APPIAH OTOO, BRIGID A., Ph.D. Three Analytics-Based Essays Examining the Use and Impact of Intelligent Voice Assistants (IVA) and Health Information Technologies (HIT) in Service Contexts. (2021)
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Recent advancements in information technology (IT) innovation, such as artificial intelligence (AI) and machine learning (ML), are changing the dynamics in the service sector by driving smart reinvention of service tasks and processes. Additionally, organisations are leveraging the capabilities of emerging information systems (IS) to make their services more efficient and customer centric. However, the decision to use recent advancements in IT can be challenging for organizations since the required initial investment for implementation is often high and the economic value and impact on service performance cannot be gauged with certainty (Kwon et al. 2015). This forces many organizations to prioritise which IT functionalities may best be suited for their needs.

To support the decision making process of organizations, regarding the adoption and use of innovative IT, scholars in the information systems (IS) and related fields are called to improve knowledge and understanding about various IT components and functionalities as well as their corresponding impact on individual users and organizations. Scholars are also expected to provide the means by which businesses can meaningfully predict the potential impact and economic value of innovative IT (Ravichandran 2018). In this three essay dissertation, we investigate how the use of various components and functionalities of innovative information systems can individually (or together) impact the quality of service delivered to end consumers. The

essays are broadly based on the intersection of artificial intelligence (AI), machine learning(ML) and services.

In the first study, we found that during encounters between eService consumers and Intelligent Voice Assistants (IVAs), typically powered by artificial intelligence, machine learning and natural language processing, the following dimensions are important for the perceived quality of service: IVA interactivity, IVA personalization, IVA flexibility, IVA assurance and IVA reliability. Among the five dimensions of IVA encounter, we found that IVA interactivity, IVA personalization and IVA reliability had positive impacts on the effective use of IVAs.

In study 2, we investigated performance of hospitals in the health service sector. We proposed a smart decision support system (DSS) for predicting the performance of hospitals based on the Health Information Technology (HIT) functionalities as applied and used in these hospitals for patient care and in improving hospital performance. We found that the predictive performance of our proposed smart DSS was most accurate when HIT functionalities were used in certain bundles than in isolation.

In study 3, we investigated the effect of hospital heterogeneity on the accuracy of prediction of our proposed smart DSS as we recognize that not all hospitals have the same set of context, opportunity, location and constraints. We found that the following sources of variations in hospitals had significant moderator effects on the accurate prediction of our smart DSS: hospital size, ownership, region, location (urban/rural) and complexity of cases treated.

In summary, this dissertation contributes to the IS literature by providing insight into the emergent use of artificial intelligence and machine learning technologies as part of IS/IT solutions in both consumer-oriented services and the healthcare sector.

THREE ANALYTICS-BASED ESSAYS EXAMINING THE USE AND IMPACT OF INTELLIGENT VOICE ASSISTANTS (IVA) AND HEALTH INFORMATION TECHNOLOGIES (HIT) IN SERVICE CONTEXTS

by

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Approved by

____
Committee Chair

I want to dedicate my work to:

Aba and Efua Appiah Otoo

APPROVAL PAGE

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CHAPTER I

INTRODUCTION TO DISSERTATION

1.1 Overview

The Internet has revolutionalised the services industry by expanding business capabilities and the utility of information systems to a universal system of interactions. Information systems support service operations by meeting diverse needs such as decision support, distant communication and documentation of vital information. Recent advancements in information technology (IT), such as artificial intelligence (AI), are changing the dynamics in the service sector by driving smart reinvention of service tasks and processes. Also, organisations are leveraging the capabilities of emerging information systems to make their services more efficient and customer centric. However, the decision to use innovative IT (e.g. Artificial Intelligence and Machine Learning) can be challenging for organizations since the required initial investment for implementation is oftern high forcing many organisations to prioritise which IT functionalities may best be suited for their business needs. Also, the economic value and impact of innovative IT on service performance cannot be gauged with certainty (Kwon et al. 2015).

To support the decision making process of organizations regarding the adoption and use of innovative IT, scholars in the information systems and its related fields are called to improve knowledge about their components and functionalities. IS research can provide the foundation for systems that can meaningfully predict the impact of innovative IT (Ravichandran 2018). By this three essay dissertation, I respond to this call by investigating how the use of various components of innovative information systems can individually (or together) impact the quality of services delivered to end consumers.

1.2 Research Motivation

Current widespread access to the internet has transformed the service by heightening the demand for quality service to be more customer-centric (Lee and Day 2019). Beyond offering a good product, customer-centric companies are focused on providing their customers gratifying service experiences. Forbes reports that companies with superior customer experiences are likely to earn 5.7 times more revenue than their competitors (Morgan 2019). While digital transformation is a critical step to becoming customer-centric, many service organizations face barriers in their decision making to adopt and use innovative technology. A review of IS literature on innovative IT shows that most of the studies are theoretically grounded in either resource-based view (RBV) (Barney et al. 2011) or the dynamic capabilities theories (Eisenhardt and Martin 2000).

Overall, the studies suggest that organizational use of innovative IT is related to improved performance. For example, Mithas et al. (2012) adopted principles from the RBV theory to investigate the impact of innovative IT on firm profitability. They found a positive relationship between innovative IT and firm profitability whereby profitability through IT-enabled revenue growth was higher than that through IT-enabled cost reduction. Drawing on the principles of Dynamic Capability Theory, Chen et al. (2015)

further studied the impacts and antecedents of organizational Big Data Analytics (BDA) usage. The researchers observed an association between BDA usage and organizational value creation. They found that, the observed relationship was moderated by environmental dynamism and technological factors (expected benefits and compatibility) directly influenced organizational BDA usage. BDA usage through top management support was further observed to be indirectly influenced by organizational (e.g. organizational readiness) and environmental (e.g. competitive pressure) factors. Based on the theoretical framework of RBV, Ping-Ju Wu et al. (2015) investigates how organizational value is created through innovative IT governance mechanisms. They found a positive, significant, and impactful association between innovative IT governance mechanisms and strategic alignment and, more so, between strategic alignment and organizational performance.

While RBV and dynamic capability theories highlight the value of IT as a resource and how they can enable organisations to build capabilities for improving their business performance (Mamonov and Peterson 2020) they do not adequately explain the dimensions of innovative IT, such as health information technology (HIT) and intelligent voice assistants (IVA), which can enhance customer experiences. By using only a few theories, the narrow theoretical foundation of IT innovation literature limits our understanding of how organizations can levarage IT advancements to achieve customer-centric service provision. We therefore aim to make both theoreotical and practical contributions to existing literature about the dimensions and functionalities of innovative IT which can help them to enhance the service experience of their customers. I adopt principles of theories from the IS and its related fields to investigate the above issues. This enables me to study the dimensions of service encounter with customers through IT as well as the impact of such encounters and the functionalities of the IT on the quality of service received. I focus my studies on e-Services and hospital care. Considering how vast the service industry is, focusing on e-Services enables me to discuss the use of IT in the context of all services that can essentially be completed via electronic (internet) means. These types of services, including aspects of healthcare (eHealth), typically involve the exchange of information between the provider and customers without a need for significant amount of face-to-face interaction. On the other hand, services like healthcare have essential components that can only be completed through planned or emergency face-to-face interaction with the service providers (Saleemi et al. 2017). I therefore study healthcare as an example of such services and how the use of IT can enhance the quality of care delivered to customers.

I focus my studies on three types of innovative technologies: Intelligent Voice Assistants (IVAs), Machine Learning algorithms and Health Information Technology (HIT) and how their use impacts the quality of service delivered to the consumers of these services. Health IT refers to information technology systems that create, store, share and manage patients’ health data (Karahanna et al. 2019). On the other hand IVAs, such as Siri and Alexa, are artificial intelligence (AI) applications, which utilize voice queries and natural-language user interfaces to assist users by answering questions, making recommendations, and performing actions by delegating requests to a set of eservices (Brill et al. 2019). Examples of eServices accessible through IVAs are weather forcast information and music streaming services. Artificial Intelligence (AI) can be defined as the ability of a computer to meaningfully interpret input data, learn from the data and utilize the learnings to complete specific tasks through flexible adaptation (Kaplan and Haenlein 2019). Through its incorporation in applications such as IVAs and machine learning, the use of AI has the potential to significantly enhance services which aim to boost the experiences of their customers. I utilize survey data from users of IVAs as well as data collected from hospitals about the use of health IT (HIT) to support my study. The data from IVA users enabled me to make theoretical contributions at the individual IT user level while findings from the hospitals which use HIT helped me to make organizational level contributions.

1.3 Objectives

For Essay 1, I aim to improve the understanding of the possible dimensions of IVA encounter with eService consumers and how they impact consumers' ability to complete relevant tasks. HIT is another form of information system which is used in the healthcare services to support a wide range of clinical processes. In Essay 2 and 3 I explore how HIT functionalities (Rudin et al. 2019), individually or together, influence the quality of healthcare service. These functionalities include Computerised Provider Order Entry (CPOE); Test Results Viewing (TRV) and Telemedicine. Listed below are the titles of my essays and specific research questions addressed under each essay:

Essay 1. Dimensions of Consumer Encounter with Intelligent Voice Assistants (IVAs) and e-Service Consumption: An Empirical Assessment

RQ1: *What are the dimensions of consumer encounter with Intelligent Voice Assistants (IVA)?*

RQ2*: How do IVA encounter dimensions affect IVA effective use leading to value and satisfaction with IVA and e-service consumption?*

Essay 2. Predicting the Effects of Health IT Functionalities on Hospital Performance: A Machine Learning Approach

RQ: *What is the predictability of hospitals' performance given their use of HIT functionalities?*

Essay 3. An Assessment of the effect of hospital heterogeneity on predicting performance

RQ: *What is the moderator effect of hospital heterogeneity on the accuracy of performance prediction?*

Recent research suggests that Intelligent Voice Assistants (IVAs) are being increasingly used by consumers worldwide (Olmstead 2017). This growth is contributing to the need for researchers and practitioners to understand what the dimensions of consumers' encounter with the IVAs may be and whether the dimensions affect consumers' ability to effectively use IVAs in the context of eService consumption. In Essay 1, I present theoretical foundation and empirical assessment of dimensions of consumer encounter with IVAs in the context of eService – specifically investigating how Service Delivery Quality and Service Content Quality along with IVA impact eService Consumer Satisfaction and Loyalty.

In the HIT literature, limited studies have investigated how specific functionalities of HIT impact the performance of hospitals with respect to patient length of stay (LOS) and cost of patient care (CPC). Reducing LOS is an important predictor of patient quality of care because it can help to avoid patient harm and unnecessary hospital-acquired conditions (HACs) (Wen et al. 2017). A hospital's ability to improve quality of care at reduced costs is an indicates of how well it is performing (Wani and Malhotra 2018). Limited literature on how the various HIT functionalities compare to each other in association to changes in LOS and CPC limits our understanding of how hospitals can leverage the functionalities to improve their performance.

From the perspectives of the technology-task fit (TTF) theory (Goodhue and Thompson 1995; Howard and Rose 2019) and Information Processing Theory (IPT) (Galbraith 1973) I assess the predictability of patient length of stay (LOS) and cost of patient care (CPC) from hospitals' HIT functionalities using machine learning algorithms. TTF provides me a framework to study the impact of information technology on workplace performance. Machine learning algorithms also enables me to review my large data sets and accurately interpret the results generated by the algortihms.

Finally, I utilize the framework of Task-Technology Fit theory (TTF) to examine the moderator effect of five observable sources of hospital variations predicting performance with health IT use. These were hospital size (numer of staffed beds);

ownership/ control; region; location (urban/rural) and the complexity of health cases treated.

1.4 Data and Methods

To support Essay 1, I analyse survey data from 280 users of IVAs using Structural Equation Modelling (SEM) with SmartPLS (Wong 2013). I present and discuss my empirical findings and research and practitioner implications in chapter 2. I then explore the functionalities of health information technology and their impact on predictiong hospital satisfaction, quality and cost of patient care as well as financial performance in essays 2 and 3. My study on HIT is based on recent secondary data from RAND Hosptial database and American Hospital Association Annual Survey of Hospitals-IT (AHA-IT) Supplement database. With acute care hospital as my unit of analysis, the predicted variables of the study, LOS and CPC, were adjusted by the hospital's Case Mix Index (CMI) obtained from the RAND data (Sharma et al. 2016).

The CMI of a hospital is an important indicator of the average complexity of a hospital's treatments hence the resources required to care for patients. CMI is defined as "the average relative case weight of all admitted patients" (McRae et al. 2020, Pg. 83). In general, the higher the average complexity of a hospital's treatments are, the higher its CMI. A healthcare provider's case mix index (CMI) is calculated as the sum of the relative weights of the facility's Diagnosis-Related Groups (DRGs) divided by the number of admissions for the period of time (often 1 year) (Mendez et al. 2014). DRGs define types "hospital products" and quantify what hospitals do. Through their definition of types of “hospital products”, DRGs enable comparisons which otherwise would not feasible (Busse et al. 2013). For example, they enable the comparison of hospitals based on the complexity of the cases treated.

For my analysis I excluded hospitals with beds fewer than 25 due to the low probability for them to need strong technology infrastructure due to small size. Also, rehabilitation centers, psychiatric centers and veteran administration centers were excluded because these facilities have significantly different operations and patients compared to acute care hospitals (Sharma et al. 2016). I utilized machine learning methods for my analysis because of the large volume of data and differences in the variables. Machine Learning algorithms are powerful computational processes which enabled me to analyse the big and complex datasets quickly with more accurate results than other analytical processes. my ability to build precise models is a major contribution for hospitals to reliably predict hospital performance and satisfaction.

1.5 Dissertation Organization

The rest of this dissertation document is organized as follows: chapters 2,3 and 4, I discuss essays 1, 2 and 3 respectively. For each study, I first give discuss a review of the literature within which the study is situated. I then discuss the theoretical backgrounds of each study. The proposed conceptual models and hypotheses are then discussed. This is followed by a discussion of the methods I adopt to complete each of the research topics as well as the expected contributions I look to make (for essay 2 and 3). For essay 1, I present and discuss findings from my analysis with conclusions. Finally, I present a broad schedule for conducting the rest of the dissertation.

CHAPTER II

DIMENSIONS OF CONSUMER ENCOUNTER WITH INTELLIGENT VOICE ASSISTANTS (IVA) AND eSERVICE CONSUMPTION: AN EMPIRICAL ASSESSMENT

2.1 Introduction

Intelligent Voice Assistants (IVA) are voice-based personal agents programmed and designed to act like humans in performing automated tasks using machine learning and natural language processing. In this research, we define IVA encounter as the goal-oriented dyadic interaction between IVAs and consumers to access and consume relevant eServices (van Doorn et al. 2017; Larivière et al. 2017). A recent report by Capgemini ("Conversational Commerce" 2018) suggests that the global individual adoption of IVAs is expected to reach 1.83 billion by 2021, at a growing rate of 29.4% compound annual growth rate (CAGR). Popular examples of IVAs are Siri, Alexa, Cortana and Google Assistant. Recent research suggests that the global number of consumers using IVAs will increase from 390 million (in 2015) to 1.8 Billion in 2021 (Tractica 2016). It is further predicted that about 46% of the U.S. adult population, mostly 18 to 49-year-old, now use intelligent voice assistants in some form to network with other smart devices (Olmstead 2017). Due to its potential to digitally change consumer encounter as well as its rapid proliferation in the U.S. and other Western countries, IVA is becoming an interesting research topic in many fields such as information systems (e.g. Knote et al. 2018; Yuan and Dennis 2019) marketing (e.g. Hoffman and Novak 2018; Steinhoff 2019), human-computer interaction (e.g.Purington et al. 2017).

Extant academic Information Systems (IS) literature has so far discussed eServices using devices such as desktops, laptops and mobile phones (Xu et al. 2013). We define eService as services offered and consumed through digital means including consumer end devices and delivered typically over the Internet. We limit our focus on eService consumption to IVAs which are accessible through dyadic voice interactions and where the IVAs demonstrate a level of *independence* from that of the human users. eService consumption through IVAs differs from those accessible through channels such as websites and mobile phones, which tend to be human-centric that is the interaction is mostly from human to device or service interface. Typically, in mobile phone-based or web site-based interactions the service technologies are passive, and they only respond if the human user provides some input such as pressing a button or clicking on a shopping cart to buy items, etc. In contrast, IVAs demonstrate independence by acting on the input provided by the human user but making choices or suggestions that are independent of further human user interventions. The interactions are dynamic and conversational, almost mimicking dyadic human interactions using natural language.

Currently, IVAs are used to access a wide range of eServices such as weather forecasts (by reporting) and utility energy (by operating gadgets like smart bulbs). They utilize artificial intelligence (AI) and machine learning (ML) technologies as well as several actuation mechanisms to interact with and assist eService consumers. IVAs have become a common component in mobile devices, such as smartphones and tablets, and could soon become their default means of input. Technology giants such as Google, Microsoft, Samsung, Amazon and Apple are looking to incorporate IVA's in other consumer products such as television, automobiles, as well as in consumer household devices such as microwaves, refrigerators, washing and drying machines, etc. (Knight 2012). The proliferation of IVAs through various connected smart devices, like smart wearables, is significantly changing the content and delivery of eServices to consumers (Bolton et al. 2018; Larivière et al. 2017). This is partly due to IVAs' unique 'dialogue-style only' nature of interactions as well as their ability to preserve context across different queries (Moorthy and Vu 2014).

Recent literature on IVAs have focused on influencing factors of IVA adoption and user behavior in the context of family use, as assistive technology and as a component of Internet of Things (IOT) (Diederich et al. 2019). However, the studies have not explicitly looked at eServices which incorporate IVAs. Interestingly, while human face-to-face interactions in service delivery as well as eServices delivered over websites, mobile phones and computers have been widely studied and received much of the attention, consumer encounters with alternate channels for eService consumption such as IVAs have received limited discussion in the IS literature (van Birgelen et al. 2006; Seck and Philippe 2013). This limits our understanding of the impact of such channels on consumers' assessment of eService quality and consumers' encounter with the IVAs and subsequent consumer satisfaction and loyalty in relation to eService consumption. To address this gap in the IS literature, we aim to study the relationships among eService quality, consumer encounter with IVA and consumer satisfaction and loyalty related to eService consumption (Hsieh et al. 2012; Tan et al. 2013).

Additionally, there is limited research on the theoretical foundations of eService quality as it relates to IVA encounter dimensions, IVA effective use, IVA satisfaction and IVA value. In this research, we adopt principles from Assemblage theory (DeLanda 2016) to explore how eService consumers and IVAs function together to effectively complete tasks within their consumer-object assemblages. Assemblage theory states that the component parts within a body (assemblage) interact with a paired capacity for entities to affect as well as be affected by each other through dynamic exteriority relations (DeLanda 2016; Deleuze and Guattari 1987). Based on assemblage theory's emphasis on the paired capacities, we conceptualize how IVAs interact with consumers in a non-human centric context.

When incorporated into the delivery of eServices, IVAs act as the eService fronts, hence the gateways through which consumers perceive the quality of the eService through their encounter with the IVAs (Yuan and Dennis 2019). Drawing on previous literature, we further develop IVA encounter dimensions in this study (Jayawardhena 2010; Raajpoot 2004a). We modify the SERVQUAL model (Parasuraman et al. 1988) to propose and test possible dimensions of the IVA encounter. We use the modified SERVQUAL model because it enables us to measure the technical and non-technical characteristics of the IVA encounter. In addition, we draw from (Burton-Jones and Grange 2013) theoretical framework of IT effective use to examine how consumers' effective use of IVAs to complete tasks affect their perceived IVA satisfaction and value as well as their satisfaction with and loyalty toward the Service. This study aims to advance academic literature on how the dimensions the of IVA encounter could affect consumer perceived quality of eServices and the perceived service satisfaction and service loyalty. By understanding the different dimensions of IVA encounter, eService providers should be able to leverage the IVA benefits in their service content and delivery design to enhance the service quality delivered to consumers.

The remainder of this study is organized as follows: the next section details definitions of key terms and reviews the relevant literature on Intelligent Voice Assistants (IVA), IVA Encounter, IVA effective use and service quality. We then present the research model and related hypotheses, followed by a description of the research methodology. We then conclude the with the discussion and conclusion section.

2.2 Related Literature and Theoretical Foundations

This section outlines the key findings from a review of relevant literature on Intelligent Voice Assistants (IVA) as well as service content quality and service delivery quality.

2.2.1 Intelligent Voice Assistants (IVA)

Intelligent Voice Assistants (IVA) are defined as software applications, typically embedded in smartphones, car speakers, and dedicated home speakers, which process human speech and respond through artificial voices (Hoy 2018). The use of voice is fast becoming the preferred mode of interaction for consumers in electronic communication environments and is gaining significant momentum in both practice-oriented (e.g., Buvat et al. 2018; Warren 2018) and academic research (e.g., Purington et al. 2017). There is no consensus universal term, in extant Information Systems (IS) literature, used currently in reference to this new and emerging phenomenon. Various studies of IVAs adopt different terms of reference such as Smart Personal Assistants (Knote et al. 2018); Intelligent Personal Assistants (Liao et al. 2019; Pradhan et al. 2018); Conversational User Interface (Sciuto et al. 2018); Voice Assistants (Palanica 2019); Conversational Agent (Purington et al. 2017), and Automated Agents (Elson et al. 2018). In this research, we use the term Intelligent Voice Assistant to refer to these collective terms.

As Amazon, Google, Apple and Microsoft introduce affordable IVAs and digital enablement of services through IVAs become more prevalent, IVAs are increasingly getting integrated in the daily lives of eService consumers (Purington et al. 2017). For instance, applications such as Siri, Alexa and Google Assistant utilize voice to enable consumers to complete tasks such as turning on/off lights and letting consumers read news hands free and interact with various eServices. While all types of IVAs seem like similar voice-based AI applications, they differ from each other in their strengths and weaknesses. Table 1 compares the characteristics of the more popular IVA options (Chokkattu 2017).

Table 1. Comparison of Intelligent Voice Assistants

Type of IVA	Interface	Strengths	Weakness
Google Assistant	Wearables; Android devices.	Advanced search commands; highly interactive.	Less personality than competitors.
Apple's Siri	iOS.	Work related tasks; entertainment.	Less expansion in new areas; Limited to iPhone devices.
Microsoft's Cortana	Windows 10 devices Xbox; One console.	Work related tasks.	No smart home or IoT devices.
Amazon's Alexa	Amazon Echo speaker.	Shopping commands; highly conversational; Great user customization and management options.	Not focused on mobile or computer purposes.
Samsung Bixby	Galaxy phones.	Full voice command compatibility; home and vision abilities.	No Internet of Things focus.

IVAs are designed as real time intelligent systems for human computer interaction (Hoy 2018). This has contributed to its wide acceptance and use in various institutions such as banks, universities and law firms due to the significant improvement in accuracy of automatic speech recognition (Negri et al. 2014). IVAs are constantly collecting human data and information about consumers to get 'smarter' through supervised, unsupervised, and reinforcement machine learning (Marsland 2015). Machine learning, a subset of AI, uses statistical learning algorithms and neural networks that can be programmed to solve new problems by extracting patterns embedded in huge quantities of data. IVAs use Machine Learning to detect and learn patterns in consumer preferences to assist consumers and perform tasks with natural language (Hauswald et al. 2015).

IVAs are designed to answer questions as well as offer related information or recommendations that help consumers through dynamic and dialog style conversational patterns. This is made possible by the architecture of IVA which includes a natural language understander (NLU) (Këpuska and Bohouta 2018). The NLU identifies information units (IU) spoken by a consumer which is then used by another architectural part the Dialog Manager (DM) to determine a response output for the IVA. The output of the DM is an abstract action that the Virtual Assistant must carry out. This action is later transformed into a specific answer by the Communication Generator (CG). The Communication Generator implements the action provided by the Dialog Manager in a natural language the consumer can understand (Eisman et al. 2012).

While practice-oriented IVA research focuses on their impact on performance and attempt to predict their future market trends, academic studies on IVAs typically focus on building and testing theories of the adoption and use of IVAs. These studies have investigated various contexts in which consumers have used IVAs including IVAs in family life (Beirl et al. 2019; Cohen et al. 2016), as assistive technology for the aged and disabled (Marston and Samuels 2019; Pradhan et al. 2018) and as a component of Internet of Things (IOT) (Ammari et al. 2019). Researchers in the Information Systems (IS) and related fields have utilized various methods to study different aspects of IVAs. For example, through laboratory experiments, factors which relate to individuals' trust or distrust of IVA recommendations (Elson et al. 2018); the effect of IVAs' conversational relevance on their perceived partner engagement and perceived humanness (Schuetzler et al. 2014) as well as the effect of IVAs' self-disclosure on consumers' privacy concerns and their self-disclosure link (Saffarizadeh et al. 2017) were explored.

Using case study method, the application of IVAs in real life scenarios (Silva-Coira et al. 2016) such as the extent to which online consumer reviews depict IVA personification and its related factors have been studied. Further, IVA interactive sociability and factors affecting its consumer satisfaction (Purington et al. 2017) have also been examined using case study method. Other researchers used interview methods for IVA studies. For example, through the analysis of consumers' sentiments, influencing factors of IVAs' adoption has been explored (Lopatovska et al. 2019). Findings from interview data have been used to develop guidelines for designing IVAs intended for creative workshops (Strohmann et al. 2018). Siddike et al. (2018) used data from 15 interviews to develop and explain a theoretical model for increasing the performance of consumers who use IVAs. Their results showed that consumers' interaction with IVAs enhanced their cognition and intelligence. These further increased consumers' capabilities and improved their performance in enhancing their quality of life and making better data-driven decisions.

