thus, to strengthen the external validity of our study, we recruited users who had an awareness of these cloud-based technologies and were keen on utilizing the applications throughout their entire care experience.

3.2 Development of Instrument (Survey)

The research model went through many phases to analyze the relationships between the constructs. The first step was to create the survey questions using relevant literature as a guide; the second step was to pilot test the survey questions; the third step was to determine an acceptable study sample size; and the fourth step was to present the survey to a relevant sample of participants. G-power was used in this investigation to determine the correct sample size to produce significant results.

3.3 Data Collection and Sample

3.3.1 Institutional Review Board Approval and Data Collection

Participants were recruited through outreach with Qualtrics on Research panels, social media (Facebook, LinkedIn), email, or listserv announcements. Qualtrics is a survey tool approved and recommended by UNCC and Belk College of Business, which is a powerful, user-friendly platform available to UNCC faculty and graduate students. Surveys were created to meet UNCC's

Level 2 data classification, and participants needed to meet the criteria of being eighteen or older and having access to a smart phone, tablet, or computer with internet access.

The researcher engaged Qualtrics to identify potential participants who fit the criteria as previously described. The account manager, acting on behalf of the researcher, reached out and invited potential participants to complete the survey. The mechanism used, including initial contact, invitation, and follow-up process, was the same as the social media and email announcements approach. The process to gain consent, survey administration, and data collection was also the same.

For social media, the researcher used primary online platforms like LinkedIn, Facebook, to identify, screen, and short-list potential participants. Firstly, the researcher used their personal (first order) connections to short-list participants with access to smart phones, tablets or computers with the internet. Second, the researcher sent direct written messages via the messenger features of the platforms, sharing details of the research and seeking their interest to participate. If they were interested and willing to participate, the message also requested them to confirm their email address and smart phone number to reach them if further information was needed. Once confirmation of interest and email address or smart phone number was received, the potential participant was recruited into the system. The mechanism to provide consent remained consistent with other respondents (i.e., through a survey) and followed UNC Charlotte's consent protocol as per the University's IRB policy.

The researcher also sought referrals from their first-order connections that fit the criteria regardless of their interest. They provided them with an anonymous survey link to forward to their contacts. Alternatively, they could choose to introduce the researcher to their contacts via the respective social media platform or emails, in which case the researcher iterated the steps mentioned above to recruit them and gain consent.

All participant information, including name, email address, and access to smart phone, tablet or computer with internet, was retained securely as password protected in the Level 2 UNCC approved storage area.

A quantitative research technique was used to examine the presented hypotheses. For empirical data collection, an online survey with around forty questions organized into three parts was employed. This was consistent with the literature, for instance, with Merhi et al., 2019. The initial section consisted of eight closed-ended questions used to determine demographic (control) variables on a nominal scale (That is Gender, Age, Race, education level, Tech experience, EHR usage frequency, EHR features usage, pre-existing conditions, mobility, geography). The second section used pre-validated scale items from Venkatesh et al.,, 2012, as well as related works such as Alalwan et al.,, 2017 and Sharma et al.,, 2004. Each of these criteria was assessed using four items. The questionnaire items were measured using a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The validity was investigated to ensure that the questions were clear, straightforward, and easily understood by responders.

The invitation for the survey was made up of an information letter and a link to the Qualtrics online survey (2022 Qualtrics, LLC). The information letter explained the study's objective and voluntary nature, the usage and anonymization of data, and the expected time required to participate (approximately 15 minutes). This information letter and an informed consent form were included in every invite. Non-response to the survey or opting out on the informed consent form was interpreted as unwillingness to participate in the study.

3.4 Data Preparation and Cleaning for Analysis

To ensure the accuracy and authenticity of our research and results, it was crucial that the data was cleaned and prepared. The procedures that were used to clean up and prepare the data for analysis are outlined below.

First, the data was exported into excel for preliminary inspection. Once the data had been successfully exported into excel, we checked for any missing values. All missing values were replaced by a sentinel, for example, "-99". Once all missing values were recoded, we checked for any outliers with the help of descriptive statistics in SPSS. This gave us a clearer picture of our dataset and also highlighted any underlying issues we may not have been able to easily identify with the use of excel.

Next, the clean dataset was imported into Smart PLS-SEM (R) with the sentinel value indicated upon import (in the case of this research "-99"). Once imported, the data file was then validated and estimated initially using a case-wise replacement model. Once results were recorded, we proceeded with other steps for our analysis to test each hypothesis. Results of the analysis were examind, and findings recorded as proposed.

3.5 Analysis

The survey data was analyzed by using partial least squares structural equation modeling (PLS-SEM) via Smart PLS®. This is consistent with similar studies in the literature especially for testing relationships within the proposed theoretical model (Ringle, Sarstedt, & Straub, 2012; Silver, Subramaniam, & Stylianou, 2020). The reliability of each construct was evaluated using Cronbach’s Alpha and composite reliability.

3.6 Measures

All scales used in the study were based on existing research, and all survey items and the construct they represent have been summarized in Appendix E while sources have been summarized in appendix A. For the responses, a 5-point Likert scale was used to measure the items (Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), or Strongly agree (5)) validated from previous studies, was also used in this research. The scales used for UTAUT2 constructs, such as performance expectancy, effort expectancy, social influence, facilitating circumstances, and behavioral intention, were adopted from Venkatesh et al (2003), and Silver et al (2020).

Technology Use was measured with a total of 19 items as provided in Appendix A, and Appendix E. The data from respondents were recorded and assessed on 5-point Likert scale was used to measure the items (Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), or Strongly agree (5).

Patient Satisfaction. was measured with a total of 16 items. These items were assessed on 5-point Likert scale was used to measure the items (Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), or Strongly agree (5).

Patient Engagement. The scales for engagement and experience were adopted from Garvin & Simon (2017) (Garvin & Simon, 2017). Patient Engagement was measured with a total of 14 items of which some items were collected following the 5-point Likert scale was used to measure the items (Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), or Strongly agree (5) while other items utilized the 4-point Likert scale where 0 (not at all or rarely), 1 (sometimes), 2 (often), 3 (most of the time).

Cloud Enabled Patient Portals was measured with a total of 10 items. Given that there was no way of finding out if the Patients could differentiate if a portal utilized the cloud or not which was actually what I wanted to measure, data was collected on the perception and awareness of cloud enabled portals and the value it provides in their healthcare. The items measuring the perception of the cloud were measured on a the 5-point Likert scale was used to measure the items (Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), or Strongly agree (5)

Virtual Healthcare Service Modality was measured with a total of 9 items. Again for this measure, data was collected on the perception of virtual healthcare service delivery on a validated 5-point Likert scale ranging from : Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), or Strongly agree (5)

3.7 Control Variables

The impact of technology on patient satisfaction and engagement largely depends on a number of control variables such as age, gender, race, education, and settlement. In this discussion, we look at each of these control variables and why they are thought to have an impact on the effect of technology use on patient satisfaction and engagement. These are all shown on the survey instrument in Appendix B.

Age. When studying the impact of technology on patient satisfaction and engagement, age is a crucial aspect to examine. Older patients may have less expertise with technology and be less at ease with it. Furthermore, elderly individuals' health needs and preferences may differ from those of younger ones. Thus, depending on the patient's age, technology may have a variable impact on patient happiness and participation. Age was measured by age group: 18-25, 26-35, 36-45, 46-55, >56.

Gender is the next control variable used in this study. Understanding the impact of gender in the research may provide insight into solutions for significantly improving efficacy in the technologies especially as different genders may prefer different features of the technology. Gender was collected as Male, Female or other.

Race. When assessing the impact of technology on patient satisfaction and engagement, race is a crucial aspect to examine. Different racial minorities may have diverse perspectives and experiences with technology. As a result, depending on the patient's race or ethnicity, the influence of technology on patient satisfaction and engagement may differ. For this study, Race was measured and coded as 1- White, 2- Black or African American, 3 – American Indian or Alaska Native, 4 – Asian, 5- Native Hawaiian or Pacific Islander.

Settlement was classified as urban, suburban, or rural. The three categories were useful in providing context for the places where respondents lived or spent the majority of their time. Although this was also kept constant for this study due to the research focus, it will be vital to investigate further for future research and industry.

Education was also collected as a categorical variable: Some High School or less, High school diploma or GED, Some College , but no degree, Associates or Technical Degree, Bachelors degree, Graduate or professional degree, and Prefer not to say.

Prior research studies utilized control variables to account for potential confounding factors that could influence the relationships between the independent and dependent variables (Reginald A. Silver et al., 2020; Venkatesh et al., 2003; Venkatesh et al., 2012; Venkatraman, Henderson, & Oldach, 1993). Most often, control variables enabled the researcher to understand the nature of the data collected and assess how well distributed the data is. Age, gender, race, education level, area of settlement (urban, suburban and rural) are commonly used control variables in research studies as they help provide insight into the observations of the study. For this study, the control variables described above were also utilized firstly due to their extensive use in healthcare outcomes research and because an understanding into the demographic groups in the study helped provide important areas of focus for practical implementation.

3.8 Research Model Testing

The theoretical Model incorporates Individual behavioral intention and technology use as the main constructs. These have been used severally in systems IS research. Drawing from the literature, a proposal was made on a relationship between behavioral intention to use technology and patient engagement and satisfaction. Similarly, this research suggests that this relationship can be affected by the type of healthcare modality used in providing service as well as whether or not the electronic health record is cloud vs non cloud based.

To evaluate the dissertation's hypotheses, Partial least squares structural equation modeling (PLS-SEM), using SmartPLS, was employed to assess validation and test the hypotheses. The PLS-SEM regression analysis was chosen because: (a) PLS-SEM reduces the influence of sample size since its computations are less vulnerable to smaller samples (Hair et al, 2011) (b) PLS- SEM is a helpful tool for studies that focus on theory construction and prediction rather than exploration and makes no assumptions about underlying data (Hair et al., 2011) (c) PLS-SEM is the recommended method when equations must be assessed concurrently (Hair Jr, Sarstedt, Ringle, & Gudergan, 2017). Furthermore, the PLS-SEM technique has enhanced communication in a number of sectors in recent years, with the use of formative indicators, small sample sizes, and non-normal data being the three main drivers of its adoption. (Hair et al., 2017; Chen et al., 2021). According to Fornell and Larcker's (1981) criterion, if the reliability (i.e., Cronbach's alpha and composite reliability) and average variance extracted (AVE) of each construct are all greater than 0.7 and 0.5, respectively, it will imply the achievement of convergent validity, which is critical in this study. (Fornell & Larcker, 1981; Hair, Risher, Sarstedt, & Ringle, 2019)

4 CHAPTER 4: RESULTS

4.1 Introduction

This chapter reports the results obtained from the survey and evaluation of the research model. The evaluations include descriptive statistics, demographics, and then a three-step approach to investigate the relationship in the proposed conceptual framework.

First, we employ a confirmatory Factor analysis (CFA) to test model fit and convergence, validity and reliability. In addition to the CFA, we evaluate the measurement model by investigating the outer loadings, tests for reliability, discriminant validity and internal consistency, correlations among variables, means, standard deviations, inferential measures with respective tables as presented and below. Our third step will be to evaluate the structural model to test the proposed relationships between the independent and dependent variables and the moderation effect by means of examining the coefficient determination (*R-squared*), path analysis and the effect size. Furthermore, we will assess the moderating effects, test alternative models and investigate the model supports the proposed hypothesis and research questions.

The evaluation tested survey responses from 130 respondents. The survey was conducted via Qualtrics an online research panel with a total of about 215 respondents reached. The data was cleaned to remove responses with missing data resulting in 130 completed responses. The response time to complete the survey was evaluated to ensure that the data was reflective of reasonable times with an average time of 18 minutes to complete the survey.

4.1 Descriptive Statistics, Demographic Characteristics and Correlation Analysis

The results from the G*Power analysis indicated an acceptable sample size of 109 based on the total number of predictors which were eight in total and an effect size of 0.15. This is shown in Appendix C. The data collection was quite successful as we achieved a total of 215 responses overall surpassing the suggested 109 from G*Power. After cleaning the data and removing all missing values, a total sample N=130 was achieved from respondents recruited from a range of sources including social media (Facebook and LinkedIn), research announcement via the university and other professional groups and associations. The removal of all observations with missing values is consistent with the literature and is suggested as best practice to avoid bias (Hair et al, 2017).

Tables 4.1 and 4.1a depict a breakdown of the descriptive statistics, Inner Model descriptive. Descriptive statistics summarize the main characteristics of a set of data, such as the mean, standard deviation, and range which are helpful in interpreting the results.

Table 4.1 Descriptive Statistics

		Gender	Age Group	Race	Education	Settlement
N	Valid	130	130	130	130	130
	Missing	0	0	0	0	0
Mean		1.79	2.61	1.72	4.77	1.78
Median		2.00	3.00	1.00	5.00	2.00
Std. Deviation		0.509	1.198	1.189	1.333	0.584

Table 4.1a Inner Model Descriptive

	Mean	Median	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	Number of observations used	Cramér-von Mises test statistic	Cramér-von Mises p value
Patient Engagement	-0.097	-0.121	-2.147	1.749	0.756	-0.248	-0.01	130	0.022	0.941
Patient Satistfaction	0.03	0.003	-1.378	2.259	0.544	1.985	0.483	130	0.122	0.056
TechnologyUse	0	0.055	-1.01	1.039	0.424	-0.411	-0.235	130	0.162	0.016

4.1.1 Correlation Analysis

The inter-item correlations for the main constructs (TU, PaSa, PaEn, BI, Cloud, and VirtualHM) based on the of the study are shown in Table 4.1b while Table 4.1c (supplemental files) shows the correlations for the individual items that constitute each co sample size of N=130 . The Pearson correlation coefficients between six variables are shown in the table: TU, PaSa, PaEn, BI, Cloud, and VirtualHM. A Pearson correlation coefficient is a measure of a two-variable linear relationship. The coefficient runs from -1 to 1, with -1 representing a totally negative correlation, 0 representing no association, and 1 representing a perfectly positive correlation.

According to the table, there is a statistically significant positive association between TU and PaSa ($r = 0.728$) and TU and VirtualHM ($r = 0.543$). BI and TU ($r = 0.902$), BI and PaSa ($r = 0.616$), and BI and VirtualHM ($r = 0.461$) all have high positive relationships. PaEn has a somewhat favorable relationship with both PaSa ($r = 0.427$) and TU ($r = 0.274$). Cloud shows weak positive correlations with PaSa ($r = 0.345$), PaEn ($r = 0.253$), and VirtualHM ($r = 0.373$). All the correlations presented in the data are significant at either the 0.01 or 0.05 level (two-tailed). Overall, the data suggests that there are significant positive correlations among the variables in the study. The correlation analysis is presented in Table 4.1b below.