Various academic studies of IVAs have drawn on theories from fields such as marketing, psychology, sociology and information systems. For example, based on the principles of social contract theory (Kruikemeier et al. 2019) and technology acceptance models, (Liao et al. 2019) explored consumers' motivations and barriers to adopt IVAs as well as their concerns about data privacy and trust. They found that, typically consumers trust IVA service providers (like Amazon for Alexa) to protect their data privacy and security as well as comply with the contractual terms of information use. Also, privacy concerns about the use of personal information formed the primary reason for non-consumers' resistance to purchase an IVA. This highlighted the important impact trust of IVA providers had on non-users' behavioral intentions as well as consumers' rejection of IVA service and technology.

Marston and Samuels (2019) also utilized principles from identity theory to study the effect of assistive IVAs on older and disabled adults as well as on the daily living of their caregivers Their study focused on the use and installation of IVAs in the homes and age-friendly places to enable them study both ageing and disabled consumers. The researchers drew on prior literature from the fields of gerontology, gerontechnology, human computer interaction (HCI) and disability. The study revealed that though the assistance of caregivers and support networks were still needed, the use of IVAs offered dependent adults' greater control of their day-to-day tasks. It also facilitated consumers' sense of identity and role in their environment giving caregivers a better sense of freedom and more time to focus on other tasks.

Perceived Value Theory (PVT) (Zeithaml 1988) formed the foundation of (Yang and Lee 2019) study of IVA users' behavior. The study focused on two of PCT's subfactors of users' utilitarian and hedonic values to explore intention to adopt and use IVAs. The researchers found that potential users' perceived usefulness and enjoyment of IVAs significantly affected their intention to use them. Perceived usefulness was strongly influenced by the content quality of the IVA. Also, content quality together with visual attraction of IVAs affected the perceived enjoyment of its use. These studies provide a strong theoretical and empirical foundation to investigate IVA encounter in the context of eService consumption – specifically the role of Service Quality in the context of IVAs and consumers' use of such services.

2.2.2 IVA Encounter Dimensions

IVA encounter is the goal-oriented dyadic interaction between IVAs and consumers to access relevant services (Surprenant and Solomon 1987). IVAs are not only passive recipients of consumers' actions but also affect their consumers during interactions to complete relevant tasks (Canniford and Bajde 2015; London 2002). Unlike a computer or a website, an IVA provides and facilitates two-way dynamic interaction between the IVA and the consumer. Here we illustrate the dynamic interaction of an IVA using Alexa as an example. Other IVAs such as Siri and Google Assistant and Cortana provide similar interactivity. For consumers to access a radio station's service, they could ask Alexa to play that station. Alexa then tunes in to that radio station on its own and plays a song for the consumer. As depicted in Figure 1 below, the Consumer-Alexa encounter makes up a human-object assemblage whereby the consumer can affect the IVA through verbal enquiry and the IVA is also able to affect the consumer by providing access to the relevant eService (Hoffman and Novak 2018).

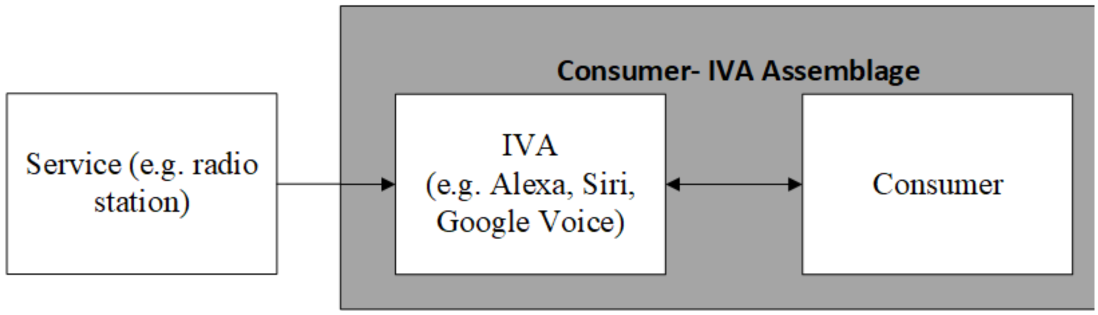

Figure 1. Consumer Assemblage with IVA to Access Relevant eServices

In such an encounter, the IVA serves as the consumption interface between the relevant eService, and the consumers (Patrício et al. 2011). Hence, consumers perceive the quality of the eService through their encounter with the IVA (Yuan and Dennis 2019). For example, if the quality of the content and delivery of a radio service is inadequate (e.g. swamped with advertisements and has breaks in delivery) the consumer may consider the particular IVA (e.g. Siri) not the ideal channel to access the radio station. They may therefore want to switch to another IVA for better eService access. However, if they are limited to only one IVA, they may want to change the radio station for a better eService. It is conceivable that the consumer and IVA and eService encounter is complex perhaps with multiple dimensions.

Various dimensions have been explored to measure different forms of service encounters in existing literature. For example, (Rhee and Rha 2009) estimated the quality-of-service encounter based on the attributes of their frontline service staff such as their listening skills, competence and efficacy. Frazer Winsted (2000) further measured the service encounter construct through three dimensions of service provider's behavior: concern, civility and congeniality (Tam 2019). Keillor et al. (2004) also studied service encounter based on the dimensions of service scope, service quality, physical product quality, service quality and behavioral intentions.

Finally, Raajpoot (2004b) proposed the following seven dimensions to measure service encounter: tangibility, reliability, assurance, sincerity, personalization, formality, and responsiveness. Using SERVQUAL as a base model, Raajpoot (2004b) identified the service encounter dimensions through literature review and focus group methods. The dimensions were aimed at measuring service encounter in a more generalizable context (beyond western perspectives). Larivière et al. (2017) explored the impact of rapidly changing technology on the concept of service encounter. They found that technology supported or replaced service personnel and could help multiple service providers to work together. They therefore called for new theory and empirical research to explore the distinct role and limitations of technology in the service encounter concept. In line with this research agenda, Robinson et al. (2019) developed a service encounter framework to reflect how artificial intelligence (AI) is changing frontline service encounters. They introduced the concepts of counterfeit service, interspecific service (AI-to-human) and inter AI service (AI-to-AI). They further called for future empirical research on AI in service encounters.

For the purposes of this study, we consider relevant dimensions among those from Raajpoot (2004b) service encounter study and SERVQUAL (Parasuraman et al. 1988) model to measure the perceived quality of IVA encounters in eServices. Both Parasuraman et al. (1988) and Raajpoot (2004b) identified responsiveness as an important dimension of the quality of the service encounter. Responsiveness is the willingness to meet consumer needs in a timely manner. Responsiveness is associated with flexibility and availability of the service provider (Johnston and Girth 2012). To be responsive, IVAs must be flexible to meet the varied consumer requests for different eServices as well as have high interactivity to respond in an effective manner. We therefore explore IVA flexibility and interactivity as separate dimensions which make up the responsiveness of an IVA.

We propose IVA interactivity, IVA reliability, IVA flexibility, IVA assurance and IVA personalization as the possible dimensions of consumers' perceived quality IVA service encounter. While past literature has on each occasion discussed only a few of the service encounter dimensions, our study presents a more comprehensive discussion in the context of IVAs. These dimensions are suitable for our study since the focus is on how consumers perceive service quality during their IVA encounters as well as the non-human centric nature of the encounter. For example, the interactivity dimension enables us to explore the assemblage nature of consumers' encounters with IVAs whereby both parties are equally able to act and react on each other. In Table 2 below, we give brief descriptions of our proposed dimensions of measuring the IVA encounter. We further cite the sources within extant literature which discusses dimensions.

Table 2. Dimensions of IVA Encounter

Dimension	Definition	Sources
IVA Interactivity	An IVA's interactivity is the state experienced by consumers as they interact with an IVA. The degree of interactivity between consumers and the IVA is dependent on the perceiver's expected adequacy from the actual interaction	(Lee et al. 2015); (Wu and Wu 2006)
IVA Reliability	The ability of an IVA to perform the promised eService dependably and accurately. Similar to human front line service providers, the quality of IVAs functioning determine how consumers perceive the reliability of the eService delivered.	(Parasuraman et al. 1985); (Raajpoot 2004b)
IVA Flexibility	IVA flexibility is the ability of IVAs to adapt and offer customized eServices to consumers. The current trend among vendors is for one IVA to act for consumers in every situation.	(Johnston and Girth 2012); (Cohen et al. 2016)
IVA Assurance	IVA's degree of knowledge, courtesy and ability to inspire trust and confidence in eService consumers	(Parasuraman et al. 1985); (Raajpoot 2004b)
IVA Personalization	Through machine learning, IVA personalization is a process that involves the identification of a person by their unique attributes such as personal preferences and biometric information.	(Raajpoot 2004b); (Cohen et al. 2016)

Next, we discuss the concept of Effective Use in the context of eService consumption where IVA is the technology by which consumers complete their tasks.

2.2.3 Service Delivery Quality, Service Content Quality and IVA Encounter

Service quality has been widely studied in extant IS literature (Parasuraman et al. 1988; Tan et al. 2013) and it remains a very relevant IS construct because of the increasing service functionalities of information technology. Though abstract in nature, service quality can be described as consumers' perceptions of the general performance of eServices offered by a provider in fulfilling the consumers transactional goals (Tan et al. 2013). Research suggests that, the major factors which drive service satisfaction and hence facilitate loyalty is service delivery and content quality (Alqahtani and Farraj 2016; Tan et al. 2013; Xiao and Benbasat 2007). Service content comprises of the functions available from a service that enable consumers to achieve their goals. On the other hand, service delivery describes the means through which the functions are made available to the consumer (Tan et al. 2013). While service delivery is often confused with service content, the two dimensions must be considered separately in the conceptualization of eService. A consumer's perception of the quality of the eService received is a combination of their perception of the quality-of-service content and the quality-of-service delivery (Gronroos et al. 2000).

Though studies of service quality have traditionally been focused on the context of human-to-human service interactions and recently through eservices that use Websites, phones, etc., more recently it has become increasingly relevant in IS research connecting humans and smart objects like IVA (Hoffman and Novak 2018). Unlike face to face and eServices via Websites and Phones, accessing eServices through IVAs differ in the interactive process which is non-human centric but dyadic in nature. This is made possible through machine learning technology which makes it more data-driven and technology- centered than traditional services (Neuhuettler et al. 2017). Hence, the evaluation of service quality in the context of IVAs must focus on the virtual servicescape (service environment) and functionalities of the IVAs rather than the characteristics of service employees as in traditional settings (Ballantyne and Nilsson

2017). Since other human agents (e.g., front desk personnel) are not involved in the eService process with IVAs, consumers' perception will depend on the quality of real-time information exchange and the usefulness of the information to achieve their goals.

2.2.4 IVA Effective Use

We adopt Burton-Jones and Grange (2013) definition of effective use as "using a system in a way that increases achievement of the goals for using the system" [p.2]. This definition is based on the fundamental assumption that systems are never used without an intended goal and that the relevant goal is essentially whatever desired outcome the system is used to achieve (Fishbach and Ferguson 2007; Gasser 1986). Researchers argue that information technology (IT), such as IVA, by itself does not affect productivity or consumers' performance. However, in order to achieve its relevant goals, the IT should be used effectively (Burton-Jones and Grange 2013). Prior research suggests that, the extent to which eService goals can be achieved through IVAs will be influenced by the characteristics of the consumers, the system (type of IVA) and the relevant task (desired eService) (Burton-Jones and Grange 2013).

Burton-Jones and Grange (2013) grounded their study of effective use on Representation Theory (Weber 2003) which asserts that IT consists of systems aimed at facilitating people's understanding of some real-life phenomenon by providing "representations" (Walsham 2005). The desired goals for which such systems are used make up the representations of the phenomenon of interest (Fishbach and Ferguson 2007). Based on Representation Theory, the researchers proposed the following dimensions of Effective Use Theory: transparent interaction, faithful representation and informed action, whereby transparent interaction was defined as “the extent to which a user is accessing the system’s representations unimpeded by the system’s surface and physical structures”. Informed action was also defined as “the extent to which a user acts upon the faithful representations he or she obtains from the system to improve his or her state” and representational fidelity was defined as “the extent to which a user is obtaining representations from the system that faithfully reflects the domain being represented by its surface and physical structures” (p.11).

Drawing on a natural link between Representation theory and Affordances Theory (Hartson 2003), Burton-Jones and Grange stated that, for effective use of IT, users must actualize the three proposed dimensions which make up a hierarchical affordance network. (Hartson 2003) defined an affordance to be the value an IT artifact offers someone which can be categorized as 1) sensory (allows senses like feeling and seeing) 2) physical (enables physical actions) 3) cognitive (enables conscious intellectual activity) and 4) functional (enables the achievement of goals). Based on the principles of Effective Use Theory, we conceptualize the effective use of IVA to be driven by the user’s (service consumer) transparent interaction with the system (IVA technology) for retrieving faithful representations to take informed action (complete relevant task). This assumes that IVAs are intended for performing tasks, which are goal-oriented activities (Savoli and Barki 2017). For example, to effectively stream music from a service provider through an IVA, the consumer first encounters the physical and sensory affordances (e.g., voice user interfaces, smart device applications, natural language processors) for transparent interaction to retrieve the needed representations (music) without hindrance from the system's interface.

The next affordance in the hierarchy of effective use is the representational fidelity which is the extent to which the consumer sees the representation (music) to accurately meet their cognitive and functional interpretation of what the concept of music should be. Finally, the accomplishes their goal for accessing the eService through the IVA (informed action). This typically entails a need to improve their state in the domain such as relaxing or feeling happy with the music (Burton-Jones and Grange 2013; Recker et al. 2019). The tasks for which IVAs are used differ from one consumer to another (e.g., weather forecasts, restaurant reservations, traffic reporting). We propose that effective use, perceived satisfaction, and the value of IVA is dependent on the consumer and their goals for use. We discuss below the Assemblage theory and how its principles inform our study.

2.2.5 Assemblage Theory, IVA Encounter and Effective Use

Assemblage theory is a nonhuman-centric framework to explain the results and implications of socio-material interactions (Canniford and Bajde 2015; Hill et al. 2014; Hoffman and Novak 2018; London 2002). Assemblage theory emphasizes ontological equivalence of human and nonhuman actors in such assemblages (Canniford and Bajde 2015; London 2002). This suggests the paired capacities of both humans and objects to affect each other in some way, though the effects may not be equal. According to assemblage theory, the nature of existing relationships within assemblages can best be understood by first evaluating the content and mode of expression of its component parts (Sesay et al. 2016). With early origins from the work of (Deleuze and Guattari 1987), assemblage theory has evolved into a useful lens for analyzing relationships among various entities in broad agential and critical realist contexts (DeLanda 2016; Harman 2016).

Principles from assemblage theory have been applied to a broad range of fields such as consumer science (Canniford and Bajde 2015; Hoffman and Novak 2018); geography (Anderson and McFarlane 2011) and information systems (IS) (Sesay et al. 2016). In the IS research, assemblage theory provides a framework to understand the underlying principles of how humans and objects function together to achieve relevant goals (Sesay et al. 2016)]. Hi-tech networks, such as the Internet, make it possible for formerly unrelated entities to now work together as assemblages (DeLanda 2016). Assemblage theory provides principles for us to study the interaction between eService consumers and IVA's without neglecting or reducing our focus on how the IVA service encounter affect consumers' perceived service quality and its link with their service satisfaction and loyalty.

2.3 Proposed Research Model

In this section, we propose and discuss a conceptual model (Figure 2) of the hypothesized relationships that exist among service content quality, service delivery quality, IVA encounter dimensions, IVA Effective Use, IVA satisfaction, IVA Value, Service Satisfaction and Service Loyalty.

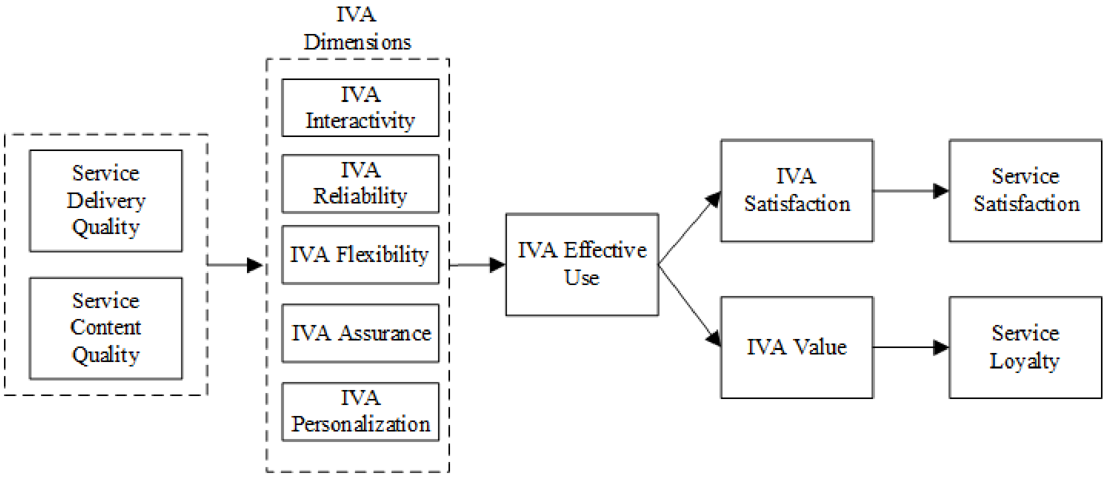

Figure 2. Research Model

2.3.1 Service Quality and IVA Encounter Dimensions

We define service quality as a consumer's perception of the value of their interaction with a service provider and how well their goals for the encounter have been met (Cenfetelli et al. 2008; Lowry and Wilson 2016). In our conceptual model, we theorize consumers' perceived service quality to be made up of its delivery and content dimensions (Tan et al. 2013). Service content quality depicts the various capabilities available from the service while service delivery quality characterizes the way by which these capabilities can be made available to (Tan et al. 2013). We further draw on the tenets of assemblage theory to conceptualize service consumers' interaction with IVAs as a form of consumer-object assemblage (a unit made up of heterogeneous parts) (Hoffman and Novak 2018; Zwick and Dholakia 2006). We expect the dimensions of this encounter to influence consumers perception of the quality of service received (Zeithaml and Berry 1996).

We define IVA assurance as consumers' perception of trust, security and confidentiality when they search for or consume a service using the IVA system. Security diagnostics of IVAs have exposed vulnerabilities and privacy threats calling for more secure IVA designs (Chung et al. 2017). While promising many useful features to its consumers, IVA as an application for eService or retail platforms will be truly valuable dependent on consumers' sense of security and assurance (Hoffmann et al. 2014). Since IVA systems capture significant volumes of personal and behavioral Information (such as personal conversations and emotional voice tones), it is critical that consumers trust in the system to continue using it (Dabholkar and Sheng 2012). IVA's must be designed with robust privacy and security controls when used for confidential tasks. The design must also ensure an assurance to do what it promises. We propose that:

H1A: Service content quality has a positive relationship with IVA assurance.

H2A: Service delivery quality has a positive relationship with IVA assurance.

Also, we conceptualize IVA flexibility as how consumers perceive service flexibility when they search for or consume an eService through an IVA system. Flexibility of information systems refers to the ease with which the system can be modified to meet the needs of consumers in a relatively short time (Pollock et al. 2007). Existing IS literature suggests that emerging technologies are designed to be quite flexible to consumers' expectations (de Albuquerque and Christ 2015; Leonardi 2011). In this study, we consider IVA flexibility to be important for consumer's perception of eService quality because of the diversity of consumer goals it will be used to accomplish. The typical consumer using an IVA can alter his/her goals and mostly expect the capability of IVA to support this change (Glaser 2017; Pentland and Feldman 2007). We hypothesize that

H1B: Service content quality has a positive relationship with IVA flexibility.

H2B: Service delivery quality has a positive relationship with IVA flexibility.

By IVA interactivity, we refer to the perception consumers develop as they interact with an IVA in the process of searching and consuming an eService. An important attribute of IVA is their ability to recognize, understand and respond to the content of human interaction through voice, touch and vision input methods (Kiseleva et al. 2016). IVA interactivity is customized to the needs, routines and preferences of consumers, as the applications systematically capture consumer data to support machine and deep learning capabilities. We hypothesize that:

H1C: Service content quality has a positive relationship with IVA interactivity.

H2C: Service delivery quality has a positive relationship with IVA interactivity.

Also, we conceptualize IVA personalization as the ability of the consumer to personalize and customize the service content as they search for and consume an eService using an IVA system. Existing studies highlight the importance of personalization to drive satisfaction and build a sense of loyalty among consumers (Alqahtani and Farraj 2016; Coelho and Henseler 2012). IVA applications leverage advancements in machine learning and deep learning capabilities to acquire knowledge about consumers' conversation patterns and other revealing personal insights (Alpaydin 2014). A major challenge with using IVA is that humans often do not communicate in an orderly manner and this differs from one individual to the other (Anders 2017). Speech technologists strive to improve the ability of these machines to progressively ‘learn’ through data collected from consumers. The attempts to improve ‘listening’ in IVA also focuses on finetuning its speaking. Machine learning has become one of the most important forces that businesses use to personalize their IVA applications (Zawadzki and Żywicki 2016). We hypothesize that:

H1D: Service content quality has a positive relationship with IVA personalization.

H2D: Service delivery quality has a positive relationship with IVA personalization.

We define IVA reliability as the ability of IVA to consistently deliver the value “promised” to the consumer. When eServices are accessed via IVAs, they act as the front end for consumer interaction. In such instances, both the content and delivery of the eService impact a consumer’s perception of how reliable the eService is in meeting the content and delivery needs of the eService consumer. For example, when Siri is used to stream music from apple music, the quality of music available as well as the delivery quality will impact the consumer’s perception of the reliability of his/her encounter with Siri. Depending on their content and delivery quality, different eServices may perform differently with a consumer’s IVA. For example, consumers may perceive Siri to be more reliable with Apple Tunes instead of Pandora. We hypothesize that

H1E: Service content quality has a positive relationship with IVA reliability.

H2E: Service delivery quality has a positive relationship with IVA reliability.

2.3.2 IVA Encounter Dimensions and Effective Use

Based on the Effective Use Theory we propose that, consumers need to achieve the three defined hierarchical affordances (transparent interaction, representational fidelity and informed action) in order to actualize their intended eService goals. At the first level of the affordances (physical and sensory) of effective use, the consumer must be able to effectively interact with the IVA interface in order to access the relevant representations from the eService. The extent to which consumers can interact with the IVAs, without impediments through its surface and physical structures, will directly affect the consumers' accessibility to desired representations from the eService (Recker et al. 2019). For example, to retrieve weather forecast information from a weather database service through Alexa (or other IVAs such as Siri, Alexa and Google Voice), the consumer must issue a request via voice to Alexa for the information.

The transparency of the interaction (easy flow of request information) while meeting the sensory affordances (ability to speak and hear commands as well as see the IVA interfaces) of consumers will influence consumers' ability to access the desired forecast information (representations). Through machine learning, the ability of the IVA to identify consumers and their preferences while interacting with them in a unique dialect will further influence consumers' ability to achieve effective use of the IVA. We hypothesize that:

H3A: IVA interactivity has a positive relationship with IVA effective use.

H3B: IVA personalization has a positive relationship with IVA effective use.

After the transparent interaction affordances are actualized, the next condition to be met for effective use of IVAs is the representational fidelity. This condition describes the extent to which the consumer perceives the representation to adequately meet their expectations of the desired eService goals (Recker et al. 2019). Faithful representations can only exist if consumers can access representations (e.g., weather information) through the IVA interface. Representational fidelity involves the achievement cognitive and functional affordances (Burton-Jones and Grange 2013). Cognitive affordance will enable consumers to meaningfully think about and understand their representations and know what to do with them. This is influenced by the IVA capability to perform dependably and accurately. For example, in the weather forecast service scenario, consumers can cognitively understand the information they receive and know the right use for it if they find it reliable. Wise et al. (Wise et al. 2016) observed that IVA are designed to complete tasks in a real-time, with a high degree of reliability if used effectively.

Functional affordance enables consumers to accomplish their ultimate objective for seeking the weather information from the weather database services through Alexa. Effective Use Theory suggests that cognitively understanding the weather information (representations) will enable consumers to accomplish their goals for accessing the eService through IVA. The assurance dimension of IVA encounter defines the degree of knowledge, courtesy and ability of the system to inspire trust and confidence in the eService consumers. These are cognitive affordances which stimulate consumers perceived IVA reliability, the IVA's ability to accomplish the promised task dependably and accurately (Raajpoot 2004b). We hypothesize that:

H3C: IVA assurance quality has a positive relationship with IVA effective use.

H3D: IVA reliability has a positive relationship with IVA effective use.

Finally, when faithful representation is actualized, effective use can be achieved when consumers do something with their representations to reach their goals (informed action condition) for accessing an eService through an IVA. Hence informed action cannot be actualized if the representations received by the consumer is not true/ faithful to the real domain sought by the consumer. The current trend is for IVAs to accomplish varied eService tasks for consumers in many situations. This is made possible by the IVA flexibility dimension. This allows the IVA to adapt to various consumers in using faithful representations to achieve their individual goals. In other words, IVA flexibility increases the chances of consumers' effectively use of IVAs to achieve their eService goals. We hypothesize that:

H3E: IVA flexibility has a positive relationship with IVA effective use.

2.3.3 Effect of IVA Effective Use on IVA Satisfaction and IVA Value

Research suggests that a system's quality has an influence on its satisfaction (Sharma 2015; Wixom and Todd 2005). Kelly (2009) described consumer satisfaction as the realization of a defined desire or goal. IVA technology per se cannot deliver the goals of the eService consumer or impact their performance, only their effective use can (Orlikowski 2000). Consumers' goals for using IVA can be achieved through effective use (Burton-Jones and Grange 2013) which will further impact their sense of satisfaction. Based on the theory of Effective Use's assumption that the desired goal for effective use is essentially whatever outcome the system is intended to attain, the consumer and the intended task for using IVAs determine the desired goal, hence effective use is. If the intended goal is met, it will positively impact the consumer's satisfaction (Tran et al. 2013). Also, being able to achieve the intended goal will positively affect the value consumers place on the IVA (Yun et al. 2018). We hypothesize that:

H4: IVA effective use has a positive relationship with IVA satisfaction.

H5: IVA effective use has a positive relationship with IVA value.

2.3.4 IVA Satisfaction, IVA Value and eService Satisfaction and eService Loyalty

Consumers' perception of satisfaction is determined through their evaluation of both the quality of the eService and their ability to achieve their goals (Zhang and Cole 2016). We are able to evaluate consumer satisfaction by comparing the consumer's perception with their expectations from the eService experience. Under a given circumstance, a consumer's satisfaction describes their feelings or attitude toward that situation (Wixom and Todd 2005). Satisfaction in consumer research has been measured by various subsets of beliefs about specific systems, information, and other related characteristics such as quality of eService. Consumer service satisfaction has a well-established impact on behaviors such as product loyalty and intention to purchase (Dabholkar and Sheng 2012).

Issues that could negatively impact the consumer's perception of IVA encounter, like most other technology concerns, may include privacy concerns, complicated design and lack of trust. For example, information security is a major issue with IVA use considering the amount of personal information that is shared with the device. Assurance therefore adds value to IVA and must be factored in the design of their applications. Also, given that one of the main reasons cited by consumers for using IVA is the ability to use it without hands, these devices must be designed to facilitate this value to achieve consumer loyalty. Research suggests that consumers' perceptions of service value influence many positive attitudinal reactions, such as loyalty and satisfaction (Tan et al. 2013). We hypothesize that:

H6: IVA satisfaction has a positive relationship with service satisfaction.

H7: IVA value has a positive relationship with service loyalty.

Although relationships among service quality dimensions, consumer satisfaction and its impact on consumer loyalty are well established in the IS literature, however it is not clear how IVA encounter dimensions and IVA effective use determine Service Satisfaction and Service Loyalty. We detail in the following sections how we test our proposed hypotheses above.

2.4 Research Method

Below are the quantitative research methods used to test the research model (Figure 2).

2.4.1 Survey, Pilot Testing and Data Collection

A field survey was employed to gather data from randomly selected consumers using IVA. We developed our survey instrument following methods from (Moore and Benbasat 1991; Straub 1989). The questionnaire was first pretested, and pilot tested to establish content and criterion validities. Here, 60 consumers using IVAs were asked to evaluate and comment on the questions for clarity. Based on the participating consumers' comments, the construct measures in the survey instruments were revised as needed. The survey was hosted on Qualtrics, an online data collection website. A URL link to the web-survey was emailed to respondents recruited through a purposive sampling method, followed by "snowball" sampling process.

Purposive sampling involves the selection of research participants or units (e.g., individuals or organizations) based on specific factors which contribute to answering a research question (Etikan 2016; Teddlie and Yu 2007). Participants were selected based on their age (18 years or older) and had to be IVA users. The snowball sampling involved sending the online survey link to identified IVA users who were encouraged in turn to refer other members of their social networks to participate in the study. In total, 523 consumers participated in our survey. Among these 23 respondents were unable to complete the survey due to an age limit of 18 years required for participation. 170 respondents had never used IVA and 37 responses were incomplete. We had data from 280 usable responses for our analysis. We summarize the descriptive statistics of respondents' characteristics in Table 3 below.

Table 3. Sample Characteristics (N=280)

Measure	Value	Frequency	Percentage
Gender	Male	139	49.64%
	Female	141	50.36%
Age	18-25	178	63.57%
	26-35	65	23.21%
	36-55	35	12.50%
	>55	2	0.71%
Education	High school	19	6.79%
	Some college	132	47.14%
	Bachelor	94	33.57%
	Master	25	8.93%
	Ph.D.	10	3.57%
Income Level	<$12,000	34	12.14%
	$12,000--$36,000	132	47.14%
	$36,000--$60,000	102	36.43%
	60,000--$96,000	7	2.50%
	>$96,000	5	1.79%

2.4.2 Measures and Scales

Existing scales were adopted to measure the constructs in the conceptual model to maximize the validity and reliability of the measurement model (See Table 4 below). Minor modifications were made to the items to fit the context of our study. All items were measured using a seven-point Likert-type scale (ranging from 1 strongly agree to 7 strongly disagree). We used scales from Tan et al. (2013) to measure service delivery quality and service content quality. Scales from Wixom and Todd (2005) were also used to measure IVA reliability and IVA flexibility. IVA interactivity was measured with scales from Novak et al. (2000); Skadberg and Kimmel (2004); Tan et al. (2013) while IVA personalization was measured with scales from (Mittal and Lassar 1996) as well as Raajpoot (2004b). IVA Assurance and the service satisfaction constructs were measured with scales from Devaraj et al. (2002) and Ribbink et al. (2004). For IVA satisfaction and IVA effective use scales from Devaraj et al. (2002) and Pavlou and El Sawy (2006) were used. Furthermore, IVA value was measured with scales from Dodds et al. (Dodds 1991) while consumer loyalty was measured with scales from Lin and Wang (2006) as well as Ribbink et al. (2004).

2.5 Data Analysis and Results

2.5.1 Measurement Validation

Summarized below in Table 4 is our entire research instrument along with the item means and standard deviations and composite reliability. We have found high loadings for most of the items. The composite reliabilities range from 0.93 and above. We also summarize in Table 5, the inter-construct- correlation matrix with the square root of the AVE values on the diagonal (in bold). It is observed in Table 5 that the square root of the AVE for each construct is higher than the inter-construct correlations. This provides evidence of discriminant validity (Fornell and Larker 1981). Typically, 0.70 is considered as acceptable threshold for internal consistencies for all variables (Nunnally and Bernstein 1994; Pavlou and Fygenson 2006). Also, all constructs have high reliability

(Cronbach's Alpha > 0.8, AVE> 0.7) as detailed in Table 6. Thus, the measurements fulfill the requirements of convergent and discriminant validities.

Table 4. Factor Loadings for the Measurement Items; Reliability and AVE for Constructs (Note Scale: 1= Strongly Agree … 5 = Strongly Disagree)

Items Used for Principal Constructs		Loading	Mean	StdDev
Service Delivery Quality (DQ) (Composite Reliability=0.933)				
DQ1:	IVA completes service consumption tasks for me.	**0.831**	2.38	0.958
DQ2:	Generally, the IVA completes tasks in an acceptable manner.	**0.946**	2.20	0.790
DQ3	Overall, the services are delivered efficiently via the IVA.	**0.942**	2.20	0.809
Service Content Quality (CQ) (Composite Reliability=0.957***)***				
CQ1:	Generally, the service content offered via IVA to support me in performing my tasks is satisfactory.	**0.927**	2.22	0.742
CQ2:	On the whole, the service content offered via IVA is highly effective in supporting me to perform my tasks.	**0.943**	2.28	0.773
CQ3:	Generally, I am pleased with the service content offered via IVA to support me in performing my tasks.	**0.946**	2.25	0.762
IVA Interactivity (INT) (Composite Reliability=0.925***)***				
INT1	I felt that I had the freedom to access services using this IVA.	**0.744**	2.16	0.755
INT2	I felt interacting with this IVA was easy.	**0.790**	2.17	0.833
INT3	When I use this IVA, there is very little waiting time between my actions and the IVA's response.	**0.811**	2.22	0.847
INT4	Commands to use IVA that I make usually load quickly.	**0.833**	2.27	0.811
INT5	I find using IVA to be engaging when I am performing my tasks.	**0.816**	2.40	0.866

Items Used for Principal Constructs		Loading	Mean	StdDev
INT6	I find using IVA a stimulating experience.	**0.775**	2.58	0.944
INT7	The IVA is responsive to my online habits.	**0.752**	2.50	0.876
INT8	The IVA is sensitive to my online habits.	**0.707**	2.53	0.879
IVA Reliability (REL) (Composite Reliability*=0.910*)				
REL1	This IVA operates reliably.	**0.914**	2.30	0.801
REL2	This IVA can access information from websites.	**0.793**	2.16	0.739
REL3	The operation of this IVA is dependable.	**0.925**	2.34	0.783
IVA Flexibility (FLE) (Composite Reliability*=0.937*)				
FLE1	This IVA can be adapted to meet a variety of needs.	**0.896**	2.25	0.739
FLE2	This IVA can flexibly adjust to new demands of conditions.	**0.913**	2.35	0.770
FLE3	This IVA is versatile in addressing needs as they arise.	**0.928**	2.29	0.766
IVA Assurance (AS) (Composite Reliability*=0.917*)				
AS1	1 felt confident about the IVA tasks.	**0.874**	2.30	0.749
AS2	I feel safe in my tasks with the IVA.	**0.854**	2.38	0.817
AS3	The IVA gave good answers to my task queries.	**0.836**	2.33	0.776
AS4	I feel secure when providing private information to this IVA.	**0.753**	2.80	1.041
AS5	This IVA is trustworthy.	**0.827**	2.60	0.891
IVA Personalization (PER) (Composite Reliability*=0.962*)				
PER1	The IVA exhibits politeness.	**0.876**	2.14	0.775
PER2	The IVA exhibits courtesy.	**0.916**	2.17	0.741
PER3	The IVA displays personal warmth during interaction.	**0.883**	2.38	0.830
PER4	The IVA displays personal warmth during behavior.	**0.879**	2.41	0.842
PER5	The IVA is pleasant.	**0.917**	2.21	0.774
PER6	The IVA is friendly.	**0.916**	2.21	0.796

Items Used for Principal Constructs		Loading	Mean	StdDev
PER7	The IVA addresses my personal needs.	**0.796**	2.40	0.823
IVA Effective Use (EU) (Composite Reliability=0.950***)***				
EU1	I found overall effectiveness of using the IVA satisfactory.	**0.832**	2.34	0.823
EU2	The IVA accurately provides real-time information when prompted.	**0.885**	2.25	0.758
EU3	The IVA is effective in completing my task.	**0.932**	2.25	0.760
EU4	The IVA is efficient in completing my task.	**0.917**	2.25	0.764
EU5	The IVA is efficient in completing my queries.	**0.877**	2.27	0.797
IVA Perceived Satisfaction (SAT) (Composite Reliability=0.953***)***				
SAT1	Overall, I am satisfied with this IVA.	**0.942**	2.26	0.749
SAT2	I did the right thing when I decided to use this IVA.	**0.914**	2.34	0.795
SAT3	I am very pleased with completing tasks using this IVA.	**0.945**	2.34	0.791
IVA Perceived value (VAL) (Composite Reliability=0.954)				
VAL1	The IVA product is very good value for me.	**0.842**	2.35	0.802
VAL2	You get the value you expect with this IVA.	**0.882**	2.32	0.711
VAL3	The prices I pay for service using this IVA represent a very good deal.	**0.795**	2.45	0.774
VAL4	The time I spend in order to complete tasks with this IVA is highly reasonable.	**0.863**	2.38	0.772
VAL5	The effort involved to complete tasks using this IVA is worthwhile.	**0.899**	2.41	0.798
VAL6	The service consumption value with this IVA is excellent.	**0.892**	2.40	0.750
VAL7	I found significant value using service through this IVA.	**0.880**	2.42	0.790
Service Satisfaction (SS) (Composite Reliability=0.959***)***				
SS1	Overall, I am satisfied with this IVA service experience.	**0.878**	2.29	0.776
SS2	The information content of the service available through the IVA met my needs.	**0.915**	2.35	0.770

Items Used for Principal Constructs		Loading	Mean	StdDev
SS3	It was possible for me to complete service tasks of my choice using the IVA.	**0.900**	2.36	0.772
SS4	Using the service via the IVA is enjoyable.	**0.876**	2.48	0.803
SS5	Consuming service through the IVA is enjoyable.	**0.869**	2.49	0.794
SS6	I am very satisfied with the services received through the IVA.	**0.914**	2.39	0.758
Consumer loyalty (CL) (Composite Reliability*=0.957*)				
CL1	I have a strong relationship with this service I consume through the IVA.	**0.784**	2.79	0.902
CL2	I will recommend the services I consume through the IVA to my friends.	**0.897**	2.52	0.876
CL3	I will choose this IVA service next time when I purchase same product.	**0.875**	2.46	0.833
CL4	I am likely to say positive things about this IVA service to other people.	**0.883**	2.45	0.845
CL5	I will recommend this IVA service to someone who seeks my advice.	**0.886**	2.43	0.822
CL6	I will encourage friends and others to complete service tasks with this IVA.	**0.896**	2.53	0.825
CL7	I plan to complete more service tasks using this IVA in the coming months.	**0.883**	2.49	0.855

To verify discriminant and convergent validities in PLS analysis, the following rules must be met: 1) loadings must be higher on their hypothesized factor than on other factors (own-loadings are higher than cross-loadings), and 2) the square root of each construct's AVE is larger than its correlations with other constructs (Chin et al. 2003; Pavlou and Fygenson 2006). As shown in tables 5 the square roots of all AVEs are above 0.7 and are much larger than all the cross-correlations. Based on the results below, we can infer adequate convergent and discriminant validity in this study.

Table 5. Construct Correlations for Discriminant Validity (Fornell-Larcker Criterion)

Principal Construct	**CL**	**EU**	**AS**	**FLE**	**INT**	**PER**	**REL**	**SAT**	**VAL**	**CQ**	**DQ**	**SS**
Consumer_Loyalty (CL)	**0.87**											
Effective_Use (EU)	0.73	**0.89**										
IVA_Assurance (AS)	0.73	0.71	**0.83**									
IVA_Flexibility (FLE)	0.63	0.68	0.66	**0.91**								
IVA_Interactivity (INT)	0.74	0.63	0.76	0.69	**0.78**							
IVA_Personalization (PER)	0.64	0.71	0.70	0.67	0.70	**0.88**						
IVA_Reliability (REL)	0.70	0.76	0.74	0.75	0.71	0.66	**0.88**					
IVA_Satisfaction (SAT)	0.79	0.85	0.77	0.66	0.77	0.68	0.75	**0.93**				
IVA_Value (VAL)	0.82	0.79	0.72	0.68	0.76	0.70	0.74	0.81	**0.87**			
Service_Content_Quality (CQ)	0.68	0.76	0.71	0.68	0.64	0.63	0.75	0.76	0.69	**0.94**		
Service_Delivery_Quality (DQ)	0.68	0.72	0.65	0.66	0.70	0.58	0.71	0.71	0.65	0.85	**0.91**	
Service_Satisfaction (SS)	0.84	0.78	0.76	0.69	0.74	0.68	0.77	0.82	0.82	0.76	0.71	**0.89**

To assess convergent and discriminant validities of our study we used PLS internal consistency score to evaluate convergent validity. Internal consistency for the constructs can be validated further through Composite Reliability and Average Variance Extracted (AVE) (Fornell and Larker 1981; Tan et al. 2013). A score of 0.70 is typically considered as the threshold of internal consistency for all variables (Nunnally and Bernstein 1994; Pavlou and Fygenson 2006). Based on our sample, most items measuring various constructs have a high reliability score (Cronbach's Alpha >=0.9) as detailed in Table 6 below. These measurements fulfilled our study's requirement for convergent validity.

Table 6. Cronbach's Alpha, Composite Reliability and Square Root of AVE for Principal Constructs

Principal Constructs	Cronbach's Alpha	Composite Reliability	Square Root of AVE	R Square Adjusted
Consumer_Loyalty	0.94	0.957	0.873	0.679
Effective_Use	0.93	0.950	0.889	0.695
IVA_Assurance	0.90	0.917	0.829	0.507
IVA_Flexibility	0.90	0.937	0.912	0.480
IVA_Interactivity	0.907	0.925	0.780	0.688
IVA_Personalization	0.95	0.962	0.884	0.401
IVA_Reliability	0.85	0.910	0.879	0.578
IVA_Satisfaction	0.93	0.953	0.933	0.729
IVA_Value	0.94	0.954	0.865	0.623
Service_Content_Quality	0.93	0.957	0.939	0.668
Service_Delivery_Quality	0.90	0.933	0.908	
Service_Satisfaction	0.95	0.959	0.892	

2.5.1.1 Testing Potential Common Method Bias

To mitigate the concern for common method bias in the survey design, we first included several reverse-scored items in the principal constructs to reduce acquiescence problem (Lindell and Whitney 2001). Using Harman's one-factor test, we then assessed common method variance after data collection was complete. This test requires all the principal constructs to be entered into a principal component factor analysis. Common method bias is found to exist when a single factor emerges from the analysis or when one general factor accounts for the majority of the covariance in the interdependent and dependent variables. Thus, the data seems not to indicate substantial common method bias.

2.5.2 Testing the Structural Model

In Figure 3 below, we summarize the PLS path coefficients from our structural model analysis. We have excluded the item loadings from Figure 3 for clear exposition. We ran bootstrapping simulation with 5000 resamples (sampling with replacement) to establish the significance of the hypothesized relationships in the structural model which proved to be satisfactory. We show the results of our bootstrapping analysis in Table 7.

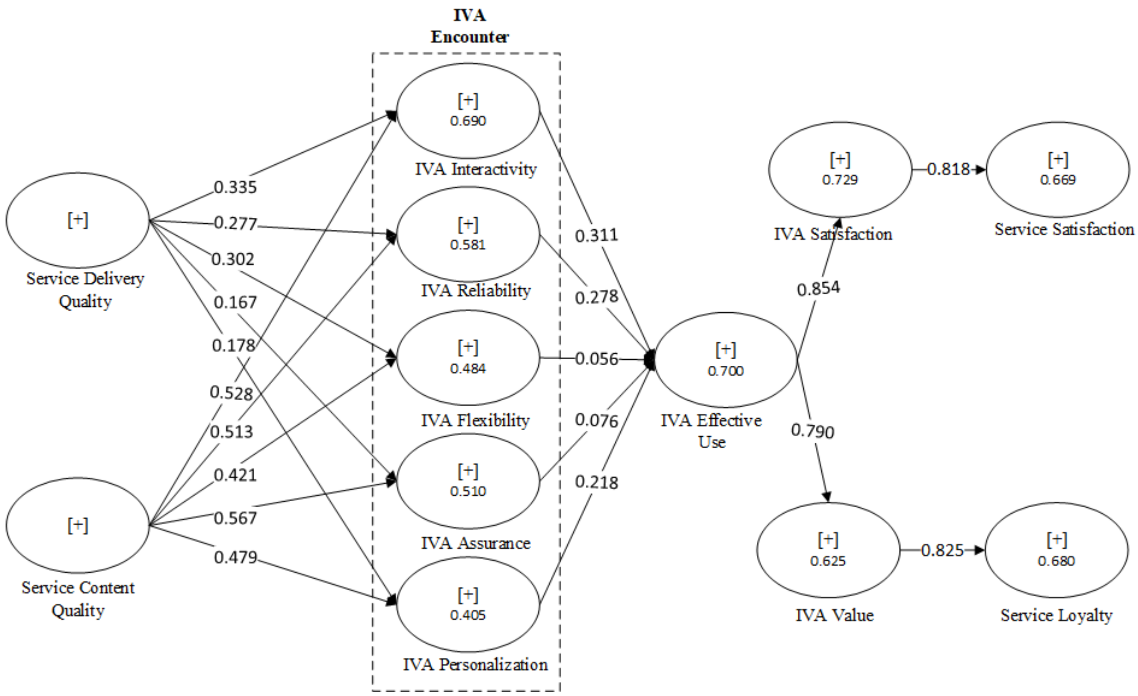

Figure 3. PLS Results for the Structural Model

Our results as shown in Table 7 suggests that service content quality has strong positive and significant influence on all the proposed dimensions of IVA encounter: IVA assurance (H1A: β=0.567, p< 0.05), IVA flexibility (H1B: β=0.421, p< 0.01), IVA interactivity (H1C: β=0.528, p< 0.001), IVA personalization (H1D: β=0.479, p< 0.05) and IVA reliability (H1E: β=0.513, p< 0.001). The service delivery quality results also showed a strong positive and significant influence on all the proposed dimensions of IVA encounter: IVA assurance (H2A: β=0.167, p< 0.001), IVA flexibility (H2B: β=0.302, p< 0.001), IVA interactivity (H2C: β=0.335, p< 0.001), IVA personalization (H2D: β=0.178, p< 0.001) and IVA reliability (H2E: β=0.277, p< 0.001). The results further showed that together, service content quality and service delivery quality were able to explain 51%, 48.4%, 69%, 40.5% and 58.1% variances of IVA assurance, IVA flexibility, IVA interactivity, IVA personalization and IVA reliability respectively. Hence the hypotheses H1A, H1B, H1C, H1D, H1E, H2A, H2B, H2C, H2D and H2E are supported with confidence intervals excluding 0 and p-values less than 0.05 (Table 7).

Also, the results from the PLS structural model analysis showed that IVA interactivity (H3A: $\beta=0.311$, $p< 0.001$), IVA personalization (H3B: $\beta=0.218$, $p< 0.01$) and IVA reliability (H3D: $\beta=0.278$, $p< 0.01$) had significant positive effects on IVA effective use. On the other hand, IVA assurance (H3C: $\beta=0.076$, $p > 0.05$) and IVA flexibility (H3E: $\beta=0.056$, $p > 0.05$) showed no significant effect on IVA effective use. This could be due to the novelty of IVAs whereby, people's expectations of what it can do may not be as high as other types of IT. Together, the proposed dimensions of IVA encounter were able to explain 70% variance of IVA effective use. The results provided significant support for hypotheses H3A, H3B and H3D with confidence intervals excluding 0 and p-values less than 0.05. On the other hand, H3C and H3E were not supported since their confidence intervals included 0 with p-values greater than 0.05 (Table 7).

Table 7. Hypotheses Tests and Analysis Results

Hypotheses	Path Descriptions	Hypothesized direction	T Statistics	P Values	CI (LL) 2.5%	CI (UL) 97.5%	Support
H1A	**Service_Content_Quality -> IVA_Assurance**	(+)	6.887***	**0.000**	0.399	0.722	**Yes**
H1B	**Service_Content_Quality -> IVA_Flexibility**	(+)	4.602***	**0.000**	0.235	0.596	**Yes**
H1C	**Service_Content_Quality -> IVA_Interactivity**	(+)	6.558***	**0.000**	0.367	0.683	**Yes**
H1D	**Service_Content_Quality -> IVA_Personalization**	(+)	5.505***	**0.000**	0.306	0.641	**Yes**
H1E	**Service_Content_Quality -> IVA_Reliability**	(+)	6.415***	**0.000**	0.351	0.661	**Yes**
H2A	**Service_Delivery_Quality -> IVA_Assurance**	(+)	2.110*	**0.035**	0.018	0.329	**Yes**
H2B	**Service_Delivery_Quality -> IVA_Flexibility**	(+)	3.377**	**0.001**	0.129	0.478	**Yes**
H2C	**Service_Delivery_Quality -> IVA_Interactivity**	(+)	4.100***	**0.000**	0.179	0.495	**Yes**
H2D	**Service_Delivery_Quality -> IVA_Personalization**	(+)	2.121*	**0.034**	0.017	0.341	**Yes**
H2E	**Service_Delivery_Quality -> IVA_Reliability**	(+)	3.524***	**0.000**	0.127	0.437	**Yes**
H3A	**IVA_Interactivity -> Effective_Use**	(+)	3.641	**0.000**	0.137	0.471	**Yes**
H3B	**IVA_Personalization -> Effective_Use**	(+)	3.222**	**0.001**	0.090	0.355	**Yes**
H3C	**IVA_Assurance -> Effective_Use**	(+)	0.949	**0.343**	-0.079	0.232	**No**
H3D	**IVA_Reliability -> Effective_Use**	(+)	3.028**	**0.002**	0.092	0.451	**Yes**
H3E	**IVA_Flexibility -> Effective_Use**	(+)	0.653	**0.514**	-0.099	0.235	**No**
H4	**Effective_Use -> IVA_Satisfaction**	(+)	35.792***	**0.000**	0.804	0.899	**Yes**
H5	**Effective_Use -> IVA_Value**	(+)	20.801***	**0.000**	0.709	0.856	**Yes**
H6	**IVA_Satisfaction -> Service_Satisfaction**	(+)	20.713***	**0.000**	0.733	0.886	**Yes**
H7	**IVA_Value -> Consumer_Loyalty**	(+)	32.451***	**0.000**	0.771	0.871	**Yes**

Note. Unstandardized regression coefficients are reported. Bootstrap sample size = 5,000. CI = confidence interval; LL = lower limit; UL = upper limit.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

The results from the structural model analysis further suggest that IVA effective use has significant positive effects on consumers' perceived IVA satisfaction (H4: $\beta=0.854$, $p< 0.001$) as well as their perceived IVA value (H5: $\beta=0.790$, $p< 0.001$). IVA effective use is able to explain 72.9% and 62.5% variances of consumers' perceived IVA satisfaction and IVA value respectively. We therefore infer that hypotheses H4 and H5 are supported with confidence intervals excluding 0 and p-values less than 0.05 (see Table 7). Also, it is observed that IVA satisfaction has a significant positive effect on consumers' perceived service satisfaction (H6: $\beta=0.818$, $p< 0.001$) and IVA value has a significant positive effect on consumers' service loyalty (H7: $\beta=0.825$, $p< 0.001$). While IVA satisfaction explains 66.9% variance of consumers' perceived service satisfaction, IVA value explains 68% of consumers' service loyalty. The results give adequate support for H6 and H7 respectively, with confidence intervals excluding 0 and p-values less than 0.05 (See Table 7).