Table 4.1b Correlation Analysis

	TU	PaSa	PaEn	BI	Cloud	VirtualHM
TU	1					
PaSa	.728**	1				
PaEn	.274**	.427**	1			
BI	.902**	.616**	.182*	1		
Cloud	.177*	.345**	.253**	.137	1	
VirtualHM	.543**	.515**	.300**	.461**	.373**	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

The respondent's demographic information like age, education level, gender and settlement are demonstrated below.

According to the results 25.4% of the respondents were male with up to 70.0% female and about 4.6% self-reported as other.

Table 4.2 Demographics: Gender

	N	%
Male	33	25.4%
Female	91	70.0%
Other	6	4.6%

Table 4.3 displays the age range for respondents in the sample. The highest age group with 34.6% was 36-45years followed by 26-35 recording 23.1% and then the 18-25 years with 22.3%, 46-55 years reporting 11.5% and finally about 8.5% for above 56 years.

Table 4.3 Demographics: Age Group

	N	%
18-25	29	22.3%
26 -35	30	23.1%
36-45	45	34.6%
46-55	15	11.5%
>56	11	8.5%

The next demographic characteristics examined in the study was race. According to **Table 4.4**, of the 130 responses analyzed, there seemed to be a relatively high response rate among the white or Caucasian and Black or African American race groups with 54.6% and 36.9% respectively. Asian and American Indian or Native American or Alaska Native reported up to 4.6% and 2.3% respectively while other and preferred not to say categories were 2.3% and 1.5% as shown below.

Table 4.4 Demographics: Race

	N	%
White or Caucasian	71	54.6%
Black or African American	48	36.9%
Asian	6	4.6%
Other	3	2.3%
Prefer Not to Say	2	1.5%

Another interesting set of demographics examined in the study were education and settlement (regions where respondents resided). About 42.3% of respondents have some form of graduate or professional degree which was quite fascinating. The next large group was bachelors degree with 22.3%, some college but no degree at 16.2%, Highschool diploma at 6.9% just below Associates and technical degree reporting at 12.3% as shown below.

Table 4.5 Demographics: Education

	N	%
High school diploma or GED	9	6.9%
Some college, but no degree	21	16.2%
Associates or technical degree	16	12.3%
Bachelor's degree	29	22.3%
Graduate or professional degree (MA, MS, MBA, PhD, JD, MD, DDS etc.)	55	42.3%

The Most part of the respondents lived or settled in suburban areas recording up to 61.5% with urban and rural settlements scoring at 30% and 8.5% respectively. This data is shown in Table 4.6 below.

Table 4.6 Demographics: Settlement

	N	%
Urban	39	30.0%
Suburban	80	61.5%
Rural	11	8.5%

Overall, in terms of demographics the sample was deemed balanced given that the survey was targeted at respondents who had access to the internet through either a computer, laptop, or phone.

4.2 The Measurement Model

The robustness of PLS-SEM in examining the interactions between independent, dependent, and moderating components in a theoretical model is why we selected the approach. (Hair, Risher, et al., 2019). The PLS-SEM evaluation consists of two steps. The measurement models are initially examined using the pertinent reflective constructions criteria. As a second stage, we evaluate the structural model (Joseph F. Hair et al., 2020). The literature recommends broad principles for PLS-SEM analysis as a general rule of thumb. We use this technique because of its extensive acceptance and implementation in research (Götz et al., 2009; Henseler et al., 2009; Mora et al., 2012).

4.2.1 Analysis of the Measurement Model

Tests were conducted for reliability, convergent validity, and discriminant validity of the reflective constructs. These tests were performed to determine whether the constructs were reliable. Convergent validity was used to measure how closely different measurements of the same constructs were aligned. It also indicated the possibility of any related or commonality of influence on the constructs. We used confirmatory composite analysis (CCA) to assess the measurement model. All constructs in our model are reflective.

To assess our model and understand the definitions of the constructs with respect to their mappings, we present a crosswalk of the variable codes and their respective definitions and the main constructs they measure. This has been demonstrated in Appendix E, Table 4.7a.

4.2.1.1 Outer Loadings and Weights

Our initial stop was to evaluate the model's fit and outside loadings. We executed a PLS-SEM algorithm calculation after plotting the model to calculate the outer loadings for each of the latent variables in order to assess the weights (Figure 4.1). Interestingly, majority of the items seemed to have loaded well over 0.708 which is the minimum threshold for accepting the item as a good fit based on the literature and best practice rule of Thumb (Hair et al.,, 2020). However, there were some items that did not load quite well as seen in Figure 4.1 and Table 4.7b below. The loadings for CSQ5 (Patient Satisfaction - CSQ1), CSQ8 (Patient Satisfaction – CSQ8), FC2

(Facilitating Conditions-FC2), FC3 (Facilitating Conditions- FC3), FC4 (Facilitating Conditions – FC4), IntQu4(Interaction Quality – 4), PAEnHeSeek2 (Patient Engagement-Helpseeking-2), PAEnHeSeek3(Patient Engagement-Helpseeking-3), PAEnHeSeek4 (Patient Engagement-Helpseeking-4), PAEnHeSeek5 (Patient Engagement-Helpseeking-5), PE3 (Performance Expectancy-3), PaEnAv1 (Patient Engagement Availability-1), PaEnAv2 (Patient Engagement Availability-2), PaEnAv3 (Patient Engagement Availability-3), PaEnColl1 (Patient Engagement Collaboration-1), PaEnTA1 (Patient Engagement Treatment Adherence1), PaEnTA3 (Patient Engagement Treatment Adherence3), PerSecP2 (Perceived Security and Privacy- PSP2), PerSecP3 (Perceived Security and Privacy- PSP3), Re1 (Reliability – 1), Re2 (Reliability – 2), Re3 (Reliability – 3), TSQ1(Usefulness of the Technology - TSQ1), TSQ2(Usefulness of the Technology – TSQ2), TSQ3(Usefulness of the Technology – TSQ3) as defined in Appendix E, Table 4.7a were below the 0.708 threshold. Items with values greater than 0.708 suggested that they sufficiently represented the constructs very well. According to Hair et al (2017) the general and acceptable rule of Thumb is that, if item loadings are below 0.708 but above 0.5, we keep the construct in the model as there is no strong significant effect on the construct. This also provides face validity of the construct given that it measures what the scale intended to measure. More information is presented in Table 4.7b and Figure 4.1.

Table 4.7b Factor Loadings

	Outer Loadings
Independent Variables	
Behavioral Intention	
BI1 <- Behavioral Intention	0.861
BI2 <- Behavioral Intention	0.814
BI3 <- Behavioral Intention	0.772
EE1 <- Behavioral Intention	0.725
EE2 <- Behavioral Intention	0.785
EE3 <- Behavioral Intention	0.763
FC1 <- Behavioral Intention	0.719
FC2 <- Behavioral Intention	0.698
FC3 <- Behavioral Intention	0.685
FC4 <- Behavioral Intention	0.665
PE1 <- Behavioral Intention	0.805
PE2 <- Behavioral Intention	0.798
PE3 <- Behavioral Intention	0.617
PE4 <- Behavioral Intention	0.782
Technology Use	
EU1 <- Technology Use	0.854
EU2 <- Technology Use	0.821
EU3 <- Technology Use	0.825
EU4 <- Technology Use	0.828
PEU1 <- Technology Use	0.845
PEU2 <- Technology Use	0.847
PEU3 <- Technology Use	0.848
PEU4 <- Technology Use	0.754
PEU5 <- Technology Use	0.818
PEU6 <- Technology Use	0.834
PU1 <- Technology Use	0.799
PU2 <- Technology Use	0.771
PU3 <- Technology Use	0.731
PU4 <- Technology Use	0.739
PU5 <- Technology Use	0.763
PU6 <- Technology Use	0.771
TSQ1 <- Technology Use	0.675
TSQ2 <- Technology Use	0.600
TSQ3 <- Technology Use	0.669

Moderators	
Cloud Vs Non-Cloud Enabled	
Re1 <- Cloud Vs Non-Cloud	0.676
Re2 <- Cloud Vs Non-Cloud	0.615
Re3 <- Cloud Vs Non-Cloud	0.608
ClouAW1 <- Cloud Vs Non-Cloud	0.756
ClouAW2 <- Cloud Vs Non-Cloud	0.798
ClouAW3 <- Cloud Vs Non-Cloud	0.819

	Outer Loadings
Dependent Variables	
Patient Satisfaction	
CSQ1 <- Patient Satisfaction	0.779
CSQ2 <- Patient Satisfaction	0.767
CSQ3 <- Patient Satisfaction	0.728
CSQ4 <- Patient Satisfaction	0.785
CSQ5 <- Patient Satisfaction	0.656
CSQ6 <- Patient Satisfaction	0.764
CSQ7 <- Patient Satisfaction	0.776
CSQ8 <- Patient Satisfaction	0.699
IntQu1 <- Patient Satisfaction	0.771
IntQu2 <- Patient Satisfaction	0.708
IntQu3 <- Patient Satisfaction	0.759
IntQu4 <- Patient Satisfaction	0.688
SaFutureUse1 <- Patient Satisfaction	0.854
SaFutureUse2 <- Patient Satisfaction	0.783
SaFutureUse3 <- Patient Satisfaction	0.776
SaFutureUse4 <- Patient Satisfaction	0.838
Patient Engagement	
PaEnAv1 <- Patient Engagement	-0.509
PaEnAv2 <- Patient Engagement	0.565
PaEnAv3 <- Patient Engagement	-0.307
PaEnColl1 <- Patient Engagement	0.679
PaEnColl2 <- Patient Engagement	0.812
PaEnColl3 <- Patient Engagement	0.780
PaEnColl4 <- Patient Engagement	0.758
PaEnTA1 <- Patient Engagement	0.647
PaEnTA2 <- Patient Engagement	0.759
PaEnTA3 <- Patient Engagement	-0.319
PAEnHeSeek1 <- Patient Engagement	0.808
PAEnHeSeek2 <- Patient Engagement	-0.445
PAEnHeSeek3 <- Patient Engagement	0.629
PAEnHeSeek4 <- Patient Engagement	-0.298
PAEnHeSeek5 <- Patient Engagement	0.654

Moderators	
Virtual Vs Non-Virtual Healthcare Modality	
CostR1 <- Virtual Vs Non-Virtual	0.831
CostR2 <- Virtual Vs Non-Virtual	0.867
CostR3 <- Virtual Vs Non-Virtual	0.873
PerSecP1 <- Virtual Vs Non-Virtual	0.800
PerSecP2 <- Virtual Vs Non-Virtual	0.552
PerSecP3 <- Virtual Vs Non-Virtual	0.667
LifeCoC1 <- Virtual Vs Non-Virtual	0.821
LifeCoC2 <- Virtual Vs Non-Virtual	0.871
LifeCoC3 <- Virtual Vs Non-Virtual	0.858
Cloud Vs Non-Cloud x Technology Use -> Cloud Vs Non-Cloud x Technology Use	**1.000**
Virtual Vs Non-Virtual x Technology Use -> Virtual Vs Non-Virtual x Technology Use	**1.000**

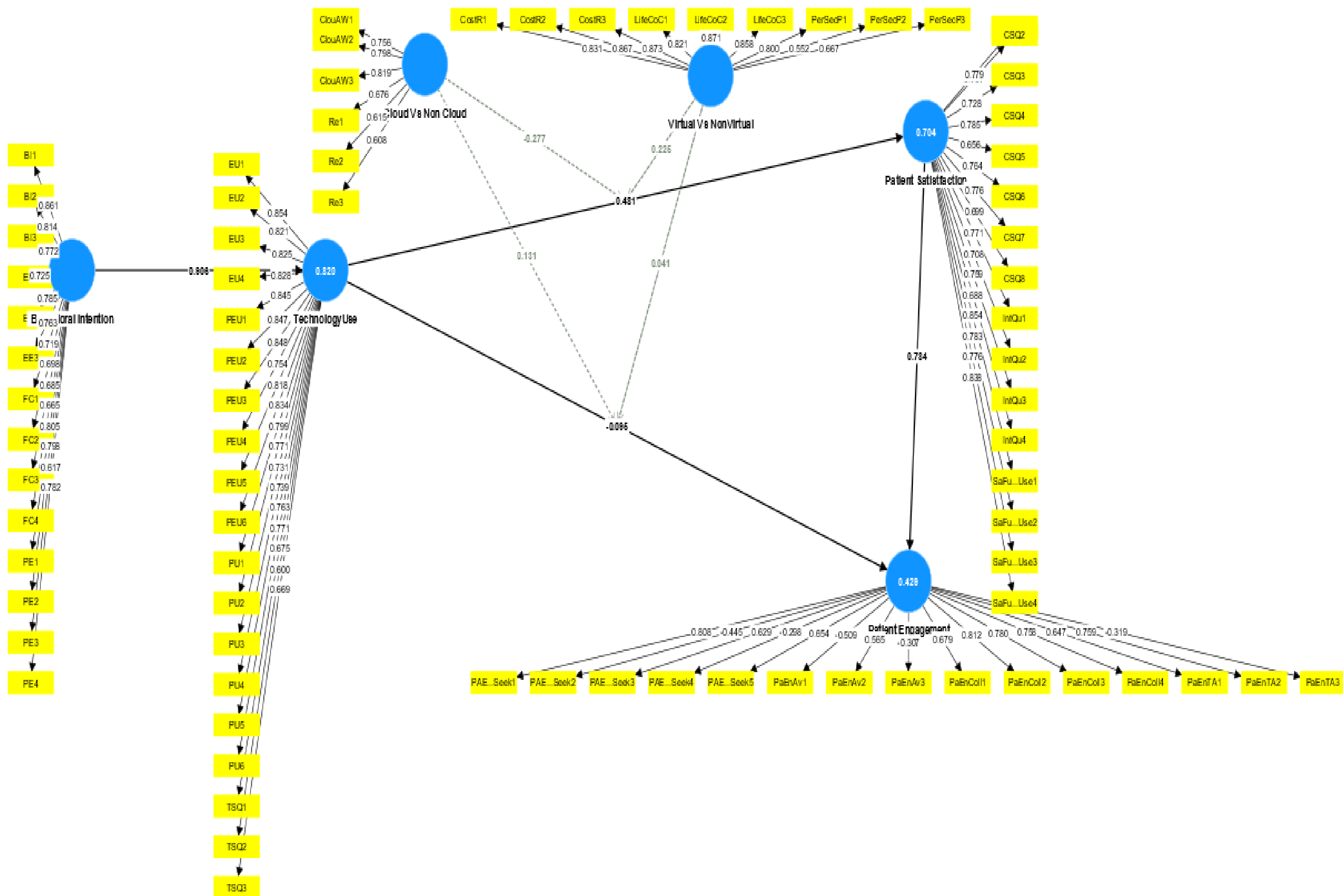

Figure 4.1: Smart PLS Constructs and Observed Indicators - Outer Loadings and Weights

4.2.2 The PLS-SEM Research Model and Hypothesis

After determining the model fit and how well the variables represented each construct, we assessed the overall relationships between the constructs in the model. The results of the PLS-SEM Model (Figure 4.2) suggest significantly strong associations especially with high path coefficients (Beta) of > 0.70 for example between Behavioral Intention and Technology Use and between Patient Satisfaction and Patient engagement (Hair et A.l; 2017). We also investigated the model with an iteration of a relationship path from Patient Engagement to Patient satisfaction which did not show any significance and therefore dropped the iteration.

Our Model (Figure 4.2) explains 70% of the variance observed in Patient Satisfaction (R^2 =0.704) and 42% of the variance observed in Patient Engagement (R^2 = 0.429). Technology Use is directly associated with Patient Satisfaction but not very much with Patient Engagement. Furthermore, the model also explains 82% of the variance observed in Technology Use (R^2 = 0.820) given its very strong association with Behavioral Intention to use a patient portal.

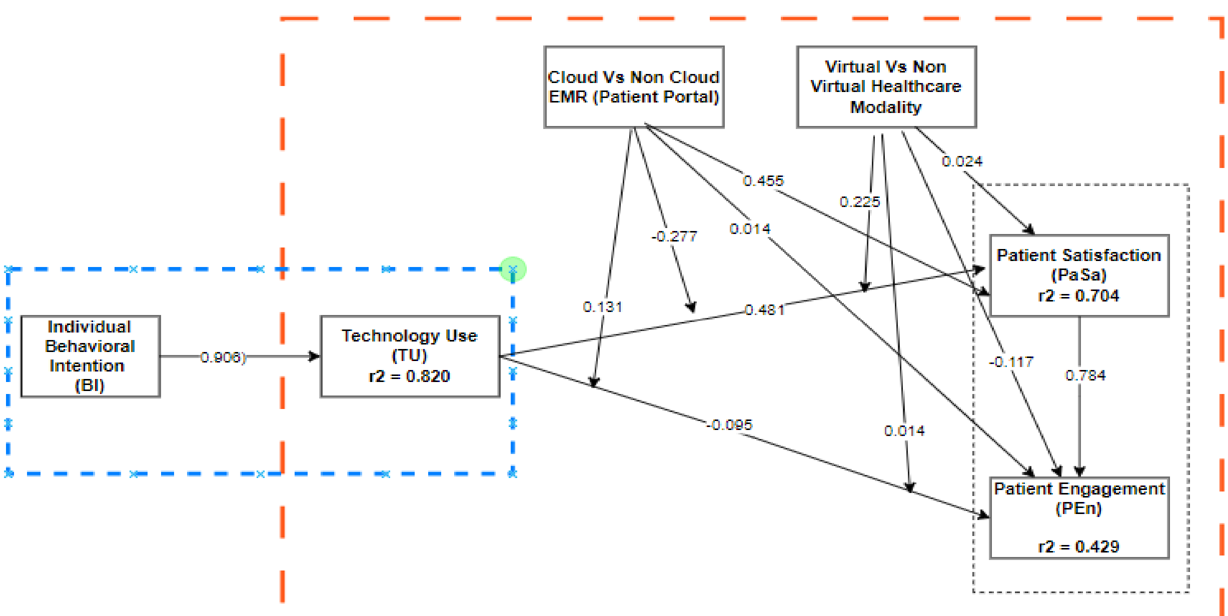

Figure 4.2: The PLS-SEM Model

4.2.2.1 Internal and Convergent Reliability

The research validated the convergent validity and reliability by applying the confirmatory composite analysis with results displayed in Appendix E Table 4.8. Convergent validity refers to the degree to which different measures of the same construct are related to each other. In other words, when many measurements of the same construct provide similar or consistent results, convergent validity is established. If all the Average Variance Extracted (AVE) values are greater than 0.50 in the context of Hair et al. (2020), it indicates that the measures are converging to measure the same construct effectively. The amount of variance explained by a construct in its indicators is measured as AVE, and it is widely employed as an indicator of convergent validity. AVE values greater than 0.50 show that the construct explains more than half of the variance in the indicators, implying that the measurements are converging well (Appendix E, Table 4.8).

Convergent validity needs to be established because it shows that the measurements are valid and dependable for measuring the desired concept. This indicates that the outcomes of these analysis can be relied upon and are appropriate for informing important decisions. It is important to remember that establishing convergent validity is not sufficient in itself and does not guarantee the validity of a construct. It is also very essential to demonstrate discriminant validity, which quantifies how closely measurements of several constructs are unrelated to one another. We demonstrate discriminant validity later in this chapter. Discriminant Validity is necessary to demonstrate that the construct being measured is distinct from other constructs and not just a variation of them.

In conclusion, convergent validity is established if all AVE values are larger than 0.50 (in our case all variables except PAEnHeSeek1 (AVE = 0.393)). This indicates that the measures are effectively convergent to assess the same constructs. Again, to guarantee the validity of all the constructs, however, discriminant validity must also be established.

Based on Appendix E Table 4.8, all the AVE values are greater than 0.50 showing convergent validity (Hair et al.; 2020). Thus, they all converge to measure the constructs well-meaning convergent validity is established. We now proceed to investigate Construct Reliability.

4.2.2.2 Construct Reliability

The reliability of the variables was assessed using Cronbach's Alpha and Composite Reliability (CR). Initially the overall sample was assessed and items having factor loadings that were smaller than 0.60 were discarded (Hair et al; 2017; 2020). The results for the reliability analysis along with factor loadings for the items are presented in Table 4.9. All the Alpha values and CRs were higher than the recommended value of 0.7. In fact, the Average Variance Extracted (AVE) were all higher than 0.50 except for Patient Engagement with a 0.389, which supports convergent validity for all constructs except Patient Engagement. According to the Literature, (Hair, Jr., Hult, Ringle, & Sarstedt, 2021) rule of thumb for construct reliability is for the values to be greater than 0.7. Convergent Reliability on the other hand is indicated when the Average Variance Extracted is greater than 0.50. Table 4.9 provides the observed measures for Cronbach's Alpha, Composite reliability and Average Variance Extracted.

Table 4.9 Reliability Analysis

	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
Behavioral Intention	0.94	0.948	0.566
Cloud Vs Non-Cloud	0.806	0.862	0.514
Patient Engagement	0.75	0.748	0.389
Patient Satisfaction	0.951	0.956	0.578
Technology Use	0.964	0.967	0.611
Virtual Vs Non-Virtual	0.931	0.94	0.64

The relatively high Cronbach alpha for all constructs as greater than 0.7. indicate that reliability across the survey instrument is deemed to be acceptable. A Cronbach alpha coefficient greater than 0.7 is generally regarded as acceptable for research purposes (Hair et al.,, 2017; 2020). This signifies that the items in the survey instrument consistently measure the same underlying construct, and reliability is quite acceptable. In addition to using Cronbach's Alpha to test for reliability, we also use the composite reliability (CR) results which also confirm excellent reliability given all results are greater than 0.7, indicating the composite reliability measure is satisfied.

4.2.2.3 Discriminant Validity (Cross-Loadings, Fornell-Larcker and HTMT)

The discriminant validity explains the extent of empirical differences between variables to determine if each construct was unique in measuring the same phenomenon as other items. This was assessed initially through cross loadings. Cross Loadings were also known as the stop check stop criterion. The higher loadings demonstrated an association with the appropriate construct indicating an initial view of discriminant validity. Appendix E, Table 4.8 displays the cross-factor loadings of all the items. It is observed that all the factor loadings are greater than their cross - loadings, which reveals discriminant validity.

The second measure utilized in this study to assess discriminant validity is the Fornell-Larcker criterion which displays the values of the square root of AVE for every construct are greater than the value or all inner constructs associated with the variable. (Table 4.10). The discriminant validity criteria is satisfied if the square root of AVE for a particular construct is higher than other correlations. The Fornell-Larcker criterion was used to determine if each construct's measurements (indicators) were more strongly associated to that construct than to any other construct in the model. The criterion involves calculating the square root of the extracted average variance (AVE) for each construct, which is a measure of how much variance in the indicators can be explained by the construct. The discriminant validity is supported if the square root of the AVE for each construct is greater than the correlation between that construct and any other construct in the model. In other words, if the construct measurements are more closely correlated with that construct than with any other construct in the model, the measures are less likely to be accurate. In Table 4.11 below, a close look at all results in the leading diagonal show all the results to be <0.85. A commonly used rule of thumb is that the square root of AVE values for each construct should be greater than 0.7 or 0.8, although some researchers suggest a minimum threshold of 0.5 or 0.6 (Hair et al., 2020). Which is what our research shows below. Thus, we can claim discriminant validity for our constructs based on Table 4.11 below for most of the constructs.

Table 4.11 Discriminant Validity - Fornell-Larcker Criterion

	Behavioral Intention	Cloud Vs Non-Cloud	Patient Engagement	Patient Satisfaction	Technology Use	Virtual Vs Non-Virtual
Behavioral Intention	**0.752**					
Cloud Vs Non-Cloud	0.464	**0.717**				
Patient Engagement	0.275	0.427	**0.624**			
Patient Satisfaction	0.616	0.719	0.591	**0.76**		
Technology Use	0.906	0.563	0.332	0.716	**0.782**	
Virtual Vs Non-Virtual	0.503	0.588	0.213	0.543	0.561	**0.800**

The "Heterotrait-Monotrait Ratio" or HTMT is a different, more reliable measure for discriminant validity which the Hensler research team recommends employing (Hensler et al., 2015). This is where we assess if all the observations below the diagonal (The numbers displayed on the HTMT matrix's leading diagonal represent the HTMT values for each construct with itself) must be lower than the results on the diagonal. This indicates that there is a greater internal than an external commonality between the constructs. The value must be less than 0.90 to prove discriminant validity (Alharbi et al., 2017). The HTMT ratio outperformed other conventional approaches for discriminant validity, according to Hair et al. (2016). Based on the literature, this study used the HTMT ratio test for assessment and established these facts, as shown in Table 4.12 and Figure 4.3 below and Figure, where all values meet the HTMT test threshold of < 0.9 except the value for Technology Use and Behavioral Intention which is slightly higher (0.938).

Table 4.12 HTMT

	Behavioral Intention	Cloud Vs Non-Cloud	Patient Engagement	Patient Satisfaction	Technology Use	Virtual Vs Non-Virtual	Cloud Vs Non-Cloud x Technology Use	Virtual Vs Non-Virtual x Technology Use
Behavioral Intention								
Cloud Vs Non-Cloud	0.509							
Patient Engagement	0.313	0.495						
Patient Satisfaction	0.635	0.808	0.631					
Technology Use	0.938	0.631	0.361	0.753				
Virtual Vs Non-Virtual	0.493	0.629	0.287	0.544	0.566			
Cloud Vs Non-Cloud x Technology Use	0.284	0.108	0.161	0.299	0.272	0.182		
Virtual Vs Non-Virtual x Technology Use	0.46	0.187	0.151	0.289	0.42	0.263	0.841	

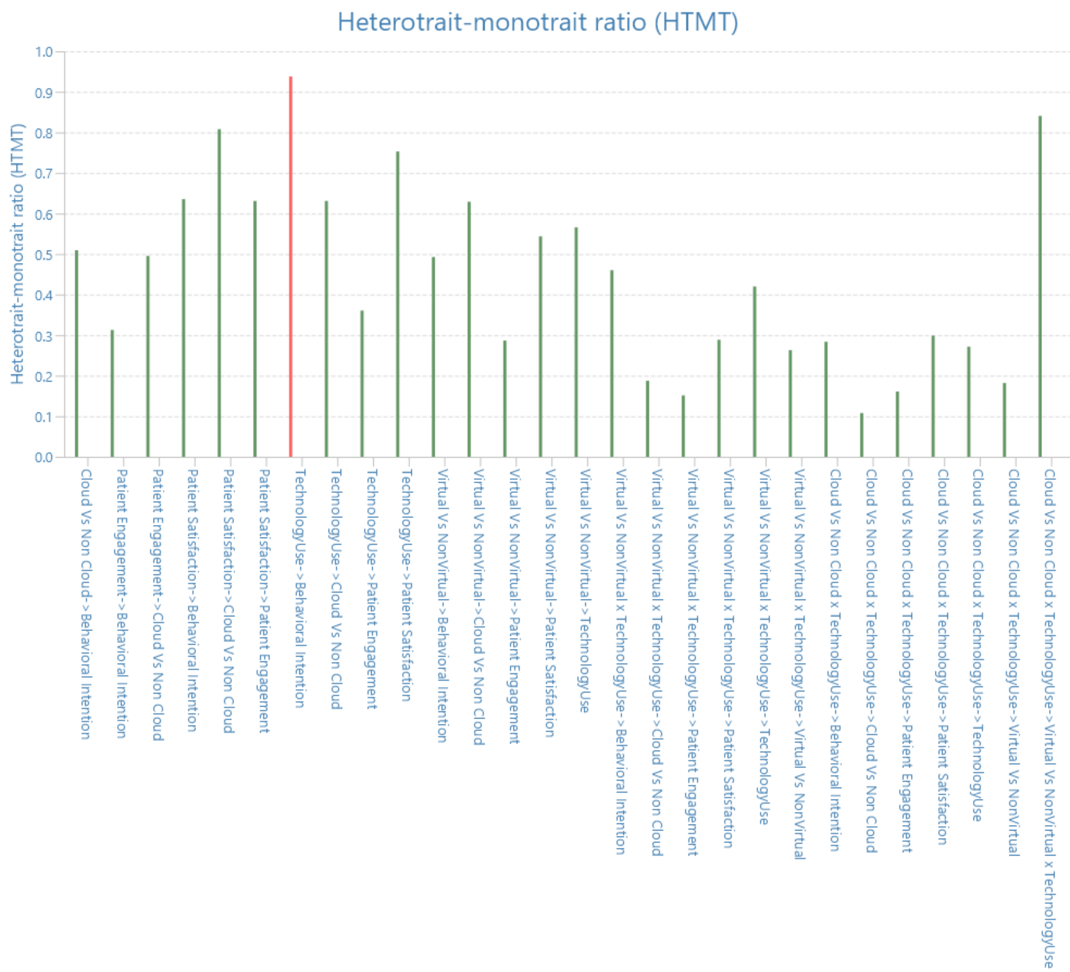

Figure 4.3: The Heterotrait-Monotrait ratio (HTMT) Bar Chart

4.2.3 Multicollinearity Statistics -Variance Inflation Factor (VIF) Values for inner model

Multicollinearity refers to the presence of substantial correlations between predictor variables. This can lead to issues while calculating path coefficients and interpreting the results. The Variance Inflation Factor (VIF) is a measure of collinearity and calculates the severity of collinearity among the indicators in a formative measurement model (Hair et al, 2017). Furthermore, Hair et al. (2017) argue that multicollinearity is not a serious concern when VIF values are less than 5. Table 4.13 displays all VIF values for the structures studied. All of the numbers in Table 4.13 are significantly lower than the recommended criterion of 5 (Hair et al., 2019; Hair Jr et al., 2017). Given the results in Table 4.13, we determine that there is no issue with multicollinearity, as such none of the variables will be eliminated.