2.6 Discussion

In this research, we proposed and empirically tested and validated a theoretical model of IVA Encounter and its dimensions. We proposed and tested how Service Quality, IVA Encounter and Effective Use determines IVA Satisfaction and Value which then subsequently affect eService Satisfaction and Loyalty. We established IVA Interactivity, IVA Reliability, IVA Flexibility, IVA Assurance and IVA Personalization as empirically validated dimensions of IVA Encounter thus providing both a theoretical and empirical foundation for further research in this important and emerging area of IS research. Additionally, we found empirical support for most of the hypotheses in our proposed theoretical model (see Table 7), thus providing a theoretical foundation for further investigation of the important role of IVA in the context of ecommerce and eServices.

Intelligent Voice Assistants (IVAs) are fast becoming the preferred means by which consumers access various eServices. Research attributes the growth in popularity of IVAs to the convenience of their unique ‘dialogue-style only’ nature of interactions with consumers (Canniford and Bajde 2015; Moorthy and Vu 2014). This makes them useful in various eService contexts such as assistive technology for the aged and disabled and as a component of Internet of Things (IOT) (Adams 2019; Ammari et al. 2019; Cohen et al. 2016). In such eService settings, the IVAs act as the interface between consumers and the eServices used (Patrício et al. 2011) hence, it is important to understand the dimensions of consumers’ encounter with IVAs and the effect of the dimensions on the eService outcomes.

Out of the 19 hypotheses proposed in this study, 17 were supported. Both Service Delivery Quality (SDQ) and Service Content Quality (SCQ) are demonstrated to have statistically significant relationships with the five IVA Encounter dimensions (see Table 7) namely IVA Interactivity, IVA Reliability, IVA Flexibility, IVA Assurance and IVA Personalization. We are able to explain 69%, 58%, 48%, 51% and 40% of the variance of the each of IVA Encounter dimensions respectively based on the relationship of these dimensions with the SDQ and SCQ. Taken together it is clear that both SDQ and SCQ not only have significant impact on these dimensions but also provide strong explanatory foundation of the underlying variance for each of the IVA Encounter dimensions. Theoretically, both SDQ and SCQ are strongly tied to the IVA Encounter dimensions thus pointing to the need for practitioners to place a strong emphasis on the Service Delivery Quality and Service Content Quality. Thus, our research provides an important practical insight for businesses as they engage with this new and emerging technology increasingly being used by millions of consumers worldwide. Also, the findings suggest that when IVAs form the front-end of eServices, the perceived quality of the service content and delivery positively affect consumers' perception of the quality of their encounter with IVAs. Based on our data, we observed that the quality of how the eService is delivered consistently had stronger association with all the dimensions of consumers' perceived IVA encounter quality than the content quality of the eService. The perceived service delivery quality had the strongest impact on the perceived assurance of IVA encounter. Hence, service delivery quality is a stronger predictor of the outcome from the service encounter with IVA than the service content quality. This suggests that, how well and timely relevant tasks are accomplished through an IVA affects a consumer's level of confidence in the IVA's ability to complete the task. For example, when music is streamed through an IVA, the streaming service's efficiency in meeting the requests of the consumer will have a strong impact on the consumer's confidence in using the IVA to access the streaming service. Also, the efficiency by which a consumer is able to subscribe and pay for the streaming service through prompts from the IVA and its connected computer applications will give the consumer a sense of privacy, security and trust in utilizing the eService through the IVA.

The results further show that the quality of IVA Interactivity, IVA Reliability and IVA Personalization are significant determinants of IVA effective use. These findings demonstrate the intimate relationship that consumers develop with IVA due to the unique “dialog or conversational style” of interaction that mimics person-to-person dyadic relationship with the interesting twist that one of the participants in the dyadic relationship is not even a human but an object. This reflects the consumer-centric part-part and consumer-centric part-whole interactions between consumers and assemblages where the consumer is conceptualized as one of the components of the assemblage (Hoffman and Novak 2018).

Unfortunately, we did not find support for IVA Assurance and IVA Flexibility as having statistically significant relationship with IVA effective use (see Table 7). There is therefore the need to continuously improve how well IVAs are able to understand consumers and in turn respond in a personable manner. This calls for further advancements in machine learning to boost safe IVA Flexibility for effective use. One possible reason for this lack of empirical support for IVA Flexibility might be that the consumers may have high expectation about the degree of adaptability, flexibility and versatility of these new and emerging IVA devices that rely on Machine Learning and Artificial Intelligence technologies. The user expectations might be far higher than what can be realistically be delivered by these new and emerging AI and ML technologies.

The IVA device manufacturers and vendors may want to provide a more realistic picture of what these devices can deliver so that the consumer expectations are in harmony with the services that the devices can deliver. Too many times not meeting or managing user or consumer expectations have led to Information Systems or Information Technology failures. We researchers need to be cognizant and practitioners need to be careful about this type of product expectation-confirmation gap that may lead to poor perceived performance among consumers.

Consumers may intend to complete specific tasks with their IVAs. Hence, they may not expect the IVA to be flexible in meeting several needs. As IVAs become more mainstream, consumers may start expecting more flexibility in their service encounter with the emergent technology. Also, due to the newness of IVAs to many consumers, they may not know what “good” and dependable functioning of IVAs should be. Hence, their expectations and perceptions of quality with using IVAs to access eServices does not depend much on how reliable they find the devices. With more experience in their use however attitudes toward IVA reliability in helping them achieve their desired eService goals may change as well.

The results also show that when consumers are able to effectively use IVAs to access eServices effectively they will be better satisfied with the technology and place more value on it. This will also facilitate their satisfaction and loyalty to the eService which incorporates the IVA. For example, when an aged or disabled person accesses a type of eService through an IVA, his/her satisfaction with the IVA and the value they place on it as an assistive tool will be enhanced depending how well their needs were met.

Our study makes four main theoretical contributions. Firstly, our study is one of the first ones to examine the theoretical foundations of IVA encounter in the study of service quality and its outcomes. Though there have been extensive discussions on the role of technology in delivering quality services to consumers and the impact on their satisfaction and loyalty, the theoretical foundations of the role of smart devices such as IVAs have been understudied. Secondly, this is the first study to propose and empirically test the effect of IVA encounter dimensions on eService quality outcomes. Previous studies had discussed the role of consumer encounter with smart objects like IVAs in eServices without breaking down the concept of this type of encounter into individual dimensions (Larivière et al. 2017; Patrício et al. 2011). By studying the IVA encounter construct in a detailed way, we have advanced the understanding of which components lead to the effective use of IVAs in accessing eServices and which aspects do not.

Thirdly, based on the non-human centric principles of Assemblage Theory, we proposed a model which incorporates IVAs' unique 'dialogue-style only' nature of interactions (Moorthy and Vu 2014) in eServices. The proposed model can extend existing studies of eService encounter with smart technology which differs from the traditional human centric technologies like desktops in service delivery. Finally, our study advances knowledge on how service delivery quality and service content quality individually predict the outcome of consumers encounter with IVAs in an eService setting. This adds more comprehensiveness and depth to the existing literature on the role effect of service quality on eService outcomes in the context of IVAs.

Previous studies have not broken-down service quality into its delivery and content dimensions to explore their effects on service encounter with smart devices such as IVAs. By exploring the effects of the two dimensions simultaneously, we gained insights on what impact each of them had on the consumers' perceived quality of their IVA encounter. However, if we had tested the effect of service quality as one dimension, we probably would not have been able to determine if there was a difference in the strength of their impacts.

2.6.1 Research Implication

Understanding the impact of information technology encounters on service quality outcomes is an important research stream in the information systems field. Our study aims to advance knowledge on the theoretical foundations of how IVA, an AI service technology, affects the link between service quality dimensions and consumer satisfaction and loyalty. Future studies can explore how the impact of the various dimensions of IVA encounter on service quality outcomes differ among the different age groups of consumers.

Also, we conducted the study at a time when IVAs were still emergent. Future research should evaluate how attitudes change towards the use of IVAs in eServices. Also, though adopting structural equation modelling approach helped us to explore several relationships simultaneously, the complexity of real-life situation could not be fully captured in the model. Further empirical studies are definitely needed to develop a more comprehensive understanding and insights related to IVA and its increasing use among consumers.

2.6.2 Implication for Practice

The study suggests that the service delivery quality is a stronger predictor of consumers' IVA encounter quality than service content quality. This implies that, providers of eServices which rely on IVA access should focus on managing how eService tasks are efficiently accessible to consumers by using IVAs. The results further suggest that while IVA interactivity, IVA assurance and personalization are significant predictors of its effective use in achieving consumers' goals, IVA reliability and flexibility are not. Hence, it is important for IVA manufacturers and eService providers to optimize the quality of the influential IVA encounter dimensions (especially IVA interactivity which has the strongest impact) for consumers to be able to effectively achieve the eService tasks for which they use IVAs.

2.7 Conclusion

By using Assemblage theory and Effective Use Theory, we have provided a holistic view of the relationships that exist among the dimensions of Intelligent Voice Assistant (IVA) encounter, IVA effective use, perceived IVA satisfaction, perceived IVA value, service quality, service satisfaction and loyalty. Through our study findings on the dimensions of IVA service encounter and the structural relationships that exist among the different constructs in our study, researchers, computer companies and consumers will have a better understanding of how to maximize the benefits and mitigate any issues of the Intelligent Voice Assistant (IVA) technology.

This study further enhances understanding of the theoretical foundations for Intelligent Voice Assistants and its effect on the eServices and corresponding consumer satisfaction and loyalty. Given that existing literature on IVA focus on consumer relationships with online recommendation agents (Li and Karahanna 2015; Zhang and Cole 2016) the effect of IVA encounter on the quality of eServices is an important contribution to existing IS literature. Incorporating the dimensions of IVA encounter as well as the two dimensions of service quality we hope adds more comprehensiveness and depth to the existing IS literature. While this paper focuses on the dimensions of IVA service encounter and how it relates to the other constructs in our model, there remains research opportunities to explore this phenomenon at the organizational level. Effective research in this area will inform the research and development, design and implementation of IVA technology and other AI applications.

CHAPTER III

PREDICTING THE EFFECTS OF HEALTH IT FUNCTIONALITIES ON HOSPITAL PERFORMANCE: A MACHINE LEARNING APPROACH

3.1 Introduction

Increasing cost and declining quality of healthcare in the US has raised the impetus towards the adoption and use of Health Information Technology (HIT) to improve the transparency of care, enhance customer safety and satisfaction, reduce cost and increase efficiency in health services. Health Information Technology (HIT) refers to technology used to record, retrieve, analyze, share and apply healthcare data, information, and knowledge for communication and decision support purposes (Health and Human Services 2013) and thereby improve the provision of healthcare. The ultimate goal of healthcare is to provide patients with high quality and accessible healthcare services at reduced costs by minimizing the effects of diseases (Bardhan et al. 2020). One of the critical determinants of healthcare quality is the patient length of stay (LOS). Hence, reducing length of stay has been a priority for many US hospitals (Anderson et al. 2014; Andritsos and Tang 2014; Oh et al. 2018). Patient length of stay can be defined as the lapse of between the first time a patient is called to see a doctor until she gets discharged (Martins and Filipe 2020).

Another major burden of the US healthcare system is the high cost of patient care which keeps rising rapidly (Fang et al. 2019). Without urgent cost containment measures, the growth of US healthcare cost is expected to overtake GDP growth from 2019 to 2028 (CMS.gov 2018). The availability of detailed information about clinical services and patient care, accumulated by the US health care systems, enables the use of data analytics methods to drive low cost of patient care (Davenport 2013; Dhar 2014).

Length of stay (LOS) is an important hospital performance metric which can improve patient care and reduce operational cost (Center for Medical Interoperability 2016; Oh et al. 2018). Few studies have discussed the impact of HIT use in the context of reducing patient length of stay (LOS). For example, based on Information processing theory, Wani and Malhotra (2018) used detailed patient-level characteristics to investigate the impact of HIT adoption on hospital performance. They observed that the adoption of HIT was related to improvement in the length of stay of patients. They also found that adequate assimilation of HITs at the hospital level significantly influenced this relationship especially when in situations where patients had severe health complications. Romanow et al. (2017) further investigated the impact extended Computerized Provider Order Entry (CPOE) use had on LOS for five patient conditions. The conditions were organ transplant, cardiovascular surgery, pneumonia, knee/hip replacement and vaginal birth. They found that, for all five conditions, hospital teams which use extended CPOE tend to be better informed about their tasks which results in better coordination among team members to achieve shorter LOS. Based on an observational study, Yanamadala et al. (2016) also investigated the effect of EHR adoption on healthcare outcomes in a difference-in-differences analysis. They found that surgical patients treated in hospitals with full EHR had shorter LOS than those treated in hospitals with partial or no EHR.

The studies on LOS (e.g., Wani and Malhotra 2018; Yanamadala et al. 2016) have not explored the specific functionalities of HIT which were associated with patients length of stay and how the effect differs among the various functionalities. The few studies which have attempted to predict LOS have also limited their study scope to the context of specific diseases. This limits our understanding of how the various HIT functionalities compare to each other and how hospitals can leverage them to improve LOS. For our second dissertation study, we developed a predictive analytics model, which was tailored to our hospital level healthcare datasets and able to predict the impact of using various HIT functionalities on length of stay (LOS). The predictive model can increase our understanding of how the use of health information technology (HIT) in hospitals in the US impacts patient length of stay at the hospitals. Below is a review of existing literature on HIT within which our proposed research is situated.

3.2 Related Literature

In the past decade, there has been an increase in the diffusion of HIT in the US via systems such as electronic health records (EHR), Clinical Decision Support (CDS), Computerized Provider Order Entry (CPOE) (Romanow et al. 2012). An EHR refers to the fundamental patient data for instant and secure sharing with all authorized healthcare providers (Sherer 2014). The potential benefits of HIT in general have been widely discussed in the information systems (IS) literature (Agarwal et al. 2010; Sharma et al. 2016; Tao et al. 2020). Many hospitals are relying on HITs to help them economically survive as well as gain competitive advantage (Bakshi 2012). Van den Broek et al. (2013)

noted that healthcare's multiple and varied stakeholders tend to emphasize different desired outcomes of using HIT. For example, while physicians and nurses may desire quality of care, top level management may focus on both patient quality and efficiency outcomes.

Despite the potential benefits of HITs, existing barriers (including high investment) have hindered the US hospitals from realizing the full potential of their widespread implementation (Adler-Milstein et al. 2014). Hence the federal government has committed unprecedented incentive payments to encourage clinicians and hospitals to use EHRs. Through the Health Information Technology for Economic and Clinical Health Act (HITECH), the incentive payments are aimed at supporting a rollout of a nationwide system of EHRs as well as their "meaningful use". Healthcare providers can achieve meaningful use (MU) when they adopt and use EHRs to achieve significant improvements in quality of care. The MU incentive program requires eligible healthcare providers to report their clinical quality information to the Centers for Medicare and Medicaid Services (CMS) (Kim and Kwon 2019).

The increasing impetus to attain HIT requires that the implications of the specified goals set by Centers for Medicare & Medicaid Services (CMS) for hospitals to be MU certified are well understood. Recognizing their unique role in advancing knowledge about the digital transformation of healthcare, Information Systems (IS) scholars have focused their studies on HIT adoption and use (Adler-Milstein et al. 2014; Kohli and Tan 2016; Sherer 2014). Based on gaps identified in a systematic literature review, Agarwal et al. (2010) called for further study on 1) the design and implementation of HIT as well as its meaningful use 2) the measurement and quantification of HIT benefits and impact; and (3) expanding the traditional scope of HIT use. Romanow et al. (2012) further identified (1) privacy concerns, (2) interoperability, and (3) resistance to change as influential variables in the ongoing discussion about HIT in the IS literature. Our review of more recent studies shows that the focus of HIT research falls under three main themes: HIT adoption, HIT impact, and HIT analytics.

3.2.1 HIT Adoption

In response to a national call for meaningful use, the rate of HIT adoption continues to rise. The percentage of US office-based physicians with EHRs increased from 34.8% in 2007 to 85.9 % in 2017 (healthIT.gov 2020). Research however shows that several social, organizational, and technical issues continue to hinder HIT development and prevalent use (Kohli and Tan 2016). For example, clinicians' resistance to change can hinder a hospital's efforts to use HIT. Also, issues with data integrity during transition from existing charting system to another can affect a hospital's willingness to use HIT. However, hospitals that overcame these barriers could achieve significantly lower costs from adopting HIT. Highfill (2020) found that hospitals who adopted basic EHR capabilities had 12% lower average costs than similar hospitals who did not adopt it.

Research further shows that, small and rural health providers lag behind their more resourced counterparts in the adoption of EHR capabilities (Adler-Milstein et al. 2014). Angst et al. (2010) found that the decision to adopt EHR systems was significantly influenced by the social contagion among the healthcare providers. Gan and Cao (2014) further argued that in addition to social contagion, a provider is likely to adopt EHR and achieve improved performance if the technology has features that fit the requirements of the task at hand.

Through a grounded theory approach, Noteboom et al. (2014) identified physicians’ lack of technical and social adaptation to HIT as a major challenge for health providers to improve efficiency after adoption of EHRs. Research further suggests that by adopting less diffused technologies like telehealth, hospitals could leverage HIT to provide unique services to their customers. Sherer et al. (2016) used institutional theory to demonstrate how government policies and industry norms affected the adoption of HITs in US healthcare. Their study showed that in situations of greater uncertainty, mimetic forces were more critical predictors of HIT adoption than coercive forces which were observed to be significant adoption predictors after the establishment of government incentives.

Several studies in the IS literature suggest that the adoption of HIT, has a positive impact on the performance of hospitals (Devaraj et al. 2013; Gardner et al. 2015; Sharma et al. 2016; Wang et al. 2018). Typically, studies which focus on only the adoption of specific HIT technologies (Agha 2014; Freedman et al. 2014; McCullough et al. 2014) or only patient level data (Barnett et al. 2016; Yanamadala et al. 2016) are unable to show clear support for HIT adoption.

Collum et al. (2016) investigated the relationship between the level of HIT adoption and hospital financial performance using the corporate financial theory. Using data from the AHA IT supplement survey, they operationalized EHR adoption as a variable with three levels: comprehensive EHR, basic EHR, and no EHR (Jha, 2010; Jha et al., 2009). They did not observe any changes in operating margin or return on assets within hospitals to be associated with changes in the level of EHR adoption. However, they observed significant improvement in the total margin after 2 years with hospitals which changed from no EHR to adopting a comprehensive EHR in all areas of their hospital.

Kutney-Lee and Kelly (2011) also studied the effect of hospital HIT adoption on nurse-assessed quality of care and patient safety. They observed significant improvement and increased efficiency in nursing care, better care coordination, and patient safety as a result of basic HIT implementation. Generally, researchers who focused on the impact of HIT use found that it had a relationship with the quality indicators of healthcare delivery such as patients' length of stay (Romanow et al. 2017). We discuss other research which focused on the impact of HIT below.

3.2.2 HIT Impact

The call for meaningful use of HIT by the US government requires hospitals to attain specified goals on healthcare process quality (Bardhan and Thouin 2013). Although HIT is expected to enhance hospital performance, existing empirical results remain inconclusive (Dobrzykowski and Tarafdar 2017). On one hand, several studies found that the use of HIT had a positive impact on process of care and medication errors quality (e.g. Yanamadala et al. 2016). Other studies found that HIT could reduce the quality of service due to increased documentation and longer interaction time with computers (Jones et al. 2014).

To gain competitive advantage, hospitals also leverage HIT to attract top medical talent (mostly physicians) as well as increase patients inflow (Karahanna et al. 2019). HITs have been shown to improve patient outcomes (e.g., McCullough et al. 2016); enhance employee safety (Jones et al. 2014); improve hospital's financial performance (e.g., Adjerid et al. 2018; Sharma et al. 2016); increase patients quality of care (e.g. King et al. 2014) as well as lower occurrence of medical errors (e.g. Truitt et al. 2016) and reduce the frequency of readmissions (Bardhan et al. 2014; Senot et al. 2015). Through multiple case studies Gastaldi et al. (2012) found that HIT is an effective solution to exploit existing medical knowledge as well as exploit new medical knowledge in hospital settings.

Based on the dynamic capability principles, Bardhan and Thouin (2013) also observed a positive association between HIT usage and patient scheduling applications as well as the conformance quality of care. They also found that HIT usage was associated with lower cost of care whereby for-profit hospitals especially exhibited lower operational expenses compared to non-for-profit hospitals. Devaraj et al. (2013) further observed that by improving the swift-even flow of patients, facilitated by HITs, hospitals can improve their efficiency and consequently their net patient revenue (NPR). Hence, they concluded that investments in HIT could influence hospitals' operational performance leading to better financial performance. Bhargava and Mishra (2014) used task-technology fit theory to show that HIT could increase physician productivity though this could not lead to substantial cost savings in the long run. They found that the longer term impact depended on the specialty of the physicians. However, a study by Hsiao et al. (2012) showed that only about 11% of physicians had the necessary capabilities required to meaningfully use their HIT systems.

In spite of the studies depicting the positive effects of HITs , other studies have argued that HIT can lead to unintended adverse effects like dosing errors, service delays, and misdiagnosis of fatal conditions (Committee on Patient Safety and Health Information Technology 2012). Also, other studies found no evidence of cost savings and little impact on quality of care with the adoption of HIT (Agha 2014). Due to the mixed results of the effect of HIT use on hospital performance, Sherer (2014) called for the use of action design research to further explore this issue. Kohli and Tan (2016) also identified predictive analytics as one of the two key research areas through which IS scholars could significantly contribute to widespread adoption and meaningful use of HITs in the US for better healthcare performance. We aim to contribute to this body of knowledge through machine learning algorithms to predict patient length of stay. Below is a review of studies which have responded to the call for predictive analytics in the HIT research area.

3.2.3 HIT Analytics

With the current availability of detailed electronic health records (EHR) data, predictive modelling in healthcare has become an encouraging direction to drive quality patient centered healthcare in the US (Davenport 2013). Several studies aimed at building knowledge on healthcare issues have focused on topics such as patient disease patterns (Bates et al. 2014; Zhang et al. 2015) and the risk of multiple patient readmissions (e.g., Bardhan et al. 2014). By utilizing EHR datasets prior studies successfully applied analytics methods such as machine learning (Lakshmanan et al. 2013; Zhang et al. 2014) and process mining (Caron et al. 2014; Huang et al. 2012) to investigate various clinical processes. For example, Lakshmanan et al. (2013) used hierarchical clustering to segment chronic heart failure (CHF) data into positive and negative outcomes. Where negative outcomes consisted of patients who were hospitalised for CHF related causes within one year of diagnosis. On the otherhand positive outcomes comprised of patients not hospitalised for CHF related causes within one year or more after diagnosis. This enabled them to perform further clustering and frequent data mining to extract insights from the patient data for planning routine checks or periodical treatments as needed. Zhang et al. (2014) also developed optimization-based models with clustering techniques to identify items belonging to various order sets of clinical conditions. The order sets were grouped based on order similarity and order time. Using data for asthma, appendectomy and pneumonia management in a pediatric inpatient setting, the researchers successfully tested their model's performance.

Adopting process mining methods, Huang et al. (2012) developed sequence mining algorithms to identify clinical pathway patterns given a specific clinical workflow log and minimum support threshold. They successfully tested their proposed approach with clinical data on bronchial lung cancer, gastric cancer, cerebral hemorrhage, breast cancer, infarction, and colon cancer from a hospital in China. Their results showed the possibility to find patterns from clinical pathways without looking from start to finish but from time differences between event logs. Similarly, Caron et al. (2014) used a process mining approach to develop the Clinical Pathway Analysis Method (CPAM) to extract information on past clinical pathway executions from the event logs of healthcare information systems. Using process mining analytics enabled to understand the dynamics of clinical pathways, based on the complete audit traces of previous clinical pathway instances. In addition, the approach enabled the researchers to asses guideline compliance and to analyze adverse events such as drug allergies, harmful drug reactions, and heart failure.

Predictive models for heathcare analytics have mainly used logistic regression models or simple Cox proportional hazard models (e.g. Bardhan et al. 2014; Donzé et al. 2013; Khanna et al. 2014). Bardhan et al. (2014) developed the beta geometric Erlang-2 (BG/EG) hurdle model, an analytics model for which predicting the propensity, frequency, and timing of readmissions of patients diagnosed with congestive heart failure (CHF). The model was also used to investigate the relationship between hospital usage of HIT and readmission risk. The researchers found that HIT usage, patient demographics, visit characteristics, payer type, and hospital characteristics, have a significant association with patient readmission risk. Also, the implementation of cardiology information systems was found to be associated with a reduced propensity and frequency of future readmissions while administrative IT systems were associated with a lower frequency of future readmissions.