Table 4.13: Construct Collinearity (VIF) Matrix

	Patient Engagement	**Patient Satisfaction**
Behavioral Intention		
Cloud Vs Non-Cloud	2.460	1.761
Patient Engagement		
Patient Satisfaction	3.381	
Technology Use	2.701	1.920
Virtual Vs Non-Virtual	1.748	1.746
Cloud Vs Non-Cloud x Technology Use	4.038	3.502
Virtual Vs Non-Virtual x Technology Use	4.330	3.936

4.3 The Structural Model

4.3.1 Analysis of The Structural Model

To Assess the Structural Model, we investigate the strength of the relationships which are the beta values of the relationship connections. Having established adequate reliability and validity or the factors in the proposed model, the next step is to assess all relationships in the model and the path coefficients. We also look at the R-squared coefficients, path analysis and effect size as shown below:

After performing a Bootstrapping analysis, the resulting path analysis. Fig 4.3 indicates the path coefficients and p-values for each relationship. The thick arrows for example indicate very strong associations between the variables for example the paths from Behavioral Intention to Technology use showing a path coefficient (Beta) of up to 0.906 ($p = 0.000$) and the path from Patient Satisfaction to Patient Engagement also recording a high 0.784 path coefficient (Beta) and a significant p-value (0.000). There is also a positive association between Technology Use and Patient Satisfaction, Cloud vs Non-Cloud and Patient Satisfaction depicted by their path coefficients of 0.481($p = 0.000$) and 0.455(0.000) respectively. The very thin arrows depict a very slight but non-significant association while the dotted lines depict the moderating effects as shown by the p-values.

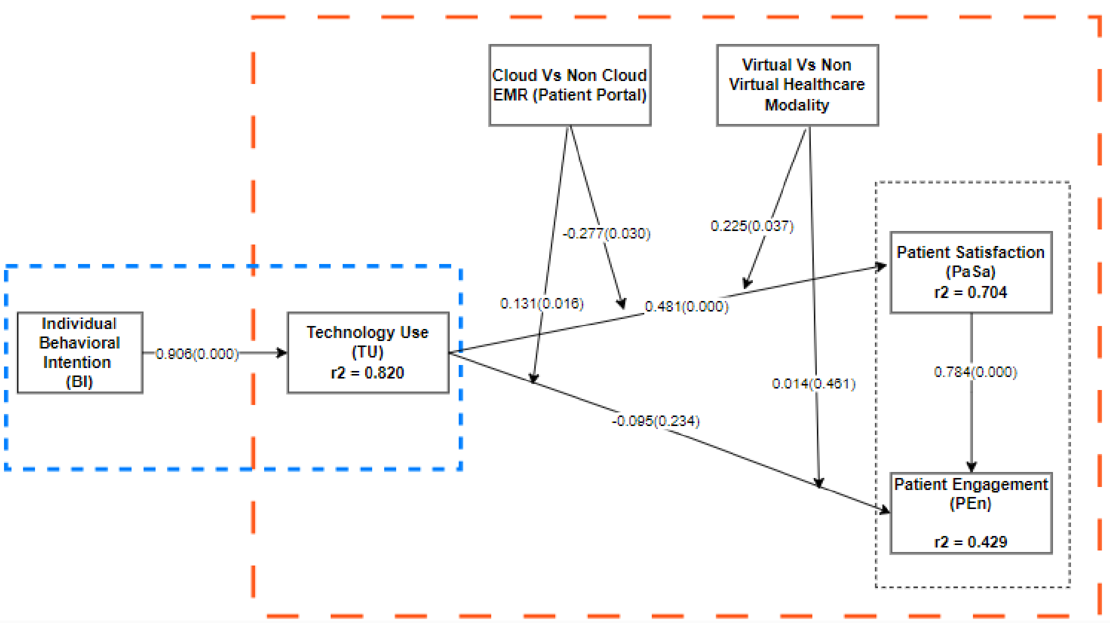

Figure 4.4: The Structural Model with Path Coefficients and Significance (P-Values)

4.3.2 Coefficient of Determination (R-squared) and Goodness of Fit

To determine the goodness of fit, the study evaluated the correlation of determination (**R^2),** effect size (**F2),** and the predictive relevance measure (Q2).

4.3.2.1 R-Squared

R-squared calculates the amount of variation explained by the predictors (exogenous constructs) in the model for each endogenous construct (dependent variable) in the model. It has a value between 0 and 1, with one indicating that the predictors in the model explain all of the variance in the endogenous construct. R-squared is calculated using the variance accounted for (VAF) values from the outer model. The R-squared number for the overall model (inner model) measures the model's overall goodness of fit.

In table 4.17, the results of the analysis reveal an R2 of 0.429 for Patient Engagement. This shows that only about 42.9% variance in Patient Engagement can be explained be associated with Patient Satisfaction and Technology Use. For Patient Satisfaction, the analysis reported an R2 value of 0.704 meaning that about 70.4% variance in Patient Satisfaction can be attributed to Technology Use and Patient Engagement. We observe these values in Table 4.14 below.

Table 4.14 R-Squared Calculations

	R^2
Patient Engagement	0.429
Patient Satisfaction	0.704
Technology Use	0.82

4.3.2.2 Effect Size (F2)

According to Hair et al., (2017), The effect size (F2) is a metric used to evaluate the relative impact of a predictive construct on an endogenous construct. From Table 4.15, we can see the relative impact explained in each other relationships in the model. The results of the effect sizes and significance are presented in Table 4.15 below.

Table 4.15 Effect Size (f2)

	Patient Engagement	**Patient Satisfaction**
Behavioral Intention		
Cloud Vs Non-Cloud	0.000	0.397
Patient Engagement		
Patient Satisfaction	0.318	
Technology Use	0.006	0.407
Virtual Vs Non-Virtual	0.014	0.001
Cloud Vs Non-Cloud x Technology Use	0.015	0.153
Virtual Vs Non-Virtual x Technology Use	0.002	0.100

4.3.2.3 Q-Squared

Q-square (Q2), also known as predictive relevance, is a model's predictive power measure. It determines if the model accurately predicts data that was not used in the model parameter estimation. The Q-Squared (Latent Variables prediction) summary is shown in Table 4.16 below.

According to the analysis, Patient Engagement had a predictive relevance of 0.063, while Patient Satisfaction had a somewhat medium to high predictive relevance of 0.54 and Technology Use had a rather high predictive relevance of 0.821.Q2 are all greater than 0.00, indicating that the latent factors are relevant (Hair et al, 2017). Table 4.16 shows all Q-squared results.

Table 4.16 Q-Squared Calculations

	Q^2
Patient Engagement	0.063
Patient Satisfaction	0.54
Technology Use	0.821

4.4 Hypothesized Relationship and Results

To test our hypothesis, we used the results from our analysis from PLS-SEM. Our initial test of the measurement model was to determine if the model was a good fit and if the constructs represented their variables well. We then conducted a model analysis with a bootstrapping sample of 5000 to determine the significance of established associations. From the Bootstrapping Analysis, we realized the following direct effects (Table 4.17) and indirect effects (Table 4.18) below.

Table 4.17: Direct Relationships

Path	Path Coefficients (Beta)	Standard deviation	T statistics	P values
Behavioral Intention -> Technology Use	0.906	0.022	42.098	0.000
Cloud Vs Non-Cloud -> Patient Engagement	0.014	0.145	0.099	0.461
Cloud Vs Non-Cloud -> Patient Satisfaction	0.455	0.106	4.277	0.000
Patient Satisfaction -> Patient Engagement	0.784	0.164	4.776	0.000
Technology Use -> Patient Engagement	-0.095	0.131	0.727	0.234
Technology Use -> Patient Satisfaction	0.481	0.117	4.120	0.000
Virtual Vs Non-Virtual -> Patient Engagement	-0.117	0.110	1.059	0.145
Virtual Vs Non-Virtual -> Patient Satisfaction	0.024	0.076	0.321	0.374
Cloud Vs Non-Cloud x Technology Use -> Patient Engagement	0.131	0.132	0.992	0.161
Cloud Vs Non-Cloud x Technology Use -> Patient Satisfaction	-0.277	0.147	1.888	0.030
Virtual Vs Non-Virtual x Technology Use -> Patient Engagement	0.041	0.099	0.417	0.338
Virtual Vs Non-Virtual x Technology Use -> Patient Satisfaction	0.225	0.126	1.788	0.037

The indirect effects in this study where quite interesting and worth looking into. While some relationships did not show any direct effects in relation to other constructs, there were however quite an interesting number of indirect effects as shown in Figure 4.18 below.

The association between two variables that is mediated by one or more intermediary variables is referred to as an indirect effect in PLS-SEM (Partial Least Squares-Structural Equation Modeling). In PLS-SEM, the concept of indirect effects is significant because it allows researchers to investigate the complicated interactions between numerous variables and obtain a deeper understanding of the underlying mechanisms that drive these relationships.

Table 4.18 Indirect Effects

	Path Coefficients (Beta)	Standard deviation	T statistics	P values
Virtual Vs Non-Virtual x Technology Use -> Patient Satisfaction -> Patient Engagement	0.176	0.106	1.656	0.049
Cloud Vs Non-Cloud x Technology Use -> Patient Satisfaction -> Patient Engagement	-0.217	0.122	1.774	0.038
Behavioral Intention -> Technology Use -> Patient Satisfaction -> Patient Engagement	0.341	0.125	2.739	0.003
Behavioral Intention -> Technology Use -> Patient Engagement	-0.086	0.119	0.729	0.233
Behavioral Intention -> Technology Use -> Patient Satisfaction	0.435	0.103	4.218	0.000
Cloud Vs Non-Cloud -> Patient Satisfaction -> Patient Engagement	0.357	0.110	3.238	0.001
Technology Use -> Patient Satisfaction -> Patient Engagement	0.377	0.138	2.724	0.003
Virtual Vs Non-Virtual -> Patient Satisfaction -> Patient Engagement	0.019	0.061	0.312	0.378

From our analysis, we found that overall, five out of the eight hypotheses were supported. This has been summarized in Table 4.19 below. The results of our PLS-SEM model suggests that significant associations exist among Behavioral Intention to use a patient portal, Technology Use, Patient Satisfaction, healthcare modalities while the cloud versus non cloud moderating effect on the relationship between Technology use and patient satisfaction was partially supported since it had a negative beta (path coefficient) of - 0.277 as shown in Table 4.17 above. Interestingly, while Patient Engagement was not significantly associated with Technology Use the main independent variable of the study, we found that Patient Satisfaction is significantly associated with Patient Engagement but not the other way round. This is demonstrated below where Hypothesis H8 is supported with a path coefficient of 0.784 ($P<0.001$). We examine this further in the Hypothesized Relationship and Results section.

4.4.1 Hypothesized Relationship and Results

H1: Behavioral Intention (BI) to use a patient portal is positively associated with technology use.

H1 evaluates whether BI has a significant impact on Technology Use. The results revealed that BI is strongly associated with Technology Use and has a significant effect on Technology Use ($\beta = 0.906$, $t = 42.098$, $p\ (0.000) <0.05$). Hence H1 was supported.

H2: Technology use is positively associated with patient satisfaction.

H2 evaluates whether Technology Use has a positive association with Patient Satisfaction. The results revealed that Technology Use is strongly associated with patient Satisfaction and has a significant effect on Technology Use ($\beta = 0.481$, $t = 4.120$, $p\ (0.000) <0.05$). Hence H2 was supported.

H3**: Technology use is positively associated with patient engagement.**

H3 evaluates whether there is a correlation between technology use and patient engagement. The findings revealed that technology use is not closely associated with and has no substantial effect on patient engagement. ($\beta = -0.095$, $t = 0.727$, $p\ (0.234)>0.05$). Hence H3 was not supported.

H4: Cloud enabled patient portal positively moderates the relationship between technology use and patient satisfaction, Cloud strengthens the relationship.

H4 assesses whether Cloud vs Non-Cloud Enabled Patient Portals have a significant effect on the relationship between Technology Use and Patient Satisfaction. The results Cloud vs Non-Cloud Enabled Patient Portals does have a negative effect on the relationship between Technology Use and Patient Satisfaction and also significant ($\beta = -0.277$, $t = 1.888$, $p\ (0.030) < 0.05$). Hence H4 was partially supported.

H5: Cloud enabled patient portal positively moderates the relationship between technology use and patient engagement. Cloud strengthens the relationship.

H5 evaluates if Cloud vs Non-Cloud Enabled Patient Portals have a significant effect on the relationship between Technology Use and Patient Engagement. The findings indicate that Cloud vs Non-Cloud Enabled Patient Portals does not have a negative effect on the relationship between Technology Use and Patient Engagement and is not significant ($\beta = 0.131$, $t = 0.992$, $p\ (0.161) > 0.05$). Hence H5 was not supported.

H6: Healthcare Modality has a positive effect on the relationship between technology use and patient satisfaction.

H6 evaluates whether Healthcare Modality has a positive effect on the relationship between Technology Use and Patient Satisfaction. The results revealed that Healthcare Modality does have a significant effect on the relationship between Technology Use and Patient Satisfaction ($\beta = 0.225$, $t = 1.78$, $p\ (0.037) < 0.05$). Hence H6 was supported.

H7: Healthcare Modality has a positive effect on the relationship between technology use and patient engagement.

H7 evaluates whether Healthcare Modality has a positive effect on the relationship between Technology Use and Patient Engagement. The results revealed that Healthcare Modality does not have a significant effect on the relationship between Technology Use and Patient Engagement (β = 0.041, t = 0.417, p (0.338) >0.05). Hence H7 was not supported.

H8: There is a positive association between Patient Satisfaction and Patient Engagement was supported by the model.

H8 evaluates if there is a positive association between Patient Satisfaction and Patient Engagement. The results revealed that Patient Satisfaction does have a strong positive association with Patient Engagement and is significant (β = 0.784, t = 4.776, p (0.000) <0.05). Thus, H8 was supported.

The results from the hypothesis (Table 4.19) indicate the supported versus non supported and partially supported results. The summary of the results is shown in Table 4.19 below.

Table 4.19: Hypothesized Relationship and Results

	Hypothesized Relationship	Results
H1	Behavioral Intention (BI) to use a patient portal is positively associated with technology use.	**Supported**
H2	Technology use is positively associated with patient satisfaction	**Supported**
H3	Technology use is positively associated with patient engagement	Not Supported
H8	There is a positive association between Patient Satisfaction and Patient Engagement	**Supported**
H4	Cloud enabled patient portal positively moderates the relationship between technology use and patient satisfaction, Cloud strengthens the relationship.	**Partially Supported**
H5	Cloud enabled patient portal positively moderates the relationship between technology use and patient engagement. Cloud strengthens the relationship.	Not Supported
H6	Healthcare Modality has a positive effect on the relationship between technology use and patient satisfaction	**Supported**
H7	Healthcare Modality has a positive effect on the relationship between technology use and patient engagement	Not Supported

4.5 Moderation Analysis Results

Furthermore, we decipher our significant hypotheses that are supported by the model by plotting a two-way interaction to further understand the moderating effects on our Independent and dependent variables.

H4: Cloud enabled patient portal positively moderates the relationship between technology use and patient satisfaction, Cloud strengthens the relationship.

This Hypothesis was partially supported but still considered as significant given it had a p value of < 0.001. According to Figure 4.6 below the two-way interaction plot shows Cloud vs Non-Cloud dampens the positive relationship between Technology use and Patient Satisfaction. The two-way interaction plot (Figure 4.6) establishes that Cloud vs Non-Cloud has a negative (weakening) effect on the relationship between Technology use and Patient Satisfaction. The steeper slope for the low effect as well as the nearly identical nature of both slopes for the high and low interactions, with equations of Y = 0.408X + 2.842 and Y = 1.516X + 0.271, respectively, demonstrate this. The weakening effect of the positive relationship between technology use and patient satisfaction when cloud-enabled technology is used could also be an indication that patients may be less satisfied with their healthcare experiences when using cloud-enabled technology compared to non-cloud-enabled technology, even though they may utilize the technology more frequently overall. This could be as a result of variations in usability, reliability, privacy, or security between the varieties of technology.

It is important to emphasize that these findings might not be applicable to all healthcare settings or patient demographics. The population studied may have been restricted in terms of demographic diversity, healthcare context, or technology type used. Furthermore, the study design may have had shortcomings that impacted the findings' validity. Further investigation would be needed to confirm and expand on these results.

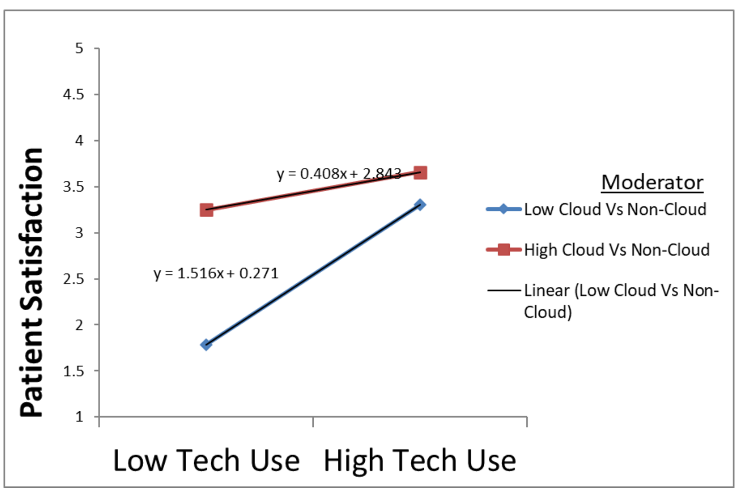

Figure 4.5: Two-way Interaction of Cloud Vs Non-Cloud Enabled on Technology Use and Patient Satisfaction relationships.

H6: Healthcare Modality has a positive effect on the relationship between technology use and patient satisfaction.

The two-way interaction plot (Figure 4.5) demonstrated that Virtual Vs Non-Virtual Healthcare Modality Strengthens the positive relationship between Technology use and Patient Satisfaction. This is shown by the high positive slope for virtual with a gradient equation of $Y = 1.412X + 0.906$ versus the low healthcare modality option with the gradient equation of $Y = 0.512X + 2.208$.

When healthcare is delivered with different modality options instead of only the traditional brick and mortar, the association between technology utilization and patient satisfaction is improved. This suggests that patients who use technology to access virtual healthcare are more likely to be satisfied with their experience than those who use technology to access non-virtual healthcare. When healthcare is delivered with options thus giving the patient more choices, the association between technology utilization and patient satisfaction is heightened. Virtual healthcare refers to healthcare services that are provided remotely, using technology such as video conferencing, messaging, or other electronic means. Non-virtual healthcare, on the other hand, refers to healthcare services that are provided in person, such as visits to a doctor's office, hospital, or clinic.

Patients are more likely to be satisfied with their experience when they use technology to access virtual healthcare services than when they use technology to access non-virtual healthcare services. This could be due to the increased convenience, accessibility, and flexibility provided by virtual healthcare services. Patients, for example, may not have to drive vast distances or take time off work to see a healthcare professional. They may also be able to obtain healthcare services outside of normal business hours.

Furthermore, virtual healthcare may increase patient participation and involvement in their care. Patients may be able to access their health records, connect with their healthcare professionals, and engage in virtual support groups or instructional sessions using technology. This has been depicted in the two-way interaction figure below.

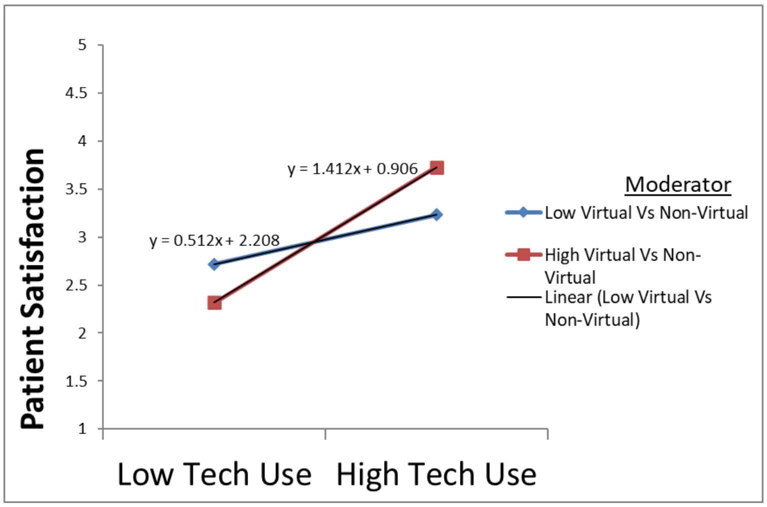

Figure 4.6: Two-way Interaction of Virtual Vs Non-Virtual Healthcare on Technology Use and Patient Satisfaction relationships

4.6 PLS-SEM Slope Analysis

The above two-way interaction is the conventional way of demonstrating significant moderating effects which has been used extensively in quite several studies in the literature. For this study, we have also added the benefit of the feature being automated in Smart PLS (4).

The conventional two-way interaction model tests for the interaction effect between two variables. For example, in the context of technology use and patient satisfaction the interaction effect between technology use and patient satisfaction level may be investigated solely. Moreover, the two-way model assumes a linear relationship between the two variables and does not account for nonlinear relationships or the effect of other moderating variables.

The PLS-SEM 4 Slope analysis, on the other hand, provides for the assessment of several moderating variables and also takes non-linear interactions between variables into consideration. It involves calculating the slope of the association between two variables at various values of the moderating variables. At different levels of the moderating variables, this analysis can indicate the degree and direction of the association between technology use and patient happiness.

For example, if age is the moderating variable, the PLS-SEM 4 Slope analysis can show how the link between technology use and patient satisfaction evolves with age. If gender is the moderating variable, the analysis can show how the connection vary between male and female patients.

Thus, we examine the PLS-SEM simple slope analysis for Cloud vs Non-Cloud (Figure 4.6) moderating effect and the Virtual vs Non-Virtual Healthcare modality effects (Figure 4.7) on the relationships between Technology Use and Patient Satisfaction as an extension of the two-way interaction analysis.

Figure 4.8 shows that the positive relationship between Technology Use and Patient Satisfaction is dampened by the moderating effect of Cloud vs Non-Cloud Technology, which is not quite what we hypothesized but a very significant relationship to investigate further. The green line above has more Cloud Enablement of the Patient Portal and the Red line has little or no Cloud-Enablement. The positive effect has a much steeper slope when there is less Cloud enablement. As a result, the slopes appear to converge which confirms the analysis from the two-way interaction approach in Figure 4.4. This might be explained further by integrating other indicators like age, gender, and settlement to provide greater insight into the behavior of the interactions.

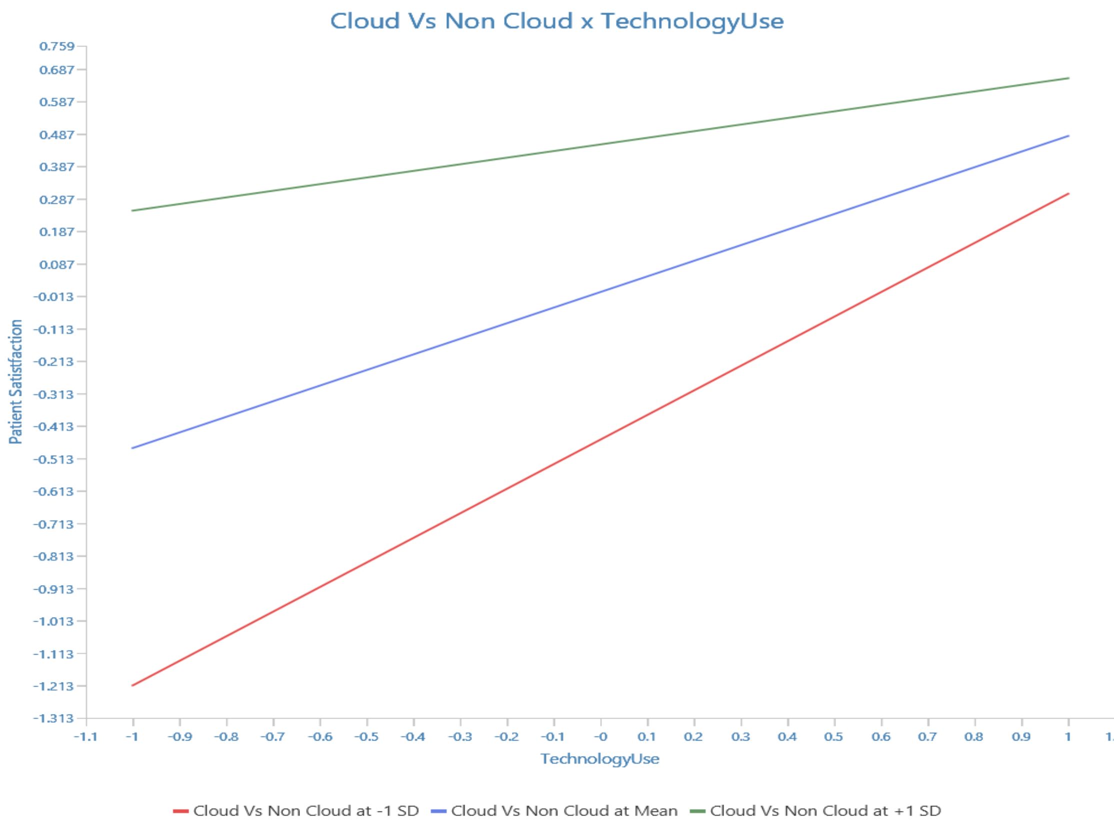

Figure 4.7 Simple PLS-SEM (4) Slope Analysis – Cloud Vs Non-Cloud Enabled effect on the Relationship between Technology Use and Patient Satisfaction

A further look into the PLS-SEM Simple slope analysis for the Virtual Vs Non-Virtual Moderating effect on the relationship between Technology and Patient Satisfaction (Figure 4.9) reveals that Virtual strengthens the relationship between Technology Use and Patient Satisfaction with a very steep slope (Depicted in Green in Figure 4.9). While with an increase in the lack of Virtual versus non-verbal (depicted with the red line) has little or no impact on Patient Satisfaction hence why the slope is not quite steep.

The less steep slope of the red line suggests that the usage of non-virtual healthcare modalities has less of an impact on the association between technology use and patient satisfaction. This indicates that the rise in patient satisfaction in non-virtual healthcare settings is less significantly correlated with the use of technology than it is in virtual healthcare settings. This discrepancy may be explained by the fact that virtual healthcare modalities may offer greater options for individualized and practical care, such as telemedicine consultations or remote patient health monitoring. These virtual healthcare technologies might make it possible for patients and healthcare professionals to communicate more frequently and promptly, which would increase patient satisfaction. Figure 4.9 provides some great visualization to this effect.