Their results suggested that patient profiles derived from their model could be used to build predictive analytics systems to identify CHF patients at high risk of readmission. Based on a retrospective cohort study Donzé et al. (2013) studied the primary diagnoses and patterns of 30 day readmissions as well as potentially avoidable readmissions in patients with common comorbidities. They found that, the top 5 most common comorbidities with potentially avoidable readmissions were infection, neoplasm, heart failure, gastrointestinal disorder, and liver disorder. They also found that the primary diagnoses of these potentially avoidable readmissions were often complications of an underlying comorbidity. Khanna et al. (2014) conducted a comparative study of machine learning algorithms used to predict the prevalence of heart diseases. Based on Cleveland Datasets, the researchers studied the differences between various classification techniques and evaluated their accuracies in predicting heart disease. The models studied were Logistic Regression, Support Vector Machines (SVM), and Neural Networks. The study found logistic regression and SVM had a high level of accuracy in predicting heart disease.

More recent studies have demonstrated the ability to build models with high predictive ability for analysing healthcare quality. For example, Cai et al. (2016) used EHR data to develop a Bayesian Network model for real-time predictions of LOS, mortality, and readmission for hospitalized patients. The model had a high predictive ability with average daily accuracy of 80% and area under the receiving operating characteristic curve (AUROC) of 0.82. The researchers found Death to be the most predictable outcome with a daily average accuracy of 93% and AUROC of 0.84. The study showed that Bayesian Networks can be used to model EHRs to provide accurate real-time predictions of patient outcomes to support decision making. Rajkomar et al. (2018) also used EHR data to propose and test Deep learning models for predicting various medical events from multiple centers without site-specific data harmonization. The deep learning models achieved high-performance accuracy for predicting in-hospital mortality (AUROC = 0.93–0.94), 30-day unplanned readmission (AUROC = 0.75–0.76), prolonged length of stay (AUROC = 0.85–0.86), and all of a patient's final discharge diagnoses (frequency-weighted AUROC 0.90). Based on the high predictive performance of the models, the researchers concluded that deep learning algorithms can be used to build accurate and scalable predictions for various clinical conditions.

Despite the numerous analytics methods available in the extant literature, EHR studies often find it necessary to develop innovative analytic models which are specially tailored for new health data to draw valuable insights (Kohli and Tan 2016). These are typically predictive models to estimate future trends or stratification models to classify or cluster subjects of interest (Ben-Assuli and Padman 2020). For example, Shams et al. (2015) proposed a tree-based classification model to predict the risk of readmission of chronic disease patients. The model was aimed at reducing readmission rates among patients with acute care conditions such as congestive heart disease. Lin et al. (2017) developed a decision support system which showed key medical insights toward the adverse healthcare planning for patients with chronic diagnoses. These insights enabled healthcare providers to determine effective interventions that were also cost efficient.

Ben-Assuli and Padman (2020) further used a longitudinal risk stratification approach to examine how the readmission risk of chronic disease patients could progress over multiple emergency department visits. This study showed that stakeholders could use logistic regression and boosted decision trees (BDT) to classify patients in a timely manner based on their presentation for emergency care. They further examined the effect of time-stable and time-varying covariates on the prediction of future readmissions based on patient latent class membership. Covariates were defined as various risk factors that could manifest overtime such as patients' chronic comorbidities. The latent classes identified and profiled a set of latent trajectories grouping patients into distinct longitudinal clusters which matched the patients' changing characteristics such as number of visits.

Prior studies using predictive analytics to study healthcare in general, and HIT use in particular, utilised their models to play six key roles (Shmueli and Koppius 2011). These were to build new theories, develop measurements, improve existing models, compare competing theories, assess relevance and assess predictability of empirical phenomena. Our study is aimed at assessing the predictability of patient length of stay based on the HIT functionalities that hospitals have implemented. Unlike prior predictive analytics studies on LOS (e.g. Yanamadala et al. 2016) which limited their study context to specific diseases, our study was based on multiple acute care conditions which made our model useful for many hospitals in the US.

3.3 Research Framework and Theoretical Foundations

To be certified for HIT meaningful use, eligible hospitals are expected to meet certain core and 5 out of 10 menu objectives. The core objectives are aimed at enhancing the quality, safety and efficiency of health services for patients. The menu objectives are classified under the following themes of meaningful use: (i) improving quality, safety and efficiency, (ii) engaging patients and families, and (iii) improving care coordination (HealthIT.gov, 2019 n.d.). Due to barriers such as high cost investments, many hospitals have struggled to meet these meaningful use requirements (Adler-Milstein et al. 2014). We argue that when hospitals have limited resources to acquire HIT, their ability to predict the performance outcome from the various functionalities of HIT will help them to choose the best options to invest in. We further argue that, together, HIT functionalities can predict the performance outcome of hospitals. Adopting principles from the Task–Technology Fit (TTF) theory and Information Processing Theory (IPT), we investigate the predictability of patient length of stay (LOS) and cost of patient care (CPC) of a hospital based on its use of HIT functionalities.

3.3.1 Information Processing Theory (IPT)

Originally developed by Galbraith (1973) the fundamental principle of Information Processing Theory (IPT) is that the central task in organisational design is the resolution of uncertainty. Whereby uncertainty was conceptualized as the absence of information about statuses of tasks and the environment (Gattiker and Goodhue 2003). The types and levels of uncertainty differ across organizations as well as among organisational sub-units. For example, based on IPT we can argue that in healthcare organisations and among the various sub-units (e.g. laboratory and radiology departments) the level and type of uncertainty regarding the status and availability of clinical information varied among one another.

IPT suggests that different forms of coordinations exist and they differ based on their suitability for coping with the type and degree of uncertainty. Hence, to achieve improved performance, organizations had to effectively match the appropriate modes of coordination with the particular uncertainties (Gattiker and Goodhue 2003). It follows that, in healthcare organisations, the types and levels of uncertainties regarding clinical information could range from mitigating information error to gaining access to objective data to plan patient care pathways. For the various forms of uncertainties in healthcare services, the forms of coordinations chosen should be suitable to cope with the type and level of uncertainty. These coordinations can be attained through the use of HIT functionalities to process clinical information (Raymond et al. 2017).

Tushman and Nadler (1978) defined information processing as “the gathering, interpreting, and synthesis of information in the context of organizational decision making” (p. 614). Based on the principles of IPT, the functionalities of HIT can be examined using two distinct means of information processing: operational use of error data and strategic use of objective data. While the operational use of error data is aimed at detecting and reducing errors, strategic use of objective data enhances clinical planning (Gardner et al. 2015). In the context of HIT, while some functionalities can help mitigate information errors (e.g. prescription errors) other functionalities may be more suited for strategic use of objective data (e.g. radiology results). Hong and Kim (2002) found that the fit of an organization's IT system with its task, data, and related needs is associated with the performance of the organization. We therefore use principles of Task-technology fit theory to support our argument that when HIT functionalities are fit for the clinical task, data and related needs of the users, it can help predict the performance of the hospital.

3.3.2 Task-Technology Fit (TTF) Theory

The TTF theory states that the alignment between technology functionalities and the requirements of a task can improve the performance of an organization (Goodhue and Thompson 1995; Howard and Rose 2019). TTF provides us a framework to study the relationship between workplace technologies and performance outcomes. Hence TTF, since its inception, has been applied to study performance in an array of contexts such as teamwork (Fuller and Dennis 2008; Rico et al. 2011); web learning (Lin 2012); system usage (Im 2014); mobile financial services (Lee et al. 2012) and decision making (Erskine et al. 2019).

Although TTF was originally proposed to operate at the individual level, Zigurs and Buckland (1998) modified it to suit the purposes of group level research. They proposed information processing, communication support, and process structuring technologies as the three types of information technology that could significantly impact the performance of organizational tasks. TTF emphasizes that the use of technology alone does not adequately explain its impact on performance. Rather, the resulting effect on performance hinges on the fit of the functionalities to the task at hand rather than the just the utilization of the technology. Hence, TTF considers the features of a technology type and how they fit the requirements of tasks in order to enhance organisational performance. This makes TTF the appropriate theory to base our study on. Our research framework is shown in Figure 4 below.

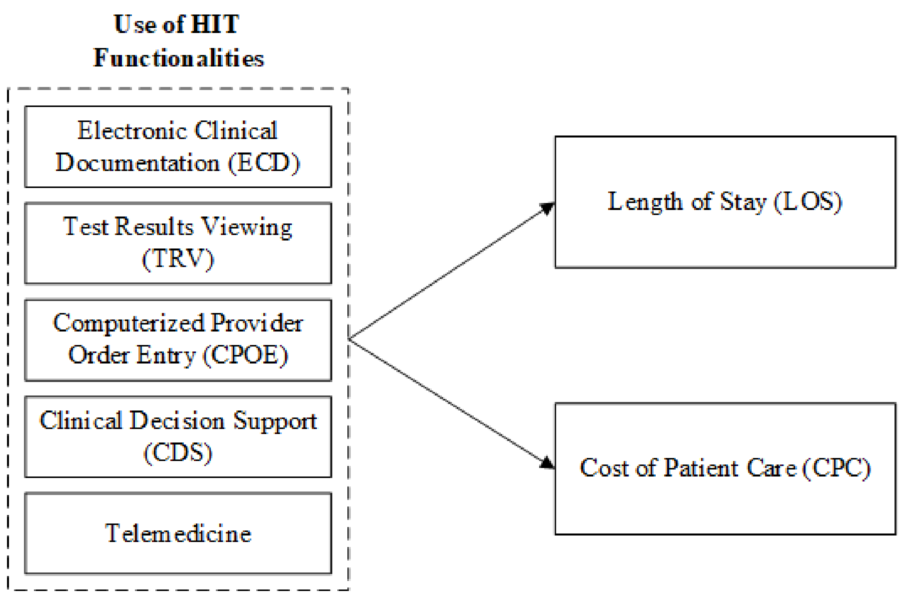

Figure 4. Research Framework

The conceptual foundations of our research draw from previous studies on HIT enabled processes, patient's length of stay (LOS) and cost of patient's care (CPC). In Table 8 below, we summarize descriptions of the key study variables.

Table 8. Definition of Key Variables

Variable		Description
HIT Functionalities (Predictor Variables)		
1	Computerized Provider Order Entry (CPOE)	Enables the direct electronic entry and transmission of medications, consultation requests, nursing orders as well as laboratory and radiology tests.
2	Clinical Decision Support (CDS)	Provides clinical guidelines and reminders, drug dosing support, drug allergy alerts, drug-drug interaction, and drug-lab interaction alerts.
3	Test Results Viewing (TRV)	Gives electronic access to radiology images, diagnostic test results, diagnostic test images, consultant reports, laboratory, and radiology test results.
4	Electronic Clinical Documentation (ECD)	Enables the entry of Clinicians' notes; making of problem and medication lists, documentation of discharge notes and advanced directives.
5	Telemedicine	The provision of health care services from a distance using telecommunication and information technology (Lokkerbol et al. 2014)
Hospital Performance (Predicted Variables)		
1	Length of Stay (LOS)	The period between the first time a patient is called to see a doctor until she gets discharged (Martins and Filipe 2020). All inpatient days/ all inpatient discharges.
2	Cost of Patient Care (CPC)	Measured as hospital's operating cost per bed includes expenses like employee salaries, supplies, training investments and other technological investments (Sharma et al., 2016).

We further discuss the above concepts under the lens of task–technology fit (TTF) and information processing theories and propose our hypotheses below.

3.3.3 Length of Stay (LOS)

Reducing patient length of stay (LOS), especially as it relates to improving quality, is a primary indicator of a hospital's performance. Improved LOS also plays an important role in keeping patients safe from unnecessary hospital-acquired conditions (HACs) which can further contribute to even longer stay (Wen et al. 2017). Furthermore, reducing LOS can free up the capacity for hospital resources, hence improve through put and enable the hospital to deliver services to more patients. Research shows that apart from the time needed for the essential medical care, avoidable conditions can significantly increase patient length of stay (Busby et al. 2015). Typical avoidable conditions include complex discharge processes with lengthy discharge information reviews and information entry processes.

US hospitals are expected to leverage HIT functionalities to mitigate the avoidable causes of long LOS. However, the theory of technology-task fit suggests that, hospitals can only achieve benefits from HIT use if there is an alignment between the HIT functionalities and the tasks to be completed. For example, HIT with accurate and accessible information analytics and other protocols can be implemented to communicate actionable data which healthcare works can use to identify high risk for LOS in order to develop timely interventions. Improved communication and coordination through HIT will further facilitate transparency and break individual staff out of their silos to work together toward the hospital's performance goals. HIT can also facilitate the development and coordination of pathways and guidelines for discharge care. A study of acute patients with UTI reported that making clinical practice guidelines accessible to healthcare providers significantly reduced patient LOS (Conway and Keren 2009). Further, suitable HIT functionalities can accelerate information entry and information review activities involved in decision making and discharge processes.

3.3.4 Cost of Patient Care (CPC)

In the IS and its related fields, several studies have investigated how Analytics and HIT can be used to support decision making to drive down the cost of patient care. However, the conclusive evidence of their effectiveness is still lacking and further research on how Analytics and HIT can be used in innovative ways to coordinate cost effective patient care is needed (Rudin et al. 2017). For example, using a combined approach of Architecture of Integrated Information Systems (ARIS) models, a micro costing approach for cost evaluation, and a Discrete-Event Simulation (DES) Rejeb et al. (2018) studied the organizational impact of HIT on patient pathway. Their study was limited to data on the consultation for cancer treatment process from three hospitals. The study results suggested that while HIT use increased the quality of consultation service to patients, it did not reduce the cost of service. However, they identified several HIT functionalities which could drive down cost of service as well as increase service quality. These functionalities included voice recognition for dictating clinical reports. Further studies were needed to confirm this.

Through a longitudinal study, Sharma et al. (2016) studied the impact of using Clinical HIT and Augmented Clinical HIT on cost and process quality outcomes. Classifying HIT based on functionality and degree of caregiver interaction, they defined Clinical HIT to be HIT systems for collecting patient data as well as for diagnosis and treatment of medical conditions. Augmented Clinical HIT on the other hand referred to systems for the integration of patient data and the facilitation of decision making by caregivers. The researchers found that the use of Clinical and Augmented Clinical HIT affected the observed level of process quality, but they did not find a similar association with cost. Results from a post-hoc analysis, which divided Augmented Clinical HIT into Electronic Medical Record (EMR) and Non-EMR technologies however showed that the effect of EMR on hospitals' cost performance differed from that of non-EMR HITs. While implementing EMR with Clinical HITs was associated with increased operating cost, implementing non-EMR with Clinical HITs reduced operating costs. These effects cancelled themselves out in the main analysis hence nullified any effect on cost.

Wu et al. (2017) further investigated whether the use of HIT can improve patient care to drive down costs at the frontlines when cost and quality objectives are set at the interorganizational level. They found that, the effective use of HIT for coordinating highly interdependent activities was key to enhancing the quality of patient care which in turn was central to achieving reduced cost of patient care. Thompson et al. (2020) studied how HIT and Analytics can improve healthcare outcomes and reduce costs through Temporal Displacement Care (TDC). They introduced the notion of TDC to be the creation of healthcare value by displacing the time at which providers and patients make clinical intervention. Their results showed how TDC effects developed over time and also revealed that the use of analytics and HIT are associated with the increased use of preventive procedures, reduced emergency department utilization and overall patient treatment costs. However, a study by Agha (2014) to investigate the impact of HIT on the quality and intensity of health care found that while HIT is related to about 1.3 percent increase in patients' billed charges, there is no proof of cost savings even five years after adoption.

The mixed results in the literature about the impact of HIT use on the cost of patient care calls for further research to improve the understanding. This increase in knowledge will help hospitals to leverage the functionalities of HIT as well as Analytics to reduce the cost of care. We aim to contribute to this body of knowledge.

3.3.5 HIT Functionalities

There are many types of HIT functionalities that support various processes in the healthcare services. We operationalized a hospital's use of a particular functionality as 1 (if used) or 0 (if not used). Meaningful Use (MU) requirements are commonly used to identify essential HIT functionalities (Yen et al. 2017) in hospitals and in literature. Similarly, we focus on four HIT functionalities based on MU requirements: Computerized Provider Order Entry (CPOE) systems, Test Results Viewing (TRV), Clinical Decision Support (CDS) Electronic Clinical Documentation (ECD). Following the recent healthcare response to COVID-19 pandemic, where social isolation was essential, we discuss Telemedicine as a fifth HIT functionality with the potential to predicting hospital performance.

Based on the information processing theory, we conceptualise HIT functionalities as coordinations for managing different types and levels of uncertainties associated with clinical information processing. We focus on two types of information processing: operational use of error data to mitigate errors in clinical information as well as strategic use of objective data to plan clinical pathways.

3.3.5.1 Computerized Provider Order Entry (CPOE)

Computerized provider order entry (CPOE) systems enable clinicians to directly enter their own orders for test, prescriptions or care procedures into an electronic system, which then transmits the order directly to the relevant recipient (e.g. pharmacy or radiology department) to complete the order (Ranji et al. 2014). CPOE mitigates transcription errors by providing an alternative to illegible handwriting of healthcare staff. Research shows that CPOEs improves access to drug information, communication among healthcare stakeholders (e.g. physicians and pharmacies) and reduces the cost of care (Coustasse et al. 2015; Vermeulen et al. 2014). By improving communication and direct input of clinician orders, CPOEs speed up the care process which can lead to reduced patient length of stay (LOS). CPOE therefore processes both error data and objective data. Depending on how well these functionalities fit the hospital's tasks and data needs, CPOE is able to predict the performance of the hospital. The frequent use of CPOE helps to reduce the mistakes by health care providers which then leads to improvements in productivity and efficiency. High productivity is likely to lead lower cost of operations. We propose the following:

Hypothesis 1a: *The use of Computerized Provider Order Entry (CPOE) functionalities will predict patient length of stay (LOS) in hospitals.*

Hypothesis 1b: *The use of Computerized Provider Order Entry (CPOE)) functionalities will predict cost of patient care (CPC) in hospitals.*

3.3.5.2 Clinical Decision Support (CDS)

Clinical Decision Support (CDS) functionalities are developed to support clinicians in making safe and quality care decisions. CDS systems typically work in combination with CPOEs to provide relevant reminders and recommendations to clinicians when making orders. For example CDS functionalities may provide basic dosage guidance for prescriptions and formulary decision support for laboratory tests and procedures. It may reduce prescription errors by giving warning signals for possible drug interactions and patients' allergies (Vazin et al. 2014). The system may also help to reduce the risk of unsafe dosage by calculating adjustments based the patient's unique characteristics like weight and renal insufficiency (Horri et al. 2014). Further, CDS functionalities help clinicians to prevent duplicate treatments and contradictions by giving them reminders about the status of patients' care (Zimmerman et al. 2019). Based on the IPT, we argue that CDS functionalities are forms of operational use of error data to improve the quality of hospital care. CDS functionalities therefore contribute to fast and efficient clinical decision making which reduces the risk of increased length of stay (LOS), helps to reduce the cost of patient care. We hypothesize that:

Hypothesis 2a: *Clinical Decision Support (CDS) functionalities will predict patient length of stay (LOS) in hospitals.*

Hypothesis 2b: *Clinical Decision Support (CDS) functionalities will predict cost of patient care (CPC) in hospitals.*

3.3.5.3 Test Results Viewing (TRV)

Through the use of Test Results Viewing (TRV) functionalities, clinicians are able to digitally view test results from various healthcare providers (e.g. laboratory and radiology tests). Hospitals use TRV systems to overcome the issues of relying on paper printed results which requires a longer time to physically share with relevant stakeholders leading to patient harm and increased length of stay (LOS). TRV facilitates timely and comprehensive review of test results for prompt diagnosis and followup with care (Callen et al. 2012). Also, research shows that, digital viewing is more cost effective for hospital than printed alternatives (Hanna et al. 2019). By viewing test results digitally, hospitals are also able to streamline access to test results as well as differentiate urgent results from routine ones to improve handover between staff working on different shifts (Dutra et al. 2018). Improved handover of result review responsibility can significantly improve the efficiency of the care process reducing the length of stay (LOS) and cost of care. We therefore propose that:

Hypothesis 3a: *Test Results Viewing (TRV) functionalities will predict patient length of stay (LOS) in hospitals.*

Hypothesis 3b: *Test Results Viewing (TRV) functionalities will predict cost of patient care (CPC) in hospitals.*

3.3.5.4 Electronic Clinical Documentation (ECD)

Electronic Clinical Documentation (ECD) functionalities ease clinicians' clerical burden by enabling them to digitally document their notes, advanced directives, discharge summaries as well as problem and medication lists. Research suggests that, on average, physicians spend about 50% of their worktime to document clinical information (Shanafelt et al. 2016). Likewise, nurses spend about 50% of their time documenting clinical information and other reports for quality assurance and accreditation purposes (Kelley et al. 2011). With the use of ECD functionalities, clinicians are able to use software packages which allow safe copying and pasting of repeat information and track errors. This allows speedy documentation of clinical information and can ease up clinicians' time for medically necessary activities.

Also, ECD functionalities enable more complete and timely account of care patients receive. Also, having digital access to patient record lookups enable clinicians to quickly respond to changes in patient trajectories which may require changes to their care plan and coordinate with other team members. By expediting coordination and delivery of care ECD decreases the risk of delays leading to increased LOS (Romanow et al. 2012). Based on IPT we argue that ECD functionalities facilitate the speedy and effective processing of objective data to enhance the efficiency and productivity of clinicians by easing up their time for clinical tasks. This can lead to reduced LOS and CPC. We propose the following:

Hypothesis 4a: *Electronic Clinical Documentation (ECD) functionalities will predict patient length of stay (LOS) in hospitals.*

Hypothesis 4b: *Electronic Clinical Documentation (ECD) functionalities will predict cost of patient care (CPC) in hospitals.*

3.3.5.5 Telemedicine

Telemedicine refers to the provision of health care services from a distance through the use of telecommunication and information technology (Lokkerbol et al. 2014). Telemedicine is aimed at overcoming geographical and time challenges with receiving care in traditional modalities. Due to the widespread use of the internet, Telemedicine is highly accessible and has been found to give the same or greater effectiveness in delivering relevant healthcare to patients (Scott Kruse et al. 2018). Studies suggest that the implementation of Telemedicine programs is associated with more favorable LOS outcomes. For example, a study by Hawkins et al. (2016) to compare LOS outcomes among three groups of ICUs using alternative comanagement strategies showed that ICU Telemedicine comanagement were associated with shorter LOS outcomes than the other comanagement strategies.

A restrospective observational study by Armaignac et al. (2018) further showed that LOS in Progressive care unit (PCU) was significantly lower for Telemedicine patients, compared with non-telemedicine patients. However, they did not observe substantial association between Telemedicine intervention and CPC incurrences. On the other hand, some studies have observed reduced CPC to be associated with the use of Telemedicine functionalities. For example, a prospective assesssment of the cost of telemedine by Nord et al. (2019) showed that Telemedicine was associated with short term savings by diverting patients from more expensive care options. The low cost of service associated with Telemedicine use could further contribute to the profitability of hospitals. For example, a case study by Spradley (2001) showed that following the start of a Telemedicine program Austin Diagnostic Clinic recorded an increase in quarterly net profit with and higher cost/benefit ratios as compared to years prior to using Telemedicine functionalities. We propose that:

Hypothesis 5a: *Telemedicine functionalities will predict patient length of stay (LOS) in hospitals.*

Hypothesis 5b: *Telemedicine functionalities will predict cost of patient care (CPC) in hospitals.*

Hospitals typically adopt multiple functionalities from the list described above to support their healthcare delivery to patients. Despite their differences, HIT functionalities independently or jointly contribute to improving the quality and cost of patient care as well as safety (Korb-Savoldelli et al. 2018). Based on the principles of Task Technology Fit theory, if the functionalities of HIT systems used by a hospital meets the requirements of their healthcare tasks, the performance of the hospital will be improved. We therefore argue that HIT functionalities used by a hospital can collectively predict its healthcare performance. We propose that

Hypothesis 6a: *HIT functionalities will collectively predict patient length of stay (LOS) in hospitals.*

Hypothesis 6b: *HIT functionalities will collectively predict cost of patient care (CPC) in hospitals.*

3.4 Materials and Methods

3.4.1 Health IT Data

To test our hypotheses, we utilized secondary data from 2903 U.S. acute care hospitals (our unit of analysis). Specifically, we extracted and combined 1) EHR adoption and use data from the American Hospital Association (AHA) IT supplement database (2018); 2) patient length of stay (LOS) and cost of patient care (CPC) information from the RAND hospital data (2018). Using machine learning and predictive modelling techiniques, we analyzed the data with a focus on the predictability of patient length of stay (LOS) and Cost of Patient Care (CPC) based on the hospitals' HIT functionalities. AHA IT supplement data has been reliably used in prior literature to explore EHR adoption and use (Collum et al. 2016; Diana et al. 2012; Kutney-Lee and Kelly 2011). To combine the two datasets, the unique Medicare provider numbers of the participating hospitals were used. A Medicare provider number classifies healthcare providers in the USA and their eligibility to provide specific services.

AHA IT supplement survey gives reliable and valid measures (Everson et al. 2014) of HIT functionalities like electronic clinical documentation, results viewing, decision support, and bar coding. It further indicates the degree of implementation of the various components within the hospital and details future plans of implementation. The dataset has a high-quality level for research purposes. We also used data from the RAND hospital database. RAND is one of the leading organizations in the collection, analysis, and processing of databases for research purposes. They provide high quality hospital care and financial data which can be used for studying the quality of healthcare in hospitals. The RAND data enabled us to measure the case mix index-adjusted values of LOS and CPC of hospitals being studied. The case mix index (CMI) of a hospital indicates how sick its patients are hence the amount of resources it requires to treat them. Typically, a hospital with a higher average complexity of a hospital treatments will have a higher its CMI.

3.4.2 Variable Measures

3.4.2.1 Predicted Variables

The data for both LOS and CPC were continuous in nature. The case mix index (CMI) measures the relative average cost a hospital incurs to treat patients depending on how complex or severe their illnesses are (Mendez et al. 2014). We measured the predicted variable, length of stay (LOS) as: All patient days/ (Inpatient Discharges*Casemix Index). Whereby RAND recorded the value of All patient days/ Inpatient Discharges to be “inpatient length of stay”. Hence dividing this value by the

Casemix Index accounted for the differences in medical cases at the various participating hospitals (Mendez et al. 2014). Second, we measured the predicted variable, Cost of Patient Care (CPC) = Operating Expenses/ (Total Number of Beds * Casemix Index). We then used the natural log of the adjusted CPC measure to reduce the impact of outliers and satisfy conditions of normality for our regression models.

3.4.2.2 Predictor Variables

Each of the five predictor variables had a number of items (ranging from 1(telehealth) to 7 (Results Viewing)) to measure it. The data for the use of HIT functionalities was categorical in nature. Whereby respondents were asked if they used the items under each type of HIT functionality (Yes = 1; No = 2 and 3 = Do not know). For our analysis, we excluded responses with 3 and those that were missing. This gave use a binomial dataset with better affirmation of the use or non-use of HIT functionalities in participant hospitals.

3.4.3 Machine Learning (ML)

We aim to use machine learning theories and algorithms to predict the impact of HIT use on patient length of stay. Machine learning is the utilization of a system's capability to learn from its past experiences, in a way similar to humans, to complete a particular task (Al-Jarrah et al. 2015). It is therefore a type of artificial intelligence (AI), the ability of a machine to correctly interpret externally supplied data, learn from it and utilize what it is learning to complete specific goals through flexible adaptation (Kaplan and Haenlein 2019). Samuel (1959), a pioneer in the field of artificial intelligence, described machine learning as a "field of study that gives computers the ability to learn without being explicitly programmed". Machine learning algorithms are ultimately aimed at facilitating software decision-making by using knowledge built from previous encounters by the system as well as predict future encounters. They vary in their approach based on the type of data which is input and output. Also, the algorithms may differ in their approach based on the task they are intended to complete. For example, machine learning algorithms can be supervised, unsupervised or semi-supervised (Ang et al. 2016).

Supervised machine learning approach involves the development of algorithms which can build mathematical models from a sample data (termed “training data”) that contains external inputs as well as the desired outputs (Singh et al. 2016). Supervised learning algorithms learn an optimal function from several iterations of a defined objective function. The learnt optimal function enables the algorithm to correctly predict the output for new inputs which were not part of the training data (Mohri et al. 2012). Two main types of supervised learning algorithms are classification and regression. On one hand, classification algorithms try to separate data into classes when the possible outputs are restricted to a limited set of values. On the other hand, regression algorithms try to find the line of best fit for data when the possible outputs can have any numerical value within a defined range (Brownlee 2017).

In an unsupervised machine learning approach, the algorithm (learner) finds patterns in a large data set or classifies the data into categories without explicitly training the data (Wang 2016). By relying on a good measure of similarities between data points, unsupervised algorithms assign data input points into subsets (called clusters) according to some predefined criteria. This process is termed clustering analysis whereby different clustering techniques adopt different assumptions about the structure of the data being analyzed. For example, a clustering method may be based on the distance or difference between clusters (Xie et al. 2016). Research suggests that machine learning algorithms which combine unlabeled data and a small amount of labeled data, in a semi supervised approach, can improve the accuracy of their learning significantly (Miyato et al. 2019).

The ability of Machine Learning algorithms to interpret inputs from various domains and provide intelligent outputs makes them useful decision-making tools for areas like financial fraud and malware detection (Arp et al. 2014). Also, prior studies have found Machine Learning algorithms to perform at human-level (or better) in completing tasks such as recognizing faces (Taigman et al. 2014), objects (Szegedy et al. 2016) and optical characters (Goodfellow et al. 2014) as well as playing games (Silver et al. 2016). In information systems and related areas, machine learning has emerged as a meaningful approach for the analysis of data from sources like financial reports (Bao and Datta 2014) and the content of blogs (Singh et al. 2014). In the healthcare literature, machine learning strategies have been adopted to study issues like the prediction of operation failures (Meyer et al. 2014), prediction of a patient’s risk of future adverse health events (Lin et al. 2017), investigation of adverse events in care processes (Caron et al. 2014) as well as the analysis of triggers and risk factors for chronic health conditions (Zhang and Ram 2020).

3.4.4 Regression Algorithms

Predictive modelling with machine learning algorithms is fundamentally aimed at minimizing the error of the model by making the most accurate predictions possible (Brownlee 2017). To achieve this, machine learning adopts statistical methods such as regression techniques (Alpaydin 2014). Regression analysis comprises of a various statistical method used to estimate the relationship between input variables and their associated output variables. The commonest form of regression used for machine learning algorithms is linear regression. Linear regression analysis is used to find a single line which most closely fits the observed data points according to some mathematical standard. The commonest mathematical criteria by which machine learning algorithms prepare the linear regression equations from the training data is the Ordinary Least Squares (OLS). Through an iterative process, supervised linear regression algorithms learn by estimating optimal parameters for a linear fit by minimizing the least squares error of the training dataset (Schuld et al. 2016). Based on the estimated best linear fit of the training data, new outputs can be predicted for inputs outside the training dataset.

When modelling non-linear problems, machine learning algorithms could adopt other forms of regression analyses such as polynomial regression and logistic regression. Polynomial regression fits polynomial curves (rather than a straight line) to data in which the relationship between the input variable and output variable is modelled in some nth degree polynomial of x. Similar to the linear regression algorithms, machine learning algorithms with polynomial functions train data by minimizing the least squares error usually according to the OLS criterion. Both polynomial regression and linear regression are types of multivariate regression analyses aimed at modelling data with continuous output values (Shanthamallu et al. 2017).

For discrete outputs, supervised machine learning algorithms can use classification approach, another form of supervised learning, to train data. One approach for classification machine learning algorithms is the logistic regression. Logistic regression is a statistical method for modelling binomial outputs. Though the input variable can have multiple features (or variables), the output can assume only 0 or 1 which is used to perform binary classification of positive from negative classes. In logistic regression algorithms, sigmoid curves are fitted to training data to output probability value used to perform the classification. In situations where multiclass classification is required, one-vs-all logistic regression can be used for machine learning algorithms.

Machine learning algorithms using various regression methods have been extensively used in the healthcare literature. For example, logistic regression learning has been used to investigate the early discovery and recognition of Glaucoma in ocular thermographs (Harshvardhan et al. 2016); predict persistent depressive symptoms in older adults (Hatton et al. 2019) and predict emergency room visits based on EHR data (Qiao et al. 2018). Also, polynomial machine learning regression algorithm have been used for example to build models for non-invasive glucose measurements (Jain et al. 2020), predict metabolic and immunological alterations linked to type-2 diabetes (Stolfi et al. 2019) and predict voxel-wise prostate cell density for tissue classification, treatment response assessment and customized radiotherapy (Sun et al. 2018).

Another approach for machine learning algorithms to learn their training data is by the use of decision trees. Decision trees can be used as predictive models whereby the input observable data make up the branches and the output data are represented in the leaves. One of the commonly used types of Decision tree-based machine learning methods is the Classification and Regression Trees (CART). In machine learning algorithms where the output data (variable) can be discrete in value, the tree models are called classification trees. When the output variables are continuous (e.g. real numbers) the decision models are called regression trees. Other Decision tree-based machine learning methods are Random Forest (RF), Logistic Model Trees (LMT), and Best First Decision Trees (BFDT) (Pham et al. 2017). The RF method is an extension of the CART tree which comprises of many trees where bootstrap samples are used to generate each tree (Rahmati et al. 2016). The LMT is a type of classification tree which comprises of logistic regression and decision tree learning algorithms to train sample data (Landwehr et al. 2005). The BFDT is a decision tree-based method where the tree is built in the best-first order as opposed to fixed order (Shi 2007).

3.4.5 Model Evaluation

Using CPOE, TRV, ECD and CDS as predictor variables, we evaluated the predictability of LOS and CDC using several supervised regression learning algorithms (both linear and nonlinear models). These algorithms were suitable for modelling because our predicted variables, LOS and CDC, were continuous in nature. We evaluated the performance of the algorithms using their Mean Absolute error (MAE), Mean Squared

Error (MSE) and root mean squared error (RMSE) measures. Based on the training of 1512 sample hospital data we observed that among the algorithms used, three non-linear models (Fast Tree (FT), Fast Forest (FF). Fast Tree Tweedie (FTT) and Generalized Additive Model (GAM) had the best performance for predicting LOS. Also, these models were suitable for our study because they can analyze different types of input variables without a need for defining preliminary assumptions, like normality, prior to use (Garosi et al. 2019). We describe below our selected learning algorithms.

3.4.5.1 Fast Forest (FF) Regressor

Fast Forest regressors are useful for predicting non-parametric distributions and can be used to rank the importance of different variables in a regression model (Boulesteix et al. 2012). They are built to handle large data at high speeds and improved memory usage. Using bootstrap draws, forest-based learning algorithms combine several regression trees into an ensemble at training time and output the mean regression of the individual trees which tend to be more accurate (Zahid et al. 2020). This method of regression learning helps to prevent the risk of "overfitting" training data with tree models. Overfitting is where the analysis produced by the learning algorithm corresponds too closely or exactly as the training set. This will not allow the model to fit (predict) data outside the sample trained (Hastie et al. 2017).

3.4.5.2 Fast Tree (FT) Regressor

Fast Tree learning algorithms train decision trees to fit target outputs based on least-square estimates. Fast Tree regressors work well with large data sets and build decision trees as fast as possible without a significant decrease in accuracy or using up more than essential memory (Purdila and Pentuic 2014). Regression Tree models, such as the Fast Tree Regressor, are suitable for measuring patient length of Stay (LOS) and cost of patient care (CPC) because they are appropriate for measuring variables whose output is expected to take continuous values (usually real numbers). Decision tree algorithms are useful for learning human decisions and behavior due to how closely they mirror human decision making (James et al. 2013). They are also robust against co-linearity, a non-zero correlation between predictor variables. Co-linearity in machine learning algorithms can result in over-fitting and model instability (Yoshida et al. 2017).

3.4.5.3 Fast Tree Tweedie (FTT)

Fast Tree Tweedie (FTT) ML algorithms utilizes the Tweedie loss function to train decision tree regression models. Tweedie loss function is especially useful for right-skewed data with long tails. Tweedie distribution is a type of exponential dispersion model (EDM) which defines the power relationship between distribution mean (μ) and variance. If the power and dispersion parameters are defined as p and ϕ respectively, the Tweedie distribution depicts the following relationship:

$$Var(x) = \phi\mu^p$$

From the above relationship, it follows that when distribution mean (μ) is used as an estimator for prediction, Tweedie loss function is defined as

$$\mathcal{L} = -\sum_i x_i \cdot \frac{\tilde{x}_i^{\,1-p}}{1-p} + \frac{\tilde{x}_i^{\,2-p}}{2-p}$$

Where x_i is the actual target value and $\tilde{x}_i$ is the predicted target for the data point i (Shi 2020).

3.4.5.4 Generalized Additive Model (GAM) Regressor

Generalized Additive Model (GAM) learning algorithms are used to train data by relating a univariate output variable to input variables through some smooth function of unspecified form (Wood et al. 2016). Originally developed by Hastie and Tibshirani (1990) GAM is a statistical model which combines the properties of generalized linear models (GLM) and additive models. This allows GAM to combine linear and nonlinear smoothing functions to learn the relationship between predictive and output variables for a better fit. The model can be defined as:

$$g(\mathrm{E}(Y)) = \beta_0 + f_1(x_1) + f_2(x_2) + \cdots + f_m(x_m)$$

Where E(Y) is an aggregate of dataset behavior, g(.) is a link function and fi(xi) is a term for each dataset instance feature x1, …,xm (Frankowski 2019). Unlike many other machine learning algorithms, the output of GAM learning algorithms is easily interpretable, though they can fit complex nonlinear functions (Petschko et al. 2014).

3.5 Experiments and Results

All experiments were performed using Jupyter Notebook 6.0.3 with .NET (C#) programming tools. We detail in the sections below our analyses and results.

3.5.1 Predicting Patients' Length of Stay (LOS)

Below is a visualization of the training data for the predictive analysis. The adjusted LOS has a normal distribution ranging from 0 to 6 days. Most of the cases were between 2 to 3 days. A few outliers of about 15 days were observed in the box plot below.

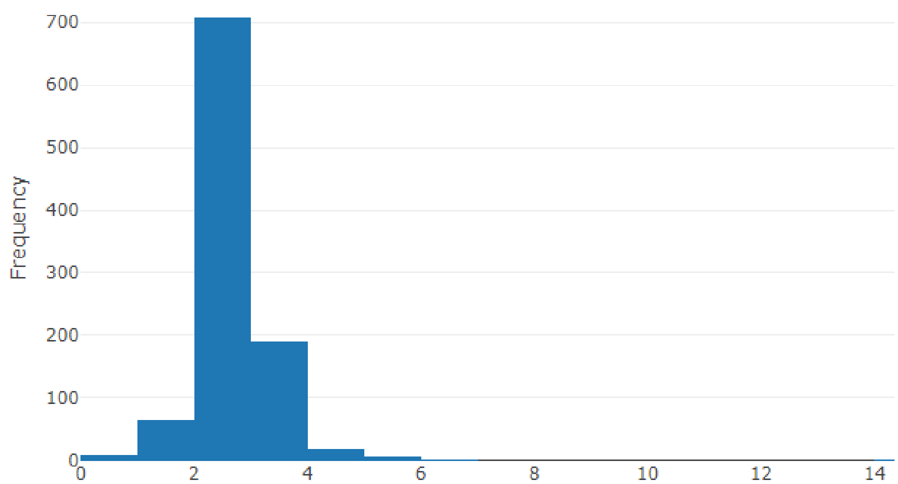

Figure 5. A Visualization of the Distribution of Adjusted Length of Stay

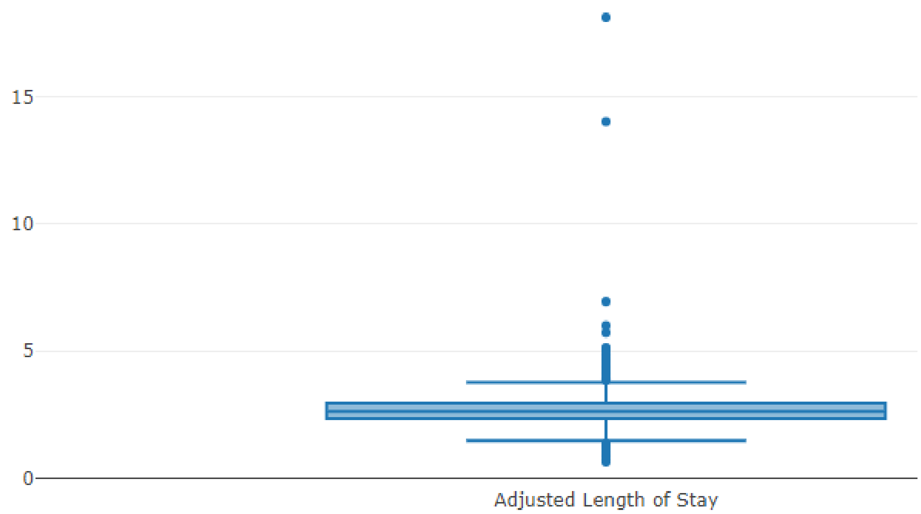

Figure 6. A Visualization of the Quartiles of Adjusted Length of Stay

3.5.1.1 Models Evaluation for LOS Prediction

Summarized in the table below are the performance metrics for data trained with Fast Tree, Fast Tree Tweedie, Fast Forest, and Generalized additive model (GAM). In Table 9 below, we compare our chosen algorithms using their Mean Absolute error (MAE), Mean Squared Error (MSE) and root mean squared error (RMSE) measures Based on the RMSE values, it was observed that Fast Forest algorithm gave the best performance for predicting LOS when all HIT functionalities are used. The visualization of how the predicted values compare to the actual test values are shown in the graphs below.

Table 9. Performance Metrics for LOS Prediction Using All Functionalities

	Fast Tree	Fast Tree Tweedie	Fast Forest	GAM
Mean Absolute Error	0.56	0.52	0.42	0.48
Means Squared Error	1.06	0.78	0.4	0.52
Root Mean Squared Error	1.03	0.88	0.63	0.72
Loss Function	1.06	0.78	0.4	0.52

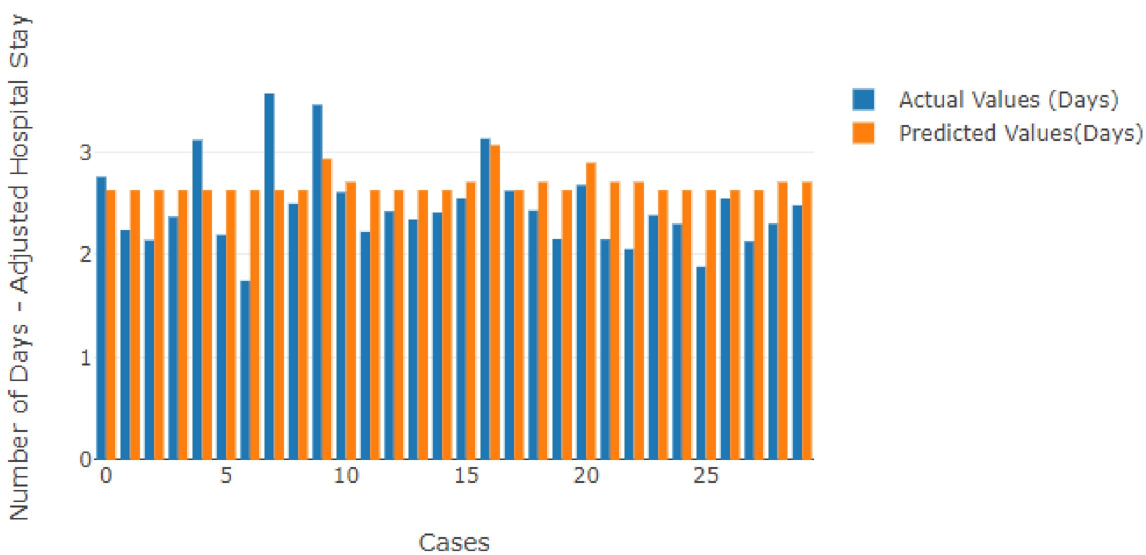

Figure 7. A Visualization of Actual LOS Compared to Predicted Values with Fast Forest

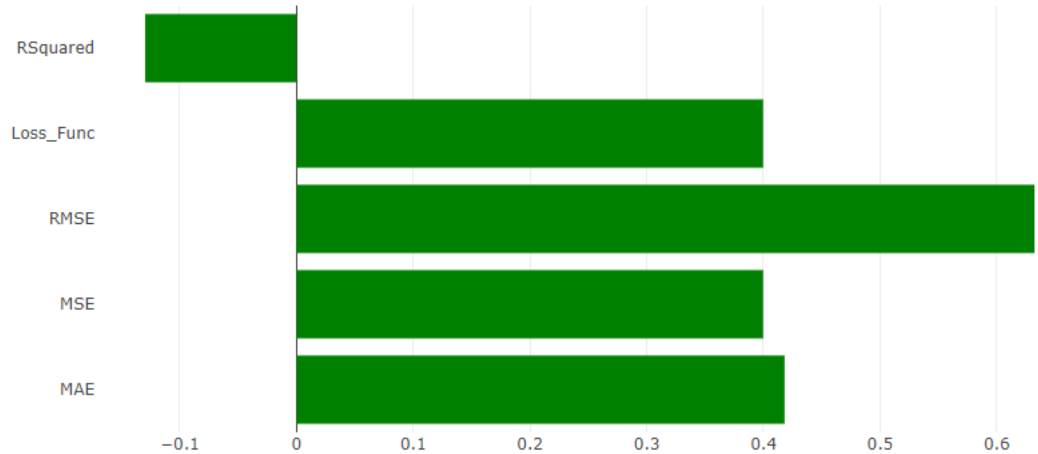

Figure 8. Quality Metrics of Fast Forest Algorithm to Predict LOS

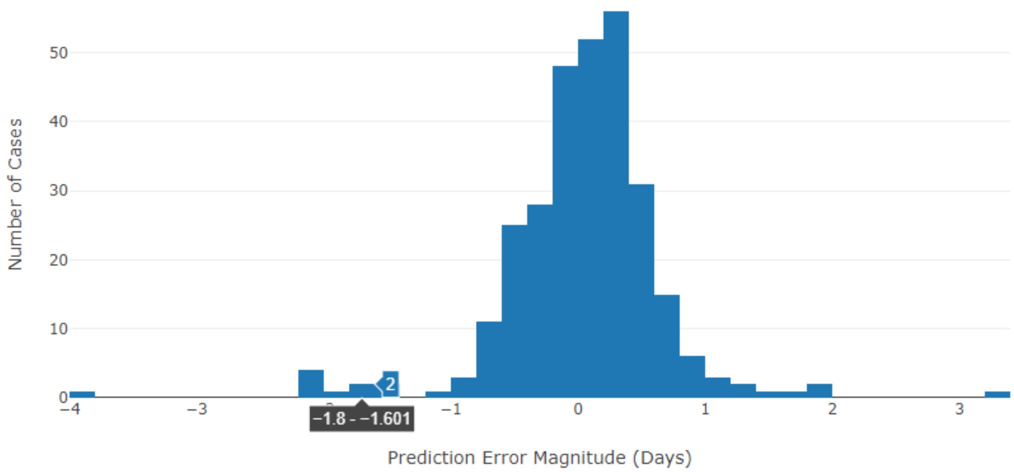

Figure 9. Visualization of the Distribution of Prediction Error Magnitude for LOS

3.5.1.2 Functionalities Selection for LOS Prediction

Using the best algorithms, Fast Forest and GAM, further predictive analyses were carried out with individual functionalities while holding all others constant. For both Fast Forest and GAM, the Test Results Viewing (TRV) functionalities gave the best prediction for LOS.