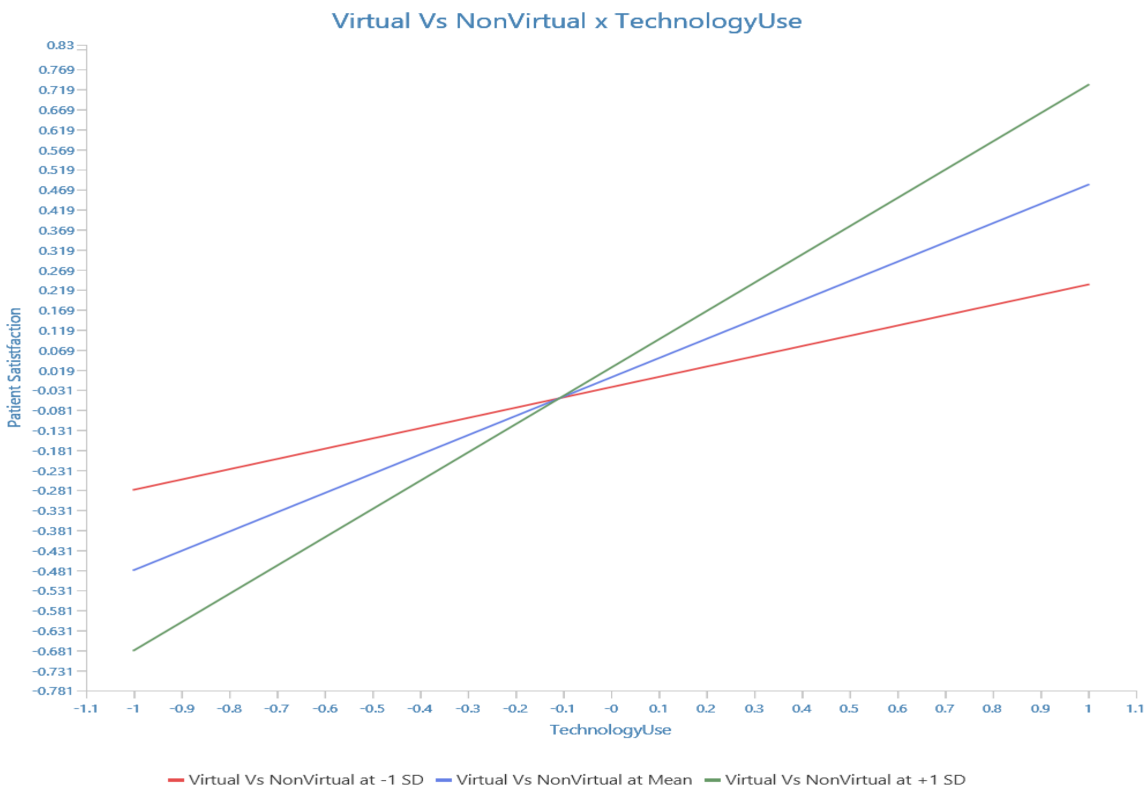

Figure 4.8 Simple PLS-SEM (4) Slope Analysis – Virtual Vs Non-Virtual Healthcare Modality effect on the Relationship between Technology Use and Patient Satisfaction

5 CHAPTER 5: DISCUSSION

This chapter provides an overview of my research, a discussion of my research findings in four major sections. The first section provides an overview of this study and the research questions. The second section offers a discussion of the findings from the tests of the hypothesized relationships in my research model. The next section describes the practical implications. The fourth section covers the limitations of the research, ideas for future research and practical ideas for industry based on the research questions.

5.1 Overview

Technology Usage has become an important topic because of disruptions in the healthcare space in recent years. Long wait times and service delivery times, decreased patient engagement and interaction with care plans, lack of access to just-in-time healthcare records, a diverse IT infrastructure with little or no interoperability, and frequent server outages are some of the critical issues that could be addressed by using current technology solutions to engage with patients prior to, during, and after encounter visits. Despite the extensive research of the Theory of Technology Use and Acceptance – revision 2 (UTAUT2), the model has not been widely applied in the literature to comprehensively examine the advantages in healthcare settings. (Venkatesh, Morris, Davis, & Davis, 2003). Some schools of thought claim that there is still a great need to improve healthcare IT resources awareness of technology usage and acceptance to significantly improve outcomes. (Nikolopoulos & Likothanassis, 2018; Venkatesh et al, 2003).This research focuses on this gap by examining possible innovative technology opportunities on how cloud technologies could be combined with different virtual, mobile and other telehealth healthcare service modality options to improve the overall patient care experience and boost healthcare outcomes.

The aim of this research is to investigate the impact of technology use on healthcare outcomes and patient experience as an extension of the Unified Theory of Acceptance and Use of Technology (UTAUT2) model. The study also investigates how healthcare service modality (virtual including mobile and hospital at home vs Brick and Mortar) influences the relationship between technology use and patient outcomes. Specifically looking at how different healthcare modality types can leverage modern technologies and disruption trends to improve patient satisfaction and patient engagement throughout the life cycle of a patient encounter visit. In attempting to investigate this relationship, we posed some research questions and hypothesized eight relationships.

5.1.1 Research Questions:

This paragraph summarizes five research questions related to the impact of technology on healthcare outcomes and patient experience. Firstly, it explores the effect of technology use on patient experience in healthcare. Secondly, it investigates the potential of cloud-based patient portals to enhance patient experience throughout the patient encounter or experience life cycle. Thirdly, it examines the influence of technology use on the behavioral intention to use cloud-based patient portals for improved patient engagement and satisfaction. Fourthly, it seeks to determine whether the level of patient satisfaction and engagement differs between cloud-enabled and non-cloud-enabled patient portals. Finally, it investigates whether there is a variation in patient satisfaction and engagement with technology use in different modalities of healthcare.

5.2 Research Findings

H1: Behavioral Intention (BI) to use a patient portal is positively associated with technology use.

Extant studies propose that there is a strong positive relationship between behavioral intention to use a technology and Technology use (Venkatesh et al, 2003; 2020). This dissertation demonstrates that this relationship does exist. Our analysis showed Behavioral intention to have a strong association with Technology use. This behavior is consistent with the research in other industries. From the theoretical point of view the obtained results differed slightly from the UTAUT2 model in that a few factors were not supported in this study while some factors were found to be quite critical compared to the original UTAUT2 study.

H2: Technology use is positively associated with patient satisfaction.

The results and analysis also show that Technology use is positively correlated with patient satisfaction and statistically significant. The respondent sample collected and analyzed represented a more general and quite diverse population with respect to age, gender, level of education and even settlement areas. According to the study about 70% variance in Patient Satisfaction is explained by the changes in Technology Use while only about 42% variance in Patient Engagement is affected by Technology use which is also consistent with the Literature (Silver, et. Al., 2021; Ampofro et al., 2021).

H3: Technology use is positively associated with patient engagement.

The direct relationship between Technology use and Patient engagement was not supported by this study. However, the analysis showed that the indirect relationship from Technology Use to Patient Satisfaction and then to Patient Engagement was supported indicating some level of mediation from Patient Satisfaction positively affecting the relationship between Technology Use and Patient Engagement. This was quite interesting and aligns with the literature on Patient Portal satisfaction and Health-Seeking Behavior (Silver, et. al, 2020). This indirect relationship showed quite a high path coefficient between Patient Satisfaction and Patient Engagement of up to 0.784.

H4: Cloud enabled patient portal positively moderates the relationship between technology use and patient satisfaction, Cloud strengthens the relationship.

Based on the analysis, Cloud enabled patient portal does appear to influence the relationship between Technology Use and Patient Satisfaction. While the expectation was for a positive strengthening relationship, the results show otherwise where Cloud enabled portal weakens the relationship between Technology Use and Patient Satisfaction even though it is significant. This prompt further discussions in the research as to what may be the underlying factors causing a negative or weakening relationship. From an industry and practical perspective, it would be crucial to investigate further to understand if the demographic factors, for example age of patients or area of settlement-whether there is access to reliable cloud-based technology or not. In fact, further investigation into other characteristics and features of the technology may also provide a better understanding as to why there is a weakening effect instead of a positive effect.

H5: Cloud enabled patient portal positively moderates the relationship between technology use and patient engagement. Cloud strengthens the relationship.

Our empirical analysis does not support the moderating effect of cloud vs non cloud enabled portals on the relationship between Technology use and Patient Engagement. We had expected to find a positive influence on patient engagement overall. Intuitively, one would think that the availability of the cloud technology use will significantly improve patient engagement with the healthcare service via the technology or patient portal. Again, this triggers future research into why this relationship does not appear to be supported in this study.

H6: Healthcare Modality has a positive effect on the relationship between technology use and patient satisfaction.

Interestingly, the study found the moderating effect of virtual vs non-virtual healthcare service modality on the relationship between Technology use and Patient Satisfaction to be statistically significant, strengthening the relationship. This is a huge factor in healthcare as there has been a strong debate as to whether changes in healthcare modality, particularly around the effectiveness of virtual healthcare and patient satisfaction. This could provide practical implications and opportunities for improving healthcare service delivery via different channels of healthcare service including but not limited to extensive provisions with virtual consults, hospital at home, mobile and telehealth, just to name a few in addition to traditional brick and mortar face to face healthcare services.

H7: Healthcare Modality has a positive effect on the relationship between technology use and patient engagement.

According to our study, Healthcare Modality does not have a significant association with Technology use and Patient Engagement. This finding is counterintuitive in that we expected healthcare modality to play a significant role in influencing the relationship between Technology Use and Patient Engagement.

The analysis however revealed an interesting indirect relationship between Healthcare Modality, Patient Satisfaction and Patient Engagement. Although the path coefficient was a little low at 0.176, the indirect relationship was supported in the study.

H8: There is a positive association between Patient Satisfaction and Patient Engagement

The study showed Patient engagement to be driven most strongly by Patient Satisfaction as demonstrated by the path coefficient of the direct relationship between Patient Satisfaction and Patient Engagement (0.784) and the indirect relationships (Virtual Vs Non Virtual x Technology Use -> Patient Satisfaction -> Patient Engagement; Cloud Vs Non Cloud x Technology Use ->

Patient Satisfaction -> Patient Engagement; Behavioral Intention -> Technology Use -> Patient Satisfaction -> Patient Engagement; Cloud Vs Non Cloud -> Patient Satisfaction -> Patient Engagement ; Technology Use -> Patient Satisfaction -> Patient Engagement; Virtual Vs Non Virtual -> Patient Satisfaction -> Patient Engagement) which were all supported in the study. These findings are consistent with the Literature that propose that the more patients are satisfied with the Healthcare service, the more engaged they will be with the healthcare team and the more they will become involved in their own care (Amporfo et al., 2020).

According to the research and analysis, there appears to be a favorable relationship between technology utilization and patient satisfaction in healthcare. The same cannot be claimed for patient engagement, which does not appear to be associated with technology use. These findings indicate that improving patient engagement may entail first making sure that patients are satisfied with the healthcare service and perhaps the innovative technologies that is used. This means that just introducing new technologies or treatment options aimed at increasing engagement may be ineffective if patients are dissatisfied with their current healthcare service delivery.

The argument emphasizes the significance of patient satisfaction with healthcare technology and how it might influence patient engagement. Healthcare practitioners should consider both criteria when implementing technology in their businesses to achieve great and better outcomes for their patients.

Based on the research findings presented, there are several important insights and implications that can be drawn regarding the use of technology in healthcare and patient satisfaction and engagement. In this discussion section, we will highlight and discuss some of these key findings and their implications.

The study found that there is a significant correlation between technology use and behavioral intention (BI) to use a patient portal. This outcome is in line with prior research investigating the concept in different industries, which suggests that there is a positive relationship between behavioral intention to use a technology and technology use. This finding has important implications for healthcare providers and organizations, as it suggests that there is a need to encourage and promote patient engagement with technology in healthcare to improve its utilization.

Second, the study revealed that Technology use is positively associated with patient satisfaction, which is consistent with previous research in the field. Furthermore, the analysis of the study demonstrated that changes in the model explain almost 70% of the variation in patient satisfaction. This finding is critical for healthcare organizations seeking to enhance patient satisfaction because it implies that to some extent investing in and encouraging the use of virtual healthcare and remote monitoring options in healthcare can result to improved patient satisfaction.

5.3 Limitations

There are four main limitations of the study. We discuss each of these in more detail below. The first limitation was the lack of data available on the usage of cloud-based application portals by patients, which is a hindrance to validating the effectiveness of such portals in healthcare. Without this data, it becomes difficult to understand the extent to which patients are using the portals and the outcomes associated with their usage. In addition to usage data, understanding the patient acuity level groups that are more likely to make use of cloud-based technology during the encounter lifecycle is also important. Given sufficient time for data collection, this information could provide insights into the patient population that is most likely to benefit from the technology and help healthcare providers tailor their services to better meet the needs of these patients.

Overall, the lack of systems data to provide validation on the actual usage of cloud-based application portals by patients is a significant challenge in healthcare. More time towards this study would have been very beneficial in addressing this issue and gathering more data on patient usage of such portals so that healthcare providers can gain valuable insights into the benefits and limitations of the technology and improve the quality of care provided to patients. This could also help to decipher critical patient groups that could benefit more from usage as it relates to speed in health care delivery and an improvement in significant metrics like length of stay, lab, x-ray and radiology and overall turnaround times for all auxiliary services within the healthcare industry.

Secondly, there was very limited time for collecting data through all anticipated channels and platforms proposed in the study due to the excessively long administrative processes for approvals particularly the IRB process. The IRB process took several months. This caused significant delays and the survey launched quite late in the research process. Even with the delay, the survey received quite a decent response rate as people were very interested in understanding how technology could improve their patient experiences and volunteering to participate, there was also the risk of people not wanting to participate or providing limited data which was very critical to this study.

The third Limitation of the study was the fact that the selected control variables were not extensively utilized and tested in the study, instead they were kept constant and mostly used to understand the overall demographic distribution of the data. The results of this study could be enhanced and further developed by investigating the control variables further to understand how different demographic groups behave with respect to the different constructs tested in the research model. This is a great opportunity for future research in this study and could also provide practical guidance for practitioners and industry implementation. The Fourth Limitation in this study is the possibility of unintentional bias in the results.

While much effort was put in to recruiting a wide and diverse population for the study, the respondents were still limited to people who had access to a computer, laptop, tablet or mobile device at the time to respond to the survey. To ensure the reliability and validity of the scales and tools of analysis, it is important to note that there is still a possibility of the results conserving the true representation of the implications of technology use as it relates to patient satisfaction and engagement. Moreover, respondents will need to have access to a smart phone, tablet or computer through which they can access the survey thus eliminating a huge population that may be genuine patients who do use patient portals but did not have access to an electronic device with internet availability to respond to the survey at the time of data collection. Interestingly, these limitations could also act as great ideas for future research.

5.4 Practical Implications

Improving patient outcomes and patient experience in healthcare remains a very complex problem. Through the research questions and hypothesis of the study, this dissertation has been able to answer very important questions and provide some guidance towards future research and practical solutions, encouraging healthcare providers to focus on implementing technology that is easy intuitive and easy to use. Cloud Enabled Technology can include patient portals, mobile apps, wearable technologies, and telemedicine platforms. By ensuring that patients can easily access and use these technologies, with different healthcare service modalities, healthcare providers can improve patient satisfaction and patient engagement thus improving the overall patient experience. Also, providing adequate awareness, training and ongoing support for healthcare technologies as mentioned above will ensure that patients are able to use technology effectively and efficiently. Healthcare providers could offer these services as part of the care package to support their patients. This could include tutorials, user manuals, and dedicated support staff who can answer questions and troubleshoot problems. By providing patients with the necessary resources and support, healthcare providers can improve patient confidence in using technology and reduce the risk of errors or misunderstandings.

Moreover, customizable technology to provide more customer-centric care could significantly improve Patient Engagement. Healthcare providers should consider tailoring technology to the specific needs of different patient populations. For example, elderly patients may require larger font sizes or simpler user interfaces, while patients with disabilities may require assistive technologies such as voice recognition software. By customizing technology to patient needs, healthcare providers can improve patient comfort and accessibility.

Continuous monitoring, upgrades and evaluating technology usage will enable healthcare providers and patient portal vendors and developers to understand the impact of technology on healthcare outcomes, healthcare providers should monitor and evaluate technology usage. This can include tracking patient engagement with portals, analyzing patient feedback, and measuring the impact of technology on clinical outcomes such as patient readmission rates. By monitoring and evaluating technology usage, healthcare providers can identify areas for improvement and optimize the use of technology to improve patient experience and healthcare outcomes.

Another important practical implication is the need for continuing to ensure data privacy and security. Healthcare providers must ensure that patient data is protected when using technology. This can include implementing secure access controls, using encryption, and complying with data protection regulations such as HIPAA. By ensuring data privacy and security, healthcare providers can improve patient trust in technology and reduce the risk of data breaches or other security incidents. This could also boost Patient Engagement with the technology and the healthcare service team.

5.5 Ideas for Future Research

An interesting dimension to extend this study will be to examine different populations and geographies, for instance extending the study to the developing World where social barriers like infrastructure (roads, hospitals, etc.) are more likely to influence behavioral intension towards utilizing cloud enabled technology to improve patient outcomes. This will provide more insight in addition to further investigating the control variables and demographic factors which were kept constant in the study.

Another great extension of the study will be to examine the role of institutional demands on attitudes and behaviors of patients and practitioners and how this could affect both behavior towards utilizing healthcare technology and the satisfaction derived from the healthcare service as well as the level of engagement with the care team.

Furthermore, an additional dimension to this study could be to evaluate the variance in results between perceived patient experience that is to include, the perceived satisfaction derived from the service and the perceived level of engagement with the care team compared to actual patient experience outcomes from real life situations. The results of this extension may be critical in informing decision makers on important aspects to include in patient care as well as provide practical recommendations towards designing more customer centric care experiences where patients are more engaged, and the healthcare service is tailored for patient satisfaction success.
Additionally examining the role of access to and distance to a healthcare facility could be another interesting factor under facilitating conditions that could possibly affect behavioral intention to utilize a healthcare Technology.

Furthermore, it will be interesting to look at the variation in behavioral intentions and patient experience (including satisfaction and engagement) across cultures or regions with an additional factor of income levels, insurance payer mix, disease condition target groups.

5.6 Conclusion

In conclusion, the study revealed quite interesting findings as a significant contribution to the literature. Particularly the significant moderating effects of cloud vs non-cloud enabled portals and healthcare service modality on the relationship between Technology use and Patient Satisfaction.

Our findings also showed a significant association through indirect relationships between Technology use, Patient Satisfaction and Patient engagement including significant and supported effects on the indirect relationships between cloud vs non cloud, Healthcare modality, and Patient Satisfaction on Patient Engagement.

Moreover, our study benefited from survey responses collected from a diverse population via Qualtrics. We tested the overall reliability of the responses and found support for existing theories from UTAUT2, Theory of Planned Behavior and Theory of Diffusion of Innovation and how these could be used in explaining the results and associations as seen in the study. Beyond filling the gap by investigating the UTAUT2 in the context of healthcare with the added cloud and healthcare modality feature, this study also provides practical implications and provides a robust stage for future research around Technology use in healthcare. This study also discussed further research opportunities, knowledge, and ideas for future industry implementations.

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APPENDICES

Appendix A Survey Instrument Sources

Construct	Dimension	Question	(Venkatesh, Morris, Davis, & Davis, 2003)	(Venkatesh, Thong, & Xu, 2012)	(Gao & Sunyaev, 2019)	Gao et al 2015	Maillet et al. (2015)	(Silver et al., 2020)	(Garvin & Simon, 2017)	(De Wilde & Hendriks, 2005)	(Tait, Birchwood, & Trower,
Performance expectancy (PE)		PE1: I find the healthcare applications useful for my healthcare visits. PE2: Using healthcare applications helps accomplish things more quickly. PE3: Using healthcare applications improves the quality of my healthcare visits. PE4: Using healthcare applications would increase my overall experience	x	x	x	x	x	x			
Effort Expectancy (EE)		EE1: learning how to use healthcare applications is easy for me. EE2: I find healthcare applications and the features easy to use. EE3: It is easy for me to become skillful at using healthcare applications devices	x	x	x	x	x	x			
Facilitating Conditions (FC)		FC1. I have the resources necessary to use mobile internet. FC2. I have the knowledge necessary to use mobile internet FC3. Mobile internet is compatible with other technologies I use FC4. I can get help from others when using mobile internet	x	x				x			
Behavioral Intention (BI)		B1: I intend to use healthcare applications in the future. B2: I intend to use healthcare applications at every opportunity in the future. B3: I plan to increase my use of healthcare applications in the future.	x		x						
Technology Use (TU)		Use: EU1: My interaction with the healthcare application is clear and understandable. EU2: I believe that it is easy to get the system to do what I want it to do. EU3: Overall, I believe that the system's features are easy to use. EU4: Learning to operate the system is easy for me. Usefulness: PU1: Using the healthcare application would enable me accomplish tasks more quickly. PU2: Using the healthcare application would improve my satisfaction with the healthcare service. PU3: Using the system in my job would increase my productivity and patient engagement with my healthcare team. PU4: Using the system would enhance effectiveness of the healthcare service. PU5: Using the system will facilitate easier and faster communication between myself and my healthcare team PU6: I would find the system useful for all my visits TSQ1: Using the technology improves my access to healthcare services TSQ2: Telehealth saves me time traveling to a hospital or specialist clinic TSQ3: Telehealth provides for my healthcare needs Ease of Use: PEU1: Learning to operate the system will be easy for me	x	x		x		x			

	PEU2: I will find it easy to complete all pre, during and post visit tasks, communication with my care team and to do what I want it to do. PEU3: My interaction with the system is clear and understandable. PEU4: I find the healthcare application to be flexible to interact with. PEU5: It would be easy for me to become skillful at using the system. PEU6: I find the healthcare application easy to use									
Patient Engagemen t	**Use:** Length/Frequency Frequency of Use by Task **Usefulness:** Benefit of the Feature Quality of Information **Ease of Use:** Locating the Feature Navigation within the Feature **Web-Based Quality of Care:** Trust in Healthcare Technology-Enabled Roles **Capabilities of Prepared Patient:** Informed Assured **Capabilities of Active Patient** Self-Management Care-Coordination **Judgement and Decision Making**	x						x		x
Patient Satisfaction	Length of Care Frequency of Care Proximity of Care Satisfaction with Care Trust in Care CSQ **Recommendation:** Doctor or Team Other						x	x	x	
	Portal Use Portal Satisfaction Perceived severity Tenure						x			

Appendix B: Survey Instrument

Section 1: Please provide some background information about yourself.

Age: _____ years. **Gender:** ___ Male ___ Female _ Non-Binary

What is your race/ethnicity? Please check all that apply

White ______ Black or African American_____ American Indian or Alaska Native_______

Asian_______ Native Hawaiian or other Pacific Islander_____ Other race (please describe) __________ _________ Prefer not to disclose_____

Settlement – Urban______ Suburban _______ Rural _______

Education: Higher Educational Degree Earned

_____High School Diploma, _____ Associate Degree (2yrs), ____Bachelor's Degree (4yrs), ____Master's Degree, ____Professional Degree, _____Doctoral Degree

Section 2: Please indicate your level of agreement with each of the statements below (1 = Strongly disagree; 5 = Strongly agree).

PE1: I find the healthcare applications useful for my healthcare visits. PE2: Using healthcare applications helps accomplish things more quickly. PE3: Using healthcare applications improves the quality of my healthcare visits. PE4: Using healthcare applications would increase my overall experience
EE1: learning how to use healthcare applications is easy for me. EE2: I find healthcare applications and the features easy to use. EE3: It is easy for me to become skillful at using healthcare applications devices
FC1. I have the resources necessary to use mobile internet. FC2. I have the knowledge necessary to use mobile internet FC3. Mobile internet is compatible with other technologies I use FC4. I can get help from others when using mobile internet
B1: I intend to use healthcare applications in the future. B2: I intend to use healthcare applications at every opportunity I can in the future. B3: I plan to increase my use of healthcare applications in the future.

Use:
EU1: My interaction with the healthcare application is clear and understandable.
EU2: I believe that it is easy to get the system to do what I want it to do.
EU3: Overall, I believe that the system’s features are easy to use.
EU4: Learning to operate the system is easy for me.

Usefulness:
PU1: Using the healthcare application would enable me accomplish tasks more quickly.
PU2: Using the healthcare application would improve my satisfaction with the healthcare service.
PU3: Using the system in my job would increase my productivity and patient engagement with my healthcare team.
PU4: Using the system would enhance effectiveness of the healthcare service.
PU5: Using the system will facilitate easier and faster communication between myself and my healthcare team
PU6: I would find the system useful for all my visits
TSQ1: Using the technology improves my access to healthcare services
TSQ2: Telehealth saves me time traveling to a hospital or specialist clinic
TSQ3: Telehealth provides for my healthcare needs

Ease of Use:
PEU1: Learning to operate the system will be easy for me
PEU2: I will find it easy to complete all pre, during and post visit tasks, communication with my care team and to do what I want it to do.
PEU3: My interaction with the system is clear and understandable.
PEU4: I find the healthcare application to be flexible to interact with.
PEU5: It would be easy for me to become skillful at using the system.
PEU6: I find the healthcare application easy to use

Patient Experience (Patient Satisfaction and Patient Engagement)

Client/Patient Satisfaction
CSQ1 How would you rate the quality of service received?
CSQ2 Did you get the kind of service you wanted?
CSQ3To what extent has our program met your needs?
CSQ4 If a friend were in need of similar help, would you recommend our program to him or her?
CSQ5 How satisfied are you with the amount of help you have received?
CSQ6 Have the services you received helped you to deal more effectively with your problems?
CSQ7 In an overall, general sense, how satisfied are you with the service you have received?
CSQ8 If you were to seek help again, would you come back to our program?

Complexity of the Application
C1: Using the healthcare application takes too much time
C2: Working with the healthcare application is so complicated, it is difficult to understand what is going on.
C3. Using the healthcare application involves too much time doing mechanical operations (e.g., data input).
C4: It takes too long to learn how to use the application to make it worth the effort.

SES-Client/ Patient Engagement
Items are rated 0 (not at all or rarely), 1 (sometimes), 2 (often), 3 (most of the time)
Availability
1The clinical team seems to make it difficult to arrange appointments
2When a visit is arranged, my clinical team are always ready and available
3The clinical team seems to avoid making appointments
Collaboration
4 Does your clinical team involve me in my care experience decisions?
5 Does your clinical team make advice, recommendations easy to follow?
6 The clinical team provides a great collaborative atmosphere for me to take an active part in the setting of goals or treatment plans
The healthcare team encourages me to actively participate in managing his/her illness
Help seeking
7 My healthcare team encourages me seeks help when assistance as needed
8 I find it difficult to ask for help via the application
9 I find it easy to seek help to prevent a crisis
10 I am not comfortable seeking help
Treatment adherence
11 I always follow my treatment plan to take any prescribed medication
12 I know where to find instructions and information about what the medications I am taking and why I am taking them.
13 My care team makes it easy to co-operate with the virtual treatment plan
14 I often have difficulty in adhering to the prescribed medication

Healthcare Modality
Please indicate your level of agreement with each of the statements below (1 = Strongly disagree; 5 = Strongly agree).
Interaction Quality
1. I could easily talk to the clinician using the telehealth system
2. I could hear the clinician clearly using the telehealth system
3. I felt I was able to express myself effectively
4. Using the telehealth system, I can see the clinician as well as if we met in person

Reliability
1.I think the visits provided over the telehealth system are the same as in-person visits

2. Whenever I made a mistake using the system, I could recover easily and quickly

3. The system gave error messages that clearly told me how to fix problem

Satisfaction and Future Use
1.I feel comfortable communicating with the clinician using the telehealth system

2.Telehealth is an acceptable way to receive healthcare services

3. I would use telehealth services again
4.Overall, I am satisfied with this telehealth system

Cloud Enabled Vs Non-Cloud Enabled benefits

Awareness
AW1 “I am aware of cloud computing services”.
AW2 “I know the advantages of using cloud computing”.
AW3 “I am likely to use in healthcare-service applications that are cloud computing-based healthcare services training programs”.