Table 10. Performance Metrics for LOS Prediction Using Individual Functionalities (Fast Forest)

Fast Forest	ECD	TRV	CPOE	CDS	TELE
Mean Absolute Error	0.43	0.41	0.42	0.42	0.53
Means Squared Error	0.4	0.37	0.4	0.4	0.55
Root Mean Squared Error	0.64	0.61	0.63	0.63	0.74
Loss Function	0.4	0.37	0.4	0.4	0.55

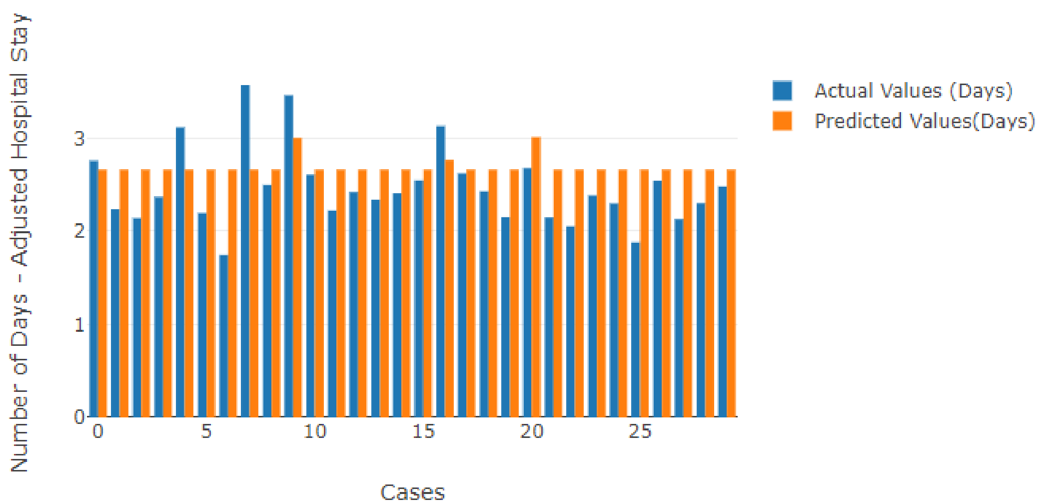

Figure 10. Actual LOS vs Predicted Values with TRV Using Fast Forest

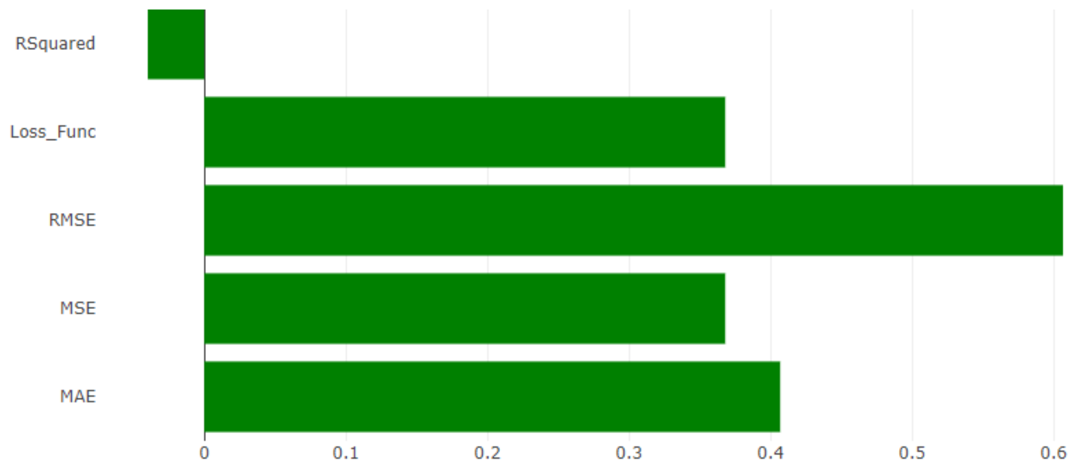

Figure 11. Quality Metrics of Fast Forest Algorithm to Predict LOS with TRV

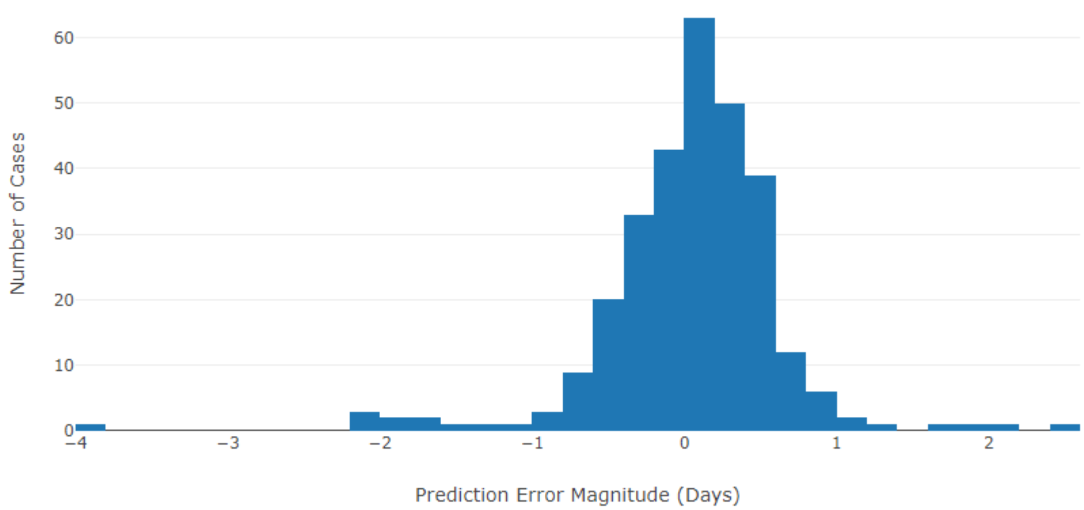

Figure 12. Distribution of Error Magnitude for LOS Predicted with TRV Using Fast Forest

As shown in Table 11. below, predicting LOS with TRV gave the best performance when using GAM algorithm. This performance was similar to that of LOS prediction using Fast Forest algorithm.

Table 11. Performance Metrics for LOS Prediction with Isolated Functionalities (GAM)

GAM	ECD	TRV	CPOE	CDS	TELE
Mean Absolute Error	0.44	0.44	0.45	0.46	0.44
Means Squared Error	0.39	0.39	0.43	0.46	0.39
Root Mean Squared Error	0.63	0.62	0.66	0.68	0.62
Loss Function	0.39	0.39	0.43	0.46	0.39

Following our analyses of the relative predictability of LOS based on individual functionalities, we further studied the performance of various HIT functionalities ensembles. As detailed in Table 12 below, it was observed that among the various ensembles tested, none of them performed better than Test Results Viewing (TRV) used alone. In fact, when bundled with the other functionalities in our study, the error margin between the predicted values of LOS and the actual widened.

Table 12. Performance of Bundled HIT Functionalities to Predict LOS with Fast Forest

Fast Forest Ensemble Selection for LOS	Mean Absolute Error	Means Squared Error	Root Mean Squared Error	Loss Function
TRV	0.406	0.368	0.607	0.368
TRV+ CDS	0.417	0.403	0.635	0.403
TRV + ECD	0.420	0.382	0.618	0.382
TRV + CPOE	0.420	0.399	0.631	0.399
TRV + ECD +CPOE	0.422	0.401	0.633	0.401
TRV + CPOE + TELE	0.426	0.405	0.637	0.406
TRV + TELE	0.447	0.411	0.641	0.411
TRV+ CDS + ECD	0.416	0.405	0.636	0.405
TRV + ECD + CPOE + CDS + TELE	0.418	0.4	0.632	0.4

3.5.2 Predicting Cost of Patient Care (CPC)

In Figure 13 below is a visualization of the distribution of the training data used to predict cost of patient care (CPC). It is observed that the log of the adjusted CPC had a normal distribution.

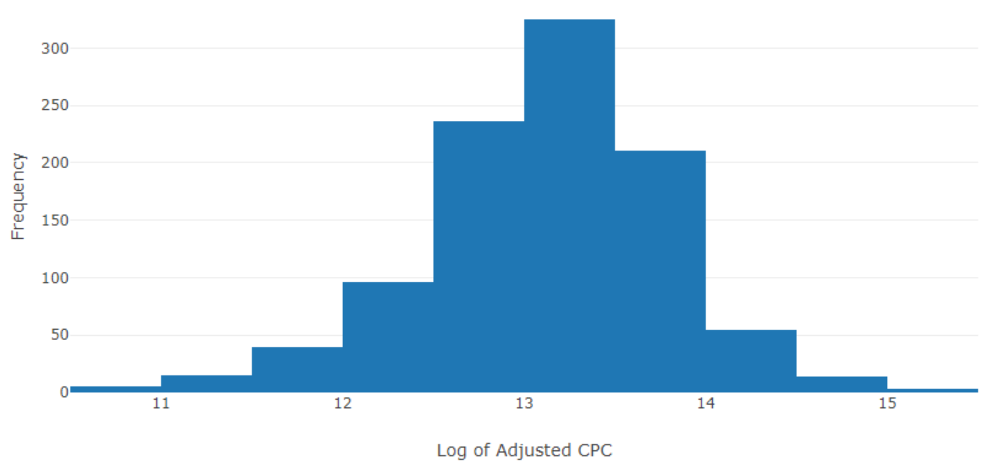

Figure 13. A Visualization of the Distribution of Adjusted Cost of Patient Care (CPC)

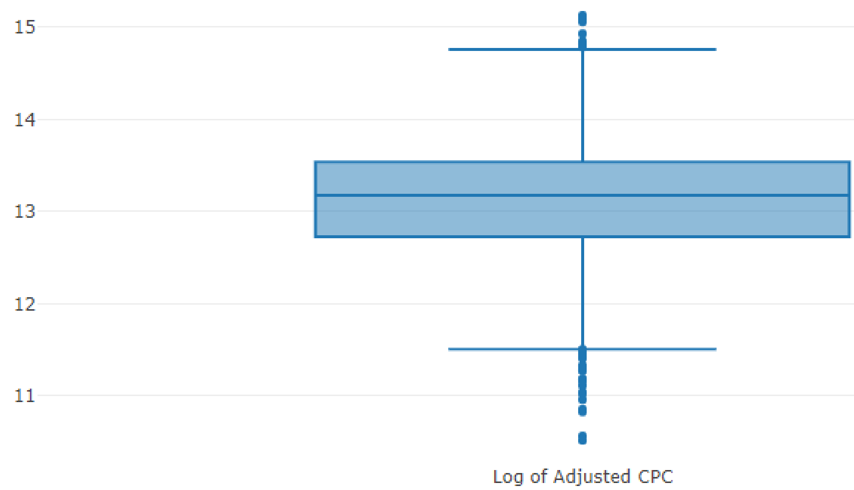

Figure 14. A Visualization of the Quartiles of Log of Adjusted Cost of Patient Care (CPC)

3.5.2.1 Models Evaluation for CPC Prediction

Summarized in Table 13 below are the performance metrics for data trained with Fast Tree, Fast Tree Tweedie, Fast Forest and Generalized additive model (GAM). Based on the RMSE values, it was observed that the Fast Forest algorithm gave the best performance for predicting CPC when all HIT functionalities are used. The visualization of how predicted values compare to the actual test values are shown in the graphs below.

Table 13. Performance Metrics for CPC Prediction Using All Functionalities

	Fast Tree	**Fast Tree Tweedie**	**Fast Forest**	**GAM**
Mean Absolute Error	0.54	0.55	0.51	0.52
Means Squared Error	0.47	0.47	0.43	0.44
Root Mean Squared Error	0.68	0.69	0.66	0.66
Loss Function	0.47	0.47	0.43	0.44

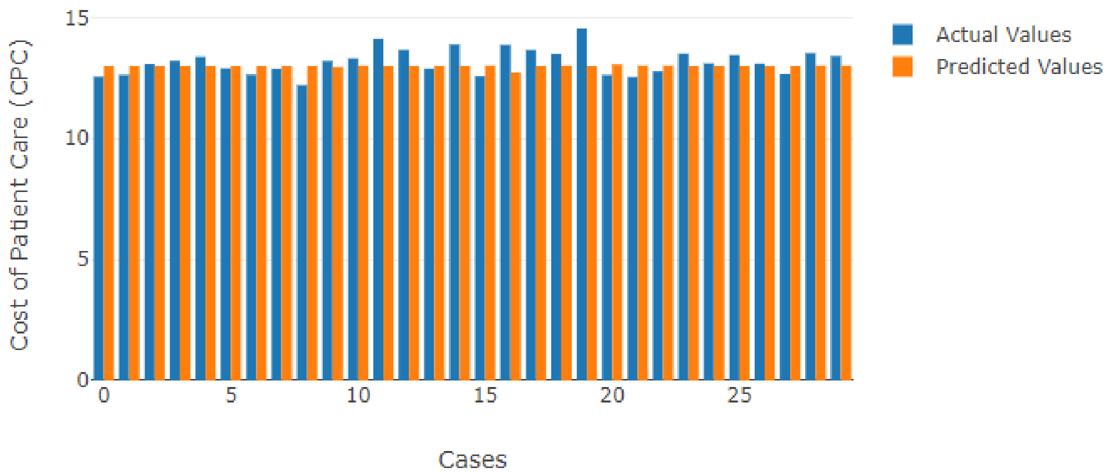

Figure 15. A Visualization of Log of Adjusted CPC Compared to Predicted Values with Fast Forest

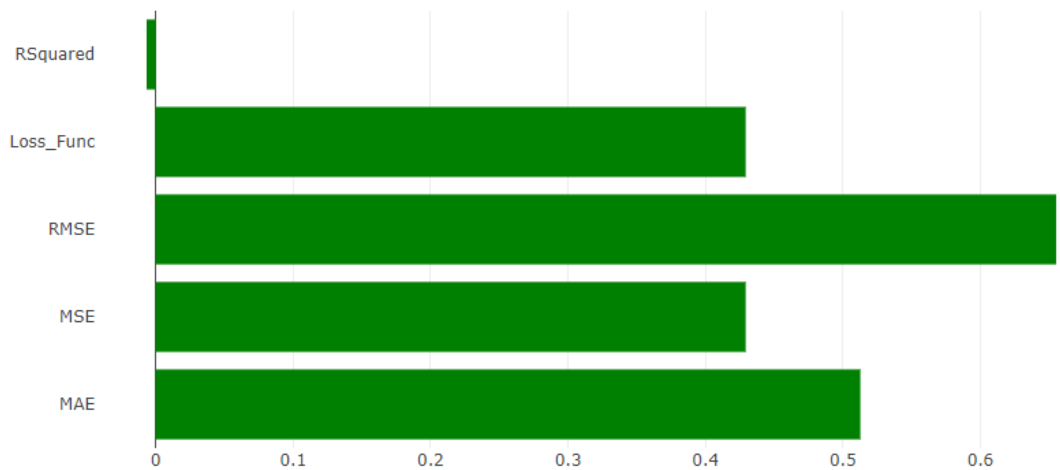

Figure 16. Quality Metrics of Fast Forest Algorithm to Predict CPC

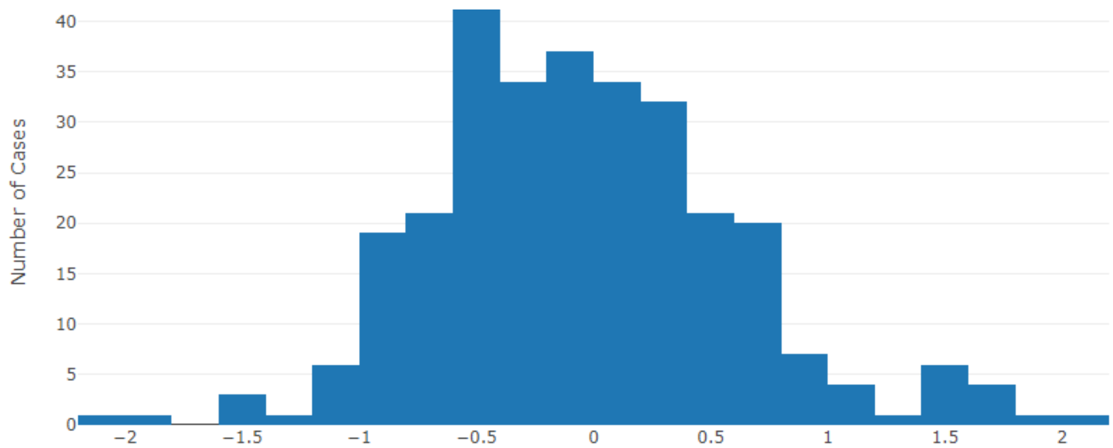

Figure 17. Visualization of the Distribution of Prediction Error Magnitude for CPC

3.5.2.2 Functionalities Selection for CPC Prediction

Using Fast Forest and GAM, further predictive analyses were carried out with individual functionalities while holding all others constant. For both Fast Forest (Table 14) and GAM (Table 15), the Computerized Decision Support (CDS) functionalities gave the best prediction for the cost of patient care (CPC).

Table 14. Predicting CPC with Specific Functionalities While Others Remain Constant (Fast Forest)

Fast Forest	**ECD**	**TRV**	**CPOE**	**CDS**	**TELE**
Mean Absolute Error	0.51	0.51	0.52	0.51	0.51
Means Squared Error	0.43	0.43	0.43	0.42	0.43
Root Mean Squared Error	0.65	0.65	0.66	0.65	0.65
Loss Function	0.43	0.43	0.43	0.42	0.43

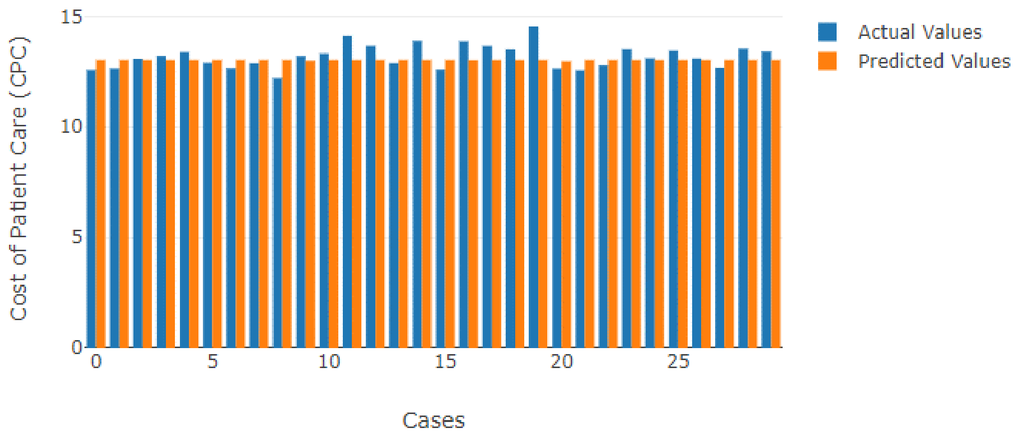

Figure 18. Log Adjusted CPC Vs Predicted Values with CDS Using Fast Forest

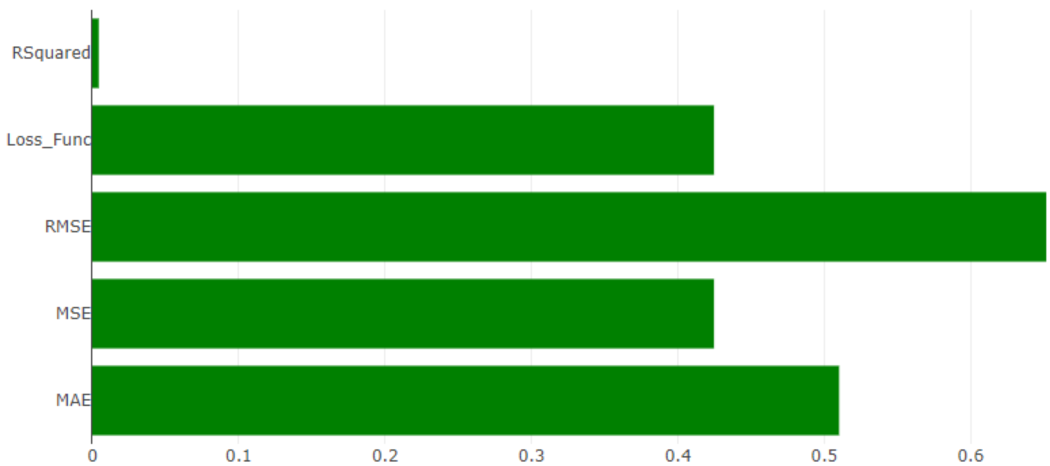

Figure 19. Quality Metrics of Fast Forest Algorithm to Predict CPC with CDS

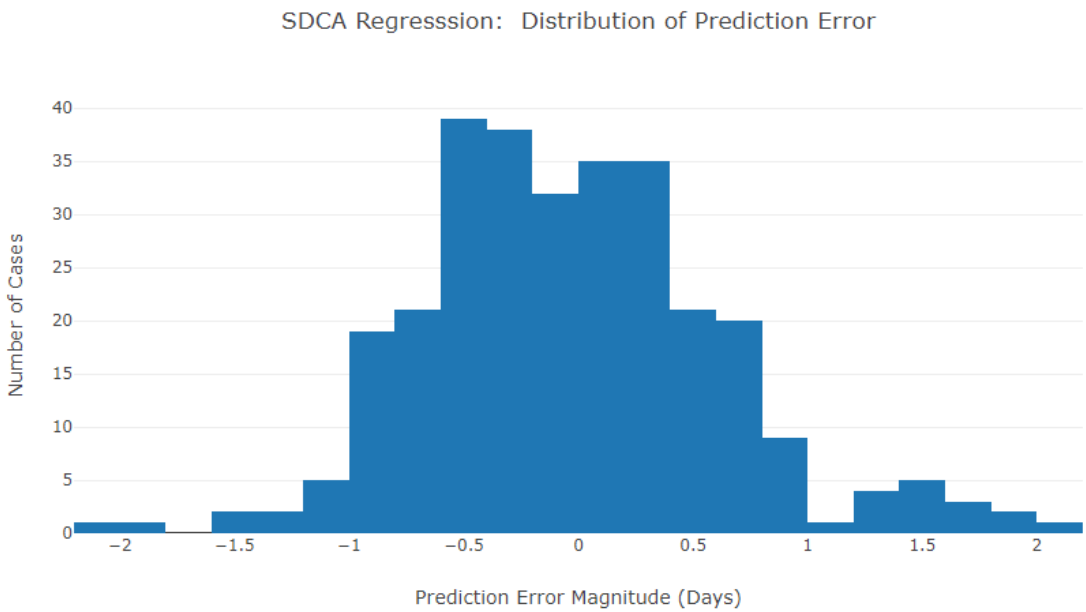

Figure 20. Distribution of Error Magnitude for CDC with CDS using Fast Forest

As summarized in Table 15 below, the validation test using GAM algorithms further determined CDS to best predict hospitals' CPC performance among the HIT functionalities in our study.

Table 15. Predicting the CPC with Specific Functionalities while Others Remain Constant with GAM

GAM	ECD	TRV	CPOE	CDS	TELE
Mean Absolute Error	0.51	0.52	0.52	0.51	0.51
Means Squared Error	0.43	0.43	0.43	0.42	0.43
Root Mean Squared Error	0.65	0.66	0.66	0.65	0.66
Loss Function	0.43	0.43	0.43	0.42	0.43

An evaluation of the predictability of CPC with various HIT functionalities ensembles showed that, CDS when bundled with ECD, TRV and Telemedicine had the least RMSE (See Table 16 below). This observation contrasted that for LOS whereby TRV when used alone gave the best prediction of hospitals' performance.

Table 16. Performance of Bundled HIT Functionalities to Predict CPC with Fast Forest ML

Fast Forest Ensemble Selection for CPC	Mean Absolute Error	Means Squared Error	Root Mean Squared Error	Loss Function
CDS	0.510	0.425	0.652	0.425
CDS + ECD	0.510	0.424	0.652	0.424
CDS + ECD + TRV	0.510	0.424	0.652	0.425
CDS + ECD + TRV + CPOE	0.511	0.428	0.654	0.428
CDS + ECD + CPOE	0.512	0.428	0.654	0.428
CDS + ECD + TRV + TELE	0.510	0.424	0.651	0.424
CDS + ECD + TELE	0.510	0.425	0.652	0.425
CDS + ECD + CPOE + TRV + TELE	0.513	0.429	0.655	0.429

3.6 Discussion

In this study, we propose a Machine Learning (ML) decision support system (DSS) which can predict the performance of a hospital based on its use of specific Health IT functionalities. Such DSS is valuable to help hospitals in prioritizing and selecting the most relevant functionalities, which can significantly predict their future performance. As a result, better decisions could be made when hospitals had to choose among HIT functionalities options to support their healthcare services. The main contributions of this study are three-fold. First, we explore which machine learning (ML) algorithms can give a better prediction of a hospital's performance as measured by their length of stay (LOS) and cost of patient care (CPC). Typically, a ML algorithm fits a dataset based on the complexity of the dataset. Hence given the HIT dataset, we explore the ML algorithms which have better predictive performance than others.

Second, we explore which HIT functionalities are better predictors of hospitals' performance with respect to their LOS and CPC. This has managerial implications whereby; hospital management can make informed decisions about selecting specific functionalities to use based on how well these can predict high performance. Finally, we explore the bundles (groupings) of HIT functionalities which give a better prediction of hospital performance. Some studies (Karahanna et al. 2019; Sharma et al. 2016) suggest HIT affects performance not as a standalone system but as a combination of technologies and their shared complementarity. Hence, the ability of our proposed DSS to determine such combinations of HIT functionalities for predicting hospital performance will be of value to management.

3.6.1 Predictability of Hospital Performance Based on HIT Functionalities Use

Based on the principles of Information Processing Theory (IPT), we argue that various forms of uncertainties regarding clinical information processing (e.g., errors and missing information) can be resolved by use of HIT functionalities leading to improved performance. We further argue by the Task Technology Fit (TTF) that to attain performance improvement, there must be an alignment between the HIT functionalities and the relevant clinical tasks. We therefore proposed that by using computerized provider order entry (CPOE); Clinical Decision Support (CDS); Test Results Viewing (TRV); Electronic Clinical Documentation (ECD) and Telemedicine functionalities, hospitals could predict their performance as measured by their length of stay (LOS) and cost of patient care (CPC). The results of our proposed ML DSS models support these arguments whereby the predicted values were consistently similar to the observed values for hospitals' LOS and CPC.

Evaluating the performance of our models by the RMSE values, example recorded values of 0.88 (Fast Tree Tweedie), 0.63 (Fast Forest) and 0.72 (Generalized Additive Model) show a high-performance ability of our ML models to predict the LOS performance of hospitals based on the use of HIT functionalities. These measures were based on the concurrent use of all the HIT functionalities; CPOE, ECD, TRV, CDS, and Telemedicine. A similar analysis to predict CPC showed similar predictive performance of our proposed ML DSS model with RMSEs of 0.69 (Fast Tree Tweedie), 0.66 (Fast Forest), and 0.66 (Generalized Additive Model). These results suggest that, by using the five HIT functionalities, hospitals can expect shorter lengths of stay as well as low cost of patient care. This is in line with the theory of IPT. For example, by using CPOE to directly input orders (e.g., for medication and laboratory tests) and transmit of such essential requests, the uncertainty associated with data entry errors can be reduced. This will in turn prevent a need for rework and delays leading to improved LOS and CPC. This further suggests that the HIT functionalities are suitable for the clinical tasks at hand. In line with the TTF theory, if the functionalities such as the Clinical Decision

Support (CDS) systems are suitably built to address the kind of challenges clinicians may face when making decisions, hospitals can expect improvement in their performance when the HIT is used.