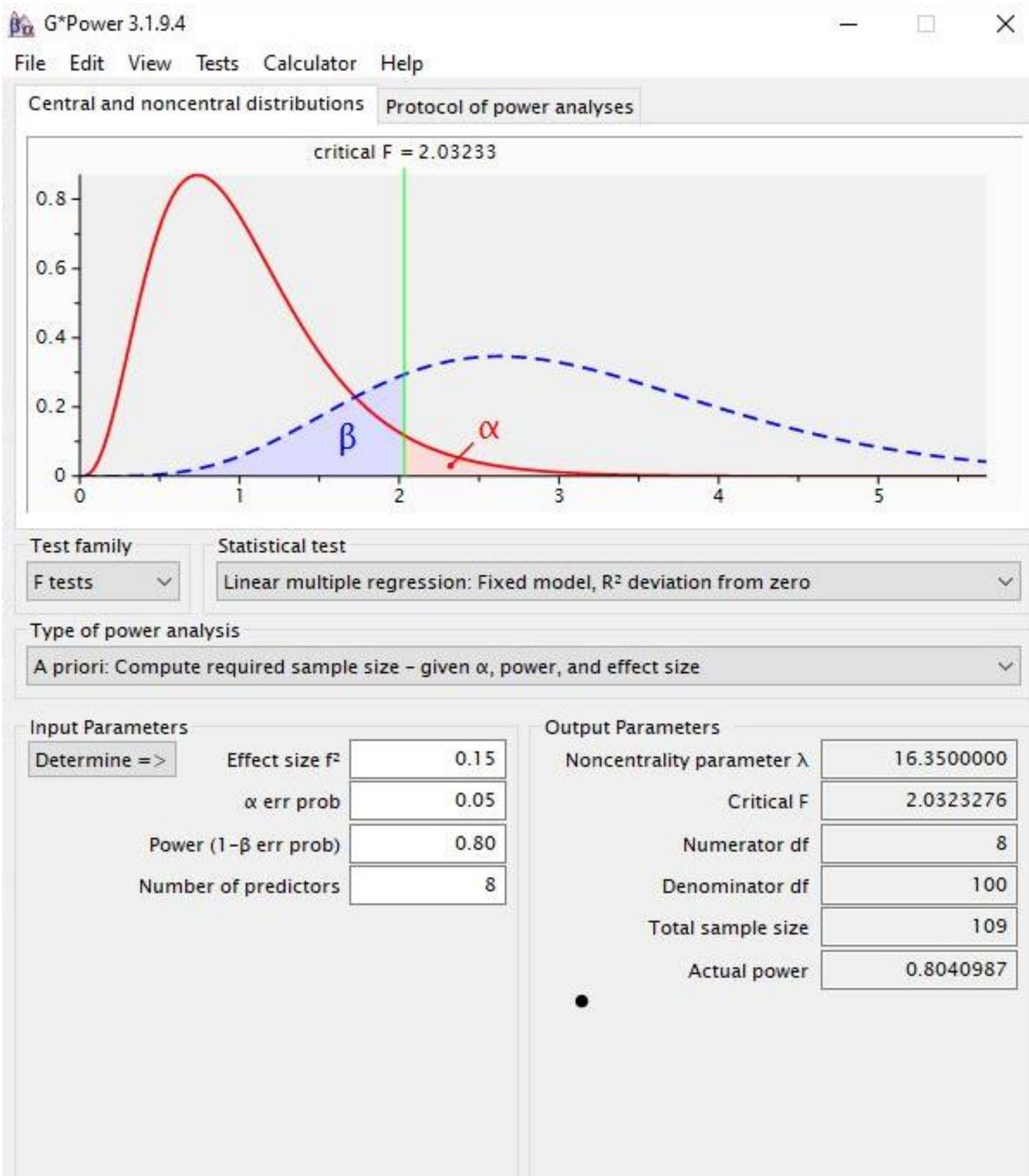
Cost reduction
CR1 “The use of cloud computing reduced the burden of overall cost of care”.
CR2 “I believe that the advantages of cloud enabled healthcare applications to me as patients are greater than the costs of not using cloud enabled healthcare application for the provision of Healthcare services”.
CR3 “I believe that the use of cloud enabled applications reduces the energy and environmental costs for healthcare”.

Perceived security and privacy

PSP1 “I believe that cloud computing provides better information security”.
PSP2 “I believe that with cloud -enabled applications no one can manipulate the data and information”.
PSP3 “I believe that using cloud computing no irrelevant person can assess and use the data for personal benefits”.

Compatibility
C1 “Using the cloud enabled applications for healthcare is compatible with all aspects of my healthcare service needs”.
C2 “I think that using the cloud enabled applications fits well with the way I like to collaborate with my healthcare team”.
C3 “Using the cloud enabled healthcare applications fits into my preferred work-life style”.

Appendix C: G*Power Calculation



Appendix D

Invitation To Take Survey

My name is Magbor Atem, and I am a doctoral student at The University of North Carolina, Charlotte. Under the guidance of Faculty Advisor Dr. Reginald Silver. I am conducting a research study to understand how healthcare organizations can leverage the capabilities of cloud-based technology use through different healthcare service delivery modalities to improve outcomes including patient engagement and patient experience. We expect significant theoretical and practical contributions from this study. This study is focused on leveraging technology use for person engagement before during and after patient visits; thus, I am looking for survey responses from participants with access to smart phones, tablets or computers with the internet. Given your healthcare visit encounters, I invite you to participate in the study. Your personal opinion will be a valuable input for this contextually significant research work.

Additional Information about this study:

1. All responses are completely anonymous.

2. This survey contains no identifiers that could point to your identity.

3. The survey will take approximately 20-25 minutes to complete.

4. Your participation is voluntary.

5. You are free to exit the survey at any time.

6. All survey data will be used exclusively for academic research only, and may be included in future academic research

7. The data may also be included in academic, or business-related or healthcare innovation and services related publications in the future.

8. The data collected from this survey will not be sold.

9. There are no known adverse consequences associated with either choosing or forgoing participation in this research study. If you are interested in participating, please click on the link below to anonymously participate. You will be required to provide your consent first before proceeding with the questionnaire.

Appendix E

Table 4.7a Construct Code, Definition and Measures

Latent Variable	Definition	Main Construct Measure
		Behavioral Intention to Use
PE1	Performance Expectancy - PE1	**a Technology**
PE2	Performance Expectancy - PE2	
PE3	Performance Expectancy - PE3	
PE4	Performance Expectancy - PE4	
EE1	Effort Expectancy - EE1	
EE2	Effort Expectancy - EE2	
EE3	Effort Expectancy - EE3	
FC1	Facilitating Conditions - FC1	
FC2	Facilitating Conditions - FC2	
FC3	Facilitating Conditions - FC3	
FC4	Facilitating Conditions - FC4	
BI1	Behavioral Intentions - B1	
BI2	Behavioral Intentions - B2	
BI3	Behavioral Intentions - B3	
EU1	Use of the Technology - EU1	**Technology Use**
EU2	Use of the Technology - EU2	
EU3	Use of the Technology - EU3	
EU4	Use of the Technology - EU4	
PU1	Usefulness of the Technology - PU1	
PU2	Usefulness of the Technology - PU2	
PU3	Usefulness of the Technology - PU3	
PU4	Usefulness of the Technology - PU4	
PU5	Usefulness of the Technology - PU5	
PU6	Usefulness of the Technology - PU6	
TSQ1	Usefulness of the Technology - TSQ1	
TSQ2	Usefulness of the Technology - TSQ2	
TSQ3	Usefulness of the Technology - TSQ3	
PEU1	Perceived Ease of Use - PEU1	
PEU2	Perceived Ease of Use - PEU2	
PEU3	Perceived Ease of Use - PEU3	
PEU4	Perceived Ease of Use - PEU4	
PEU5	Perceived Ease of Use - PEU5	
PEU6	Perceived Ease of Use - PEU6	
CSQ1	Patient Satisfaction - CSQ1	**Patient Satisfaction**
CSQ2	Patient Satisfaction - CSQ2	
CSQ3	Patient Satisfaction - CSQ3	
CSQ4	Patient Satisfaction - CSQ4	
CSQ5	Patient Satisfaction - CSQ5	
CSQ6	Patient Satisfaction - CSQ6	
CSQ7	Patient Satisfaction - CSQ7	
CSQ8	Patient Satisfaction - CSQ8	
IntQu1	Interaction Quality - 1	

IntQu2	Interaction Quality - 2	
IntQu3	Interaction Quality - 3	
IntQu4	Interaction Quality - 4	
SaFutureUse1	Satisfaction and Future Use1	
SaFutureUse2	Satisfaction and Future Use2	
SaFutureUse3	Satisfaction and Future Use3	
SaFutureUse4	Satisfaction and Future Use4	
PaEnAv1	Patient Engagement - Availability1	**Patient Engagement**
PaEnAv2	Patient Engagement - Availability2	
PaEnAv3	Patient Engagement - Availability3	
PaEnColl1	Patient Engagement Collaboration1	
PaEnColl2	Patient Engagement Collaboration2	
PaEnColl3	Patient Engagement Collaboration3	
PaEnColl4	Patient Engagement Collaboration4	
PAEnHeSeek1	Patient Engagement - HelpSeeking1	
PAEnHeSeek2	Patient Engagement - HelpSeeking2	
PAEnHeSeek3	Patient Engagement - HelpSeeking3	
PAEnHeSeek4	Patient Engagement - HelpSeeking4	
PAEnHeSeek5	Patient Engagement - HelpSeeking5	
PaEnTA1	Patient Engagement Treatment Adherence1	
PaEnTA2	Patient Engagement Treatment Adherence2	
PaEnTA3	Patient Engagement Treatment Adherence3	
Re1	Reliability - 1	**Cloud Enabled Vs Non-Cloud Enabled**
Re2	Reliability - 2	
Re3	Reliability - 3	
ClouAW1	Cloud Aware- AW1	
ClouAW2	Cloud Aware - AW2	
ClouAW3	Cloud Aware - AW3	
ApC1	Application Complexity - C1	
ApC2	Application Complexity - C2	
ApC3	Application Complexity - C3	
ApC4	Application Complexity - C4	
CostR1	Cost Reduction- CR1	**Healthcare Service Modality**
CostR2	Cost Reduction- CR2	
CostR3	Cost Reduction- CR3	
PerSecP1	Perceived Security and Privacy- PSP1	
PerSecP2	Perceived Security and Privacy- PSP2	
PerSecP3	Perceived Security and Privacy- PSP3	
LifeCoC1	Lifestyle Compatibility - C1	
LifeCoC2	Lifestyle Compatibility - C2	
LifeCoC3	Lifestyle Compatibility - C3	

Appendix F

Table 4.8 Convergent Validity - Factor Loadings and Weights (Latent Variables)

	Outer loadings	Cronbach's alpha	Composite reliability	AVE
ApC1 <- ApC	0.918	0.945	0.960	0.858
ApC2 <- ApC	0.944			
ApC3 <- ApC	0.900			
ApC4 <- ApC	0.943			
BI1 <- BI	0.922	0.918	0.948	0.859
BI2 <- BI	0.932			
BI3 <- BI	0.927			
CSQ1 <- CSQ	0.853	0.939	0.950	0.703
CSQ2 <- CSQ	0.879			
CSQ3 <- CSQ	0.854			
CSQ4 <- CSQ	0.847			
CSQ5 <- CSQ	0.822			
CSQ6 <- CSQ	0.806			
CSQ7 <- CSQ	0.890			
CSQ8 <- CSQ	0.751			
ClouAW1 <- ClouAW	0.908	0.921	0.949	0.860
ClouAW2 <- ClouAW	0.946			
ClouAW3 <- ClouAW	0.928			
CostR1 <- CostR	0.914	0.907	0.941	0.843
CostR2 <- CostR	0.925			
CostR3 <- CostR	0.915			
EE1 <- EE	0.941	0.934	0.958	0.883
EE2 <- EE	0.940			
EE3 <- EE	0.939			
EU1 <- EU	0.920	0.947	0.962	0.864
EU2 <- EU	0.937			
EU3 <- EU	0.945			
EU4 <- EU	0.916			
FC1 <- FC	0.958	0.952	0.965	0.874
FC2 <- FC	0.939			
FC3 <- FC	0.945			
FC4 <- FC	0.896			
IntQu1 <- IntQu	0.903	0.903	0.933	0.777
IntQu2 <- IntQu	0.896			
IntQu3 <- IntQu	0.933			
IntQu4 <- IntQu	0.786			
LifeCoC1 <- LifeCoC	0.830	0.901	0.938	0.835
LifeCoC2 <- LifeCoC	0.955			
LifeCoC3 <- LifeCoC	0.951			
PAEnHeSeek1 <- PAEnHeSeek	0.728	0.218	0.182	0.393
PAEnHeSeek2 <- PAEnHeSeek	-0.724			
PAEnHeSeek3 <- PAEnHeSeek	0.652			
PAEnHeSeek4 <- PAEnHeSeek	-0.403			
PAEnHeSeek5 <- PAEnHeSeek	0.570			
PE1 <- PE	0.886	0.908	0.936	0.784
PE2 <- PE	0.885			
PE3 <- PE	0.879			
PE4 <- PE	0.893			
PEU1 <- PEU	0.896	0.946	0.957	0.790

PEU2 <- PEU	0.897			
PEU3 <- PEU	0.913			
PEU4 <- PEU	0.797			
PEU5 <- PEU	0.905			
PEU6 <- PEU	0.917			
PU1 <- PU	0.875	0.940	0.953	0.770
PU2 <- PU	0.902			
PU3 <- PU	0.907			
PU4 <- PU	0.888			
PU5 <- PU	0.843			
PU6 <- PU	0.850			
PaEnAv1 <- PaEnAv	0.879	0.383	0.507	0.506
PaEnAv2 <- PaEnAv	-0.408			
PaEnAv3 <- PaEnAv	0.762			
PaEnColl1 <- PaEnColl	0.803	0.879	0.916	0.732
PaEnColl2 <- PaEnColl	0.863			
PaEnColl3 <- PaEnColl	0.896			
PaEnColl4 <- PaEnColl	0.859			
PaEnTA1 <- PaEnTA	0.849	0.333	0.589	0.504
PaEnTA2 <- PaEnTA	0.855			
PaEnTA3 <- PaEnTA	-0.244			
PerSecP1 <- PerSecP	0.906	0.884	0.926	0.807
PerSecP2 <- PerSecP	0.887			
PerSecP3 <- PerSecP	0.900			
Re1 <- Re	0.770	0.726	0.843	0.641
Re2 <- Re	0.850			
Re3 <- Re	0.780			
SaFutureUse1 <- SaFutureUse	0.890	0.923	0.945	0.812
SaFutureUse2 <- SaFutureUse	0.895			
SaFutureUse3 <- SaFutureUse	0.909			
SaFutureUse4 <- SaFutureUse	0.911			
TSQ1 <- TSQ	0.817	0.826	0.896	0.742
TSQ2 <- TSQ	0.857			
TSQ3 <- TSQ	0.908			