Comparing the relative performance of the ML algorithms for our proposed DSS model, it is observed that the Fast Forest is best for predicting both LOS (MSE= 0.40) and CPC (MSE= 0.43). Though the performance metrics of all the algorithms used in the study were close in measurement, Fast Forest consistently yielded the lowest mean difference between predicted values and observed hospital measures. This suggests that, for our proposed DSS and future models based on similar data, Fast Forest is a good ML algorithm option. This algorithm is able to fit well to hospital performance and HIT use data and effectively model future trends. This has managerial implications for hospitals that look to predict their performance based on ML models. Based on our study results, managers can make an informed choice about the type of ML algorithm that will fit their type of data well for good predictions.

3.6.2 HIT Functionalities Selection

When choosing HIT functionalities, hospitals must decide on the best options based on their ability to yield desired performance outcomes. The Information Processing Theory (IPT) suggests that, to resolve the type and degree of information uncertainty they typically deal with, hospitals must choose the right functionalities (Gattiker and Goodhue 2003). Based on the Task-Technology Fit (TTF) we argue that by effectively matching their HIT functionalities with the right tasks, hospitals can attain improved performance as measured by their LOS and CPC (Howard and Rose 2019). Researchers further argue that, the performance of hospitals are best determined by HIT functionalities when bundled with others instead individually used.

Our analyses showed that, while Test Results Viewing (TRV) functionalities best predicted LOS, Clinical Decision Support (CDS) was best for predicting CPC. For these analyses, we used the Fast Forest algorithm and then used Generalized Additive Model (GAM) algorithms for validation. In line with the tenets of IPT and TTF, the TRV by facilitating timely and comprehensive preview of test results (Callen et al. 2012) is the best predictor of LOS among the HIT functionalities in our study. Additionally, resolving the delays and uncertainties associated with physical test results view and sharing (information processing), TRVs when used by hospitals can be a major predictor of their LOS performance. This further suggests that TRV functionalities fit hospitals' test information processing activities well to enhance efficiency (Dutra et al. 2018).

Similarly, by mitigating the risk of prescription errors (Vazin et al. 2014) and the need for corrections, Clinical Decision Support (CDS) systems can be good predictors of hospitals' Cost of Patient Care (CPC) performance. Our findings align with the principles of the Information Processing Theory (IPT) because, TRV functionalities are designed to resolve the uncertainty (and risk) of duplicate treatments by giving clinicians reminders about the status of patients' care (Zimmerman et al. 2019). TRV functionalities therefore reduce the occurrence of errors and complication rates (Chen Jian et al. 2019). This enhances the efficiency of clinical decision-making processes and helps to reduce the cost of patient care. Hence, TRV functionalities by aligning well with the decision-making tasks of Clinicians enhance the performance of hospitals' CPC as stated by the theory of TTF.

Our results further showed that while CDS predicted CPC best when bundled with ECD, TRV and Telemedicine, TRV predicted LOS best when used alone. A better predictability of CPC by ensembles of HIT functionalities than CDS alone supports research which suggests that bundling HIT functionalities enhance hospital performance better than their isolated use (Karahanna et al. 2019; Sharma et al. 2016). However, the opposite is observed for the predictability of LOS. A possible explanation for the superior prediction of LOS by the isolated use of TRV is the unintended increase in time spent by clinicians on updating information on computer systems with HIT functionalities (Romanow et al. 2017). Hence, while TRV use can speed up the care process to reduce LOS, adding up other functionalities may increase the process time and resultant LOS.

On the other hand, the complementarity of using other functionalities with CDS further enhanced the predictability of cost performance. The possible reason for this is that the cost of patient care is an aggregate of many factors in the care process. These factors include cost reduction due to error reduction (e.g., from CDS), faster care process (e.g., from ECD), operational cost reduction (e.g., from telemedicine). Hence using a bundle of HIT functionalities and the complementarity among them could collectively predict the performance of hospitals' CPC better than the isolated use of specific ones like CDS.

3.7 Conclusion

In the US healthcare industry, the widespread adoption and use of HIT functionalities to boost hospitals' performance is a key issue (Adjerid et al. 2018; Agha 2014). Due to the Medicare and Medicaid Electronic Health Record (EHR) Incentive Program, hospitals are expected to attain meaningful use (MU) by utilizing HIT functionalities to improve quality of healthcare delivery and decrease cost of patient care. Under this context, the use of a decision support system (DSS) based on a data-driven model to predict the performance of hospitals based on the use of HIT functionalities is a valuable tool for managers. In this study, we propose such a decision support system using a machine learning (ML) approach for selecting HIT functionalities and ensembles. Our results further show the ML algorithms which fit HIT data well and give the best performance for predicting hospitals' performance as measured by the length of stay (LOS) and cost of patient care (CPC).

CHAPTER IV

AN ASSESSMENT OF THE EFFECT OF HOSPITAL HETEROGENEITY ON HOSPITAL PERFORMANCE PREDICTION

4.1 Introduction

In the US healthcare system, there exists substantial variations in the characteristics of hospitals. Research suggests that hospital heterogeneity can significantly affect healthcare performance (Lobo et al. 2020). Hospital heterogeneity can be defined as the variation in the hospital population characteristics that can impact or modify the magnitude of the treatment effect (Biasutti et al. 2020; West et al. 2010). In study 2 we proposed and tested a smart decision- support system which is aimed at predicting the performance of hospitals based on the HIT functionalities used. As a follow-up study, we investigate in this essay the potential moderator effects of the heterogeneity of hospitals on the accuracy of the performance of our proposed smart DSS. Our unit of analysis is a US hospital.

The literature on the relationship between hospital heterogeneity and performance is vast (Ali et al. 2018; Lobo et al. 2020; Roh et al. 2013). While hospitals which adopt HIT functionalities are expected to perform better than those who have not adopted such functionalities (Bojja and Liu 2020), the predictability of such performance is not clear in the literature and has remained under-studied. Moreover, limited studies have discussed hospital heterogeneity in the context of HIT functionalities use and their integration. This limits the ability of hospital management in deciding on the right HIT functionalities for them to adopt and use based on their characteristics. The decision support for such adoption decisions is especially important for hospitals with limited budget and looking to prioritise specific functionalities to achieve performance in areas such as reduced length of stay (LOS) for patients and cost of patients' care (CPC). Our previous study (Essay 2) was aimed at filling this gap. By investigating the impact of various sources of hospital variation (heterogeneity) on the accuracy of predictive performance of our smart decision support system, hospitals can be better informed about the implications of their specific characteristics on making such performance predictions and corresponding HIT functionalities and related adoption decisions.

The Task Technology Fit (TTF) theory states that the alignment between technology functionalities and the requirements of a task can improve the performance of an organization (e.g., Goodhue and Thompson 1995; Howard and Rose 2019). Using the tenets of this theory in essay 2, we established the predictability of hospital performance based on the Health Information Technology (IT) they use. We found that Fast Forest machine learning (ML) algorithm had the best performance for predicting hospital performance based on the type of data used from AHA IT and RAND databases. We therefore utilize the Fast Forest ML algorithm in this study for our analysis.

4.2 Related Literature

In this section, we review the literature on hospital heterogeneity and performance. While hospitals can be characterized in different ways, we review the literature on the most predominantly discussed sources of variation. Many studies include hospital size as an internal factor which affects the performance of the hospital (Ali et al.

2018; Kolstad and Kowalski 2012; Roh et al. 2013). Typically, the size of a hospital is measured by the number of staffed beds (Adler-Milstein et al. 2014; Karahanna et al. 2019). The existing literature on the relationship between hospital size and performance has mixed conclusions. While some studies find that increasing hospital size leads to improved hospital performance, other studies argue that, increasing the size of hospitals could negatively affect their performance. For example, Rahimisadegh et al. (2021) observed that, with the use of health IT the average length of stay (LOS) of hospitals significantly increased when the number of beds increased. They found that the LOS of hospitals with 400-600 beds were nearly 3 times higher than those with 32 beds.

A study by Azevedo and Mateus (2014) showed that some hospitals could be too small or too large to benefit from economies of scale and the optimal hospital size is about 230 beds. This is in line with an earlier study by Kristensen et al. (2008) which found the optimal size for acute care hospitals to range from 200 to 400. On the other hand, Preyra and Pink (2006) found that hospitals with 180 beds performed better than those with more and less beds. Similarly, Roh et al. (2013) found medium hospitals (126-250 beds) in the US had significantly higher performance than their counterparts. These findings show the inconclusive empirical results of research on the impact of hospital size on performance.

In extant research, ownership is one of the most widely discussed characteristics of hospitals which is used to classify them. In their research, Herrera et al. (2014) found no clear differences in performance among public, private not-for-profit, and private for-profit hospitals. Other studies found the performance of public hospitals to be at least as efficient or better than private hospitals (Kruse et al. 2018). Burgess and Wilson (1996) further concluded that it is not easy to prove that one type of hospital ownership has a universally superior impact on performance. They classified US hospital ownership into four categories: private non-profit, private for-profit, federal government as well as state and local government hospitals. However, Chang et al. (2004) found that public hospitals have better performance than private hospitals in Taiwan. Similarly, research on German hospitals found public types to significantly perform better than their private for profit and non-profit types (Tiemann et al. 2012; Tiemann and Schreyögg 2009). In contrast, Guerrini et al. 2018 observed that public regional hospitals in Italy had significantlybetter productivity and cost savings than private hospitals. Also, some studies suggest that non-profit private hospitals have higher operational performance than their for profit counterparts (Hollingsworth 2008; Kao et al. 2021).

In addition to the size and ownership of hospitals, their geographic regions have been identified as a factor in determining their performance (Kao et al. 2021). Most studies stratify US Hospital data by four regions; Northeast vs. Midwest vs. West vs. South (Kolstad and Kowalski 2012). Trends in hospital performance in the contexts of mortality, length of stay, cost and discharge disposition across various regions were studied by (Akintoye et al. 2017). They found that there was significant regional variation in performance for all measures. For example, the in-hospital mortality was highest for Northeast hospitals and lowest for Midwest hospitals. Also, Northeast hospitals on average have the longest LOS and the lowest risk of routine home discharge. In terms of cost of patient care (CPC), hospital performance was highest in the west and lowest in the

South. The researchers concluded that compared to other regions in the US, Northeast hospitals performed worst over all in performance. O'Loughlin and Wilson (2021) further observed that hospitals in the Midwest and South on average out-performaed those in the Northeast and West in terms of efficiency and productivity. However, The Leapfrog Group 2018 reported that Northeast and Midwest regions are not significant predictors of hospital care performance.

The empirical results of the impact of a hospital's location (rural/urban) on their performance are inconclusive. Some prior studies suggest that rural hospitals perform significantly better than their urban counterparts in healthcare quality performance but worse in the cost of care (Holmes et al. 2017). On the other hand, Akintoye et al. 2017 found that the performance as measured in mortality rate in rural locations are significantly higher than in urban locations. Some studies further suggest that urban teaching hospitals tend to be more efficient and have higher performance than the non-teaching types due to the higher expertise of staff that they are typically able to attract (Mujasi et al. 2016; Nayar et al. 2013). Other studies argue that teaching hospitals tend to have lower performance than non-teaching hospitals especially in the context of long stays. This could lead to the under-utilization of hospital beds for other patients (Farzianpour et al. 2016; Liu et al. 2016). However, other studies suggest that the academic affiliation of hospitals are not significant predictors of their performance (The Leapfrog Group 2018).

The complexity of cases treated at hospitals is highly correlated with an internationally recognized index called the Case Mix Index (CMI) (Chang and Zhang

2019). To assess the predictability of hospitals' performance based on the use of HIT functionalities it is important to factor in their clinical complexity. These could impact the performance of the hospitals in various ways. For example, a study by Fuller et al. (2017) found that as a hospital's clinical complexity increased, its performance increased as well. Due to similar observations, some studies even use the CMI score as a proxy for hospitals' efficient performance (Tonboot et al. 2018). Contrary to the prevalent finding that CMI is positively correlated with hospital performance and efficiency, Lewis (2020) argued that both hospital size and CMI had a statistically negative impact on hospitals efficiency and cost performance.

From our review of the literature, we conclude that while the impact of hospital heterogeneity on performance is well discussed, limited studies have focused on their role in the predictability of performance in terms of length of stay (LOS) and cost of patient care (CPC). Moreover, limited studies have discussed hospital heterogeneity in the context of HIT functionalities use and integration. We aim to fill this gap. This study extends the literature to further explore how differences in hospital characteristics can affect the prediction of performance based on the use of health IT. We measure hospital performance by length of stay (LOS) and cost of patient care (CPC). Using machine learning methods, we investigate the possible moderator effects of hospital size, region, location (urban/rural), ownership and case complexity.

4.3 Data Analysis

In this study, we used hospital data (N= 1512) from the AHA survey (2018) and RAND (2018) to capture key hospital characteristics. The data from AHA survey was linked to that of RAND data using the Medicare provider number for each hospital. The sample data used from AHA survey consisted of acute care hospitals across the US hence critical access hospitals were not part of the study. We utilize Fast Forest (FF) machine learning algorithm to investigate the moderating effect of hospital heterogeneity on performance prediction. Using the stratification criteria of AHA and RAND, we categorized the data based on six key hospital characteristics (see Table 17). These were hospital size, Case Mix Index (CMI), ownership, region, and location (urban or rural). We further categorized the urban hospitals by their academic affiliation (teaching or non-teaching).

The hospital size ranges were Small (0-199 beds); Medium (200- 399 beds) and Large (≥400 beds). CMI was categorized as Low (0-1.5); Medium (>1.5-2) and High (>2). The data was also stratified by AHA into four regional clusters: Northeast; Midwest; South and West. The states and three-digit zip codes of the hospitals were implicit stratification variables included in the dataset. Finally, the hospitals were categorized based on their ownership as government, private for profit, and private not for profit. The predictive performance of our proposed decision support system (DSS) was assessed to determine the moderator effect of hospital heterogeneity on the prediction accuracy.

Table 17. Sample Characteristics

	Hospital Type	Frequency	Percent
Size	Small (0-199 beds)	782	51.7
	Medium (200- 399 beds)	437	28.9
	Large (≥400 beds)	293	19.4
Case Mix Index (CMI)	Low (0-1.5)	466	30.8
	Medium (>1.5-2)	845	55.9
	High (>2)	201	13.3
Owner/Control	Government	176	11.6
	Non-Profit	1077	71.2
	For profit	259	17.1
Region	Northeast	250	16.5
	Midwest	428	28.3
	South	628	41.5
	West	206	13.6
Rural/Urban Location	Rural	107	7.1
	Urban_Teach	665	44.0
	Urban_NonTeach	740	48.9

Table 18. Performance Metrics for LOS Prediction with Fast Forest

Fast Forest / LOS	**Type**	**MAE**	**MSE**	**RMSE**	**LF**
Full Sample	**All hospitals**	0.42	0.4	0.63	0.4
Size	Small	0.663	2.328	1.526	2.328
	Medium	0.306	0.153	0.391	0.153
	Large	0.268	0.104	0.322	0.104
CMI	low	0.608	0.619	0.787	0.619
	Medium	0.372	0.228	0.477	0.228
	High	0.480	0.383	0.619	0.383
Owner	Govt	0.428	0.294	0.542	0.294
	Non-Profit	0.479	0.973	0.986	0.973
	For-Profit	0.969	7.32	2.706	7.321
Region	Northeast	0.339	0.164	0.406	0.164
	Midwest	0.489	0.661	0.813	0.661
	South	0.578	2.619	1.618	2.619
	West	0.380	0.284	0.533	0.284
Rural/ Urban	Rural	0.16	1.101	1.049	1.101
	Urban_ Teaching	0.281	0.196	0.442	0.196
	Urban_ Non-Teaching	0.318	1.245	1.116	1.245

Table 19: Performance Metrics for LOS Prediction with GAM Algorithm

GAM /LOS	Type	MAE	MSE	RMSE	LF
Size	Small	0.71	2.94	1.72	2.94
	Medium	0.3	0.15	0.39	0.15
	Large	0.27	0.11	0.33	0.11
CMI	low	0.72	0.76	0.87	0.76
	Medium	0.37	0.23	0.48	0.23
	High	0.49	0.39	0.62	0.39
Owner	Govt	0.4	0.29	0.53	0.29
	Non-Profit	0.49	0.99	1	0.99
	For profit	1.11	8.42	2.9	8.42
Region	Northeast	0.34	0.16	0.4	0.16
	Midwest	0.54	0.72	0.85	0.72
	South	0.63	2.87	1.69	2.87
	West	0.38	0.28	0.53	0.28
Rural/ Urban	Rural	0.26	1.09	1.04	1.09
	Urban_ Teaching	0.29	0.19	0.44	0.19
	Urban_ Non-Teaching	0.38	1.41	1.19	1.41

Table 20. Performance Metrics for CPC Prediction with Fast Forest

Fast Forest / CPC	**Type**	**MAE**	**MSE**	**RMSE**	**LF**
Full Sample	**All hospitals**	0.51	0.43	0.66	0.43
Size	Small	0.558	0.483	0.695	0.483
	Medium	0.511	0.382	0.618	0.382
	Large	0.470	0.344	0.587	0.344
CMI	low	0.563	0.543	0.737	0.543
	Medium	0.508	0.451	0.672	0.451
	High	0.549	0.443	0.665	0.443
Owner	Govt	0.518	0.431	0.656	0.431
	Non-Profit	0.471	0.361	0.601	0.361
	For-Profit	0.696	0.664	0.815	0.664
Region	Northeast	0.495	0.317	0.563	0.317
	Midwest	0.516	0.434	0.659	0.434
	South	0.509	0.44	0.663	0.44
	West	0.497	0.370	0.608	0.370
Rural/ Urban	Rural	0.0612	0.045	0.211	0.045
	Urban_ Teaching	0.385	0.32	0.57	0.32
	Urban_ Non-Teaching	0.297	0.285	0.534	0.285

Table 21. Performance Metrics for CPC Prediction with GAM Algorithm

GAM /CPC	Type	MAE	MSE	RMSE	LF
Size	Small	0.58	0.53	0.73	0.53
	Medium	0.56	0.45	0.67	0.45
	Large	0.47	0.34	0.58	0.34
CMI	low	0.59	0.55	0.74	0.55
	Medium	0.54	0.5	0.71	0.5
	High	0.52	0.4	0.64	0.4
Owner	Govt	0.57	0.54	0.74	0.54
	Non-Profit	0.48	0.37	0.61	0.37
	For-Profit	0.71	0.76	0.87	0.76
Region	Northeast	0.45	0.28	0.53	0.28
	Midwest	0.51	0.44	0.67	0.44
	South	0.51	0.45	0.67	0.45
	West	0.5	0.35	0.59	0.35
Rural/ Urban	Rural	0.11	0.05	0.23	0.05
	Urban_ Teaching	0.41	0.32	0.56	0.32
	Urban_ Non-Teaching	0.33	0.29	0.54	0.29

4.4 Results

Our analyses showed that the five sources of hospital variations moderated the accuracy of performance prediction using Fast Forest ML agorithms. The findings are detailed below:

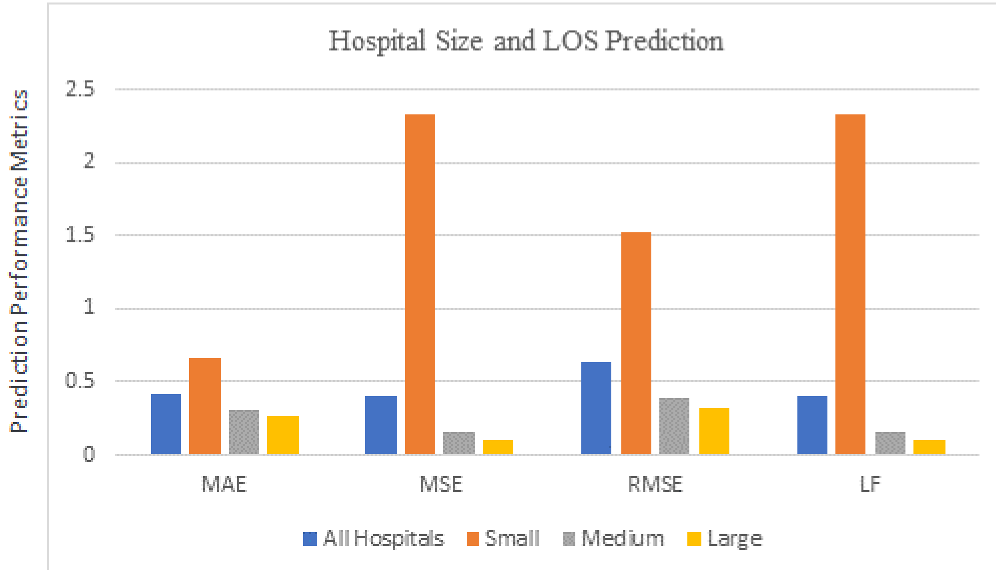

Figure 21. Hospital Size and LOS Prediction

An analysis of the impact of hospital size on the prediction of patients' length of stay (LOS) showed that predicting LOS with a sample of large hospitals (≥ 400 staffed beds) gave the highest level of accuracy (RMSE=0.322). This was better than the predictive performance of the proposed smart decision support model using the full sample with all hospitals (RMSE=0.63). When predicting LOS , the worst accuracy of prediction (RMSE= 1.526) was recorded for the sample of small hospitals (≤199 staffed beds).

Looking at the HIT functionalities and characteristics of large hospitals (such as >400) (Adler-Milstein et al. 2015), the above observations suggest that by increasing the size (number of beds) of hospitals, the complexity of managing so many patients and their care increase proportionately. Hence the role of HIT functionalities becomes more prominent. For smaller hospitals with fewer patients, the role of HIT may not be that prominent since medical staff are in closer proximity to each other and to their patients. The social network theory (SNT) suggests that proximity could be a driver for effective communication (Liu et al. 2017). In line with this argument, we observe that the size of a hospital (using HIT) affects its performance in terms of length of stay of patients. This may be due to the closeness of hospital staff to patients and strong ties allowing deep patient knowledge to be shared among doctors, nurses and patients to facilitate care processes. Since large hospitals do not or cannot allow for such proximity and strong ties among doctors, patients and nurses and other staff, they may rely on HIT functionalities to facilitate certain care processes. So as predictors of hospital performance HIT are better for large hospitals than for small hospitals given everything else remains the same.

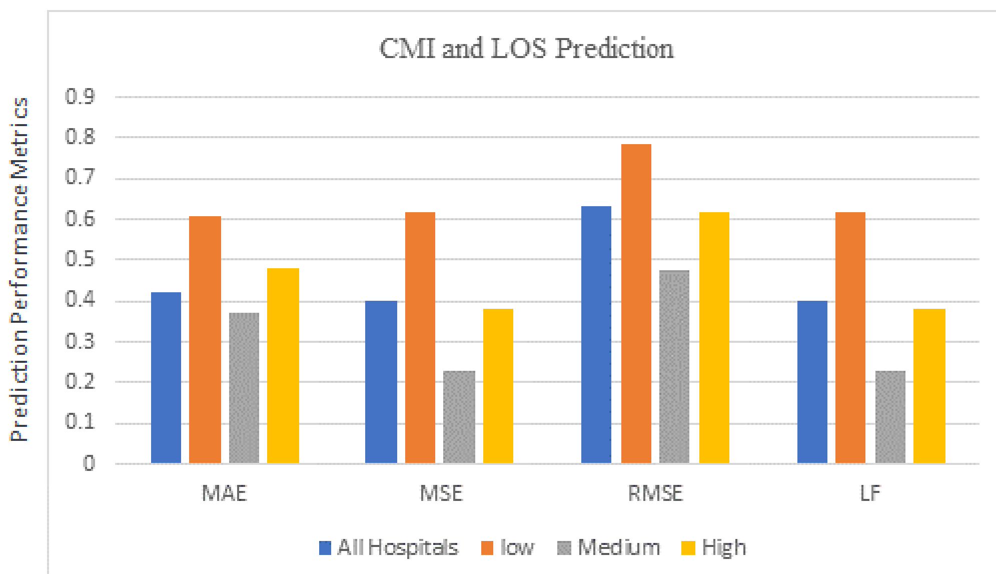

Figure 22. CMI and LOS Prediction

Our results showed that hospitals, stratified based on the complexity of the cases they handled, had a significant moderator effect on the predictability of hospitals performance measured as patients' length of stay (LOS). As illustrated in the graph above, hospitals with low case complexity (≤ 1.5 CMI) had the worst prediction accuracy performance (RMSE = 0.87). The accuracy of predicting performance with the full sample of hospitals was slightly better (RMSE = 0.63) than the sample with low CMI. The prediction with sub-sample of medium CMI hospitals performed most accurately with predicting the LOS of its hospitals (RMSE= 0.48).

From the results, we observe that the role of HIT functionalities as predictors of hospital performance increases up to a point with the increase in complexity of hospital cases and declines. The case mix index (CMI) by indicating the complexity of cases handled by hospitals also suggests the need for resources to treat patients. Among such resources are HIT functionalities which have the potential to support decision making and facilitate care processes. Hence we observe that the role of HIT as a predictor of hospital LOS performance increases with the increase in CMI. However, when the CMI reaches a certain level (>2) we observe a decline in the role of HIT as a predictor of performance. This could be due to the need for increased human expertise in making critical decisions as cases got very complex. At this level of CMI, the cost of mistakes may be so high and critical that hospitals can not rely only on the recommendations from HIT systems but may need teams of medical specialists to make care decisions and complete processes such as complex surgeries. This reduces the role of HIT functionalities compared to human expertise as predictors of hospital performance in reducing the length of stay of patients.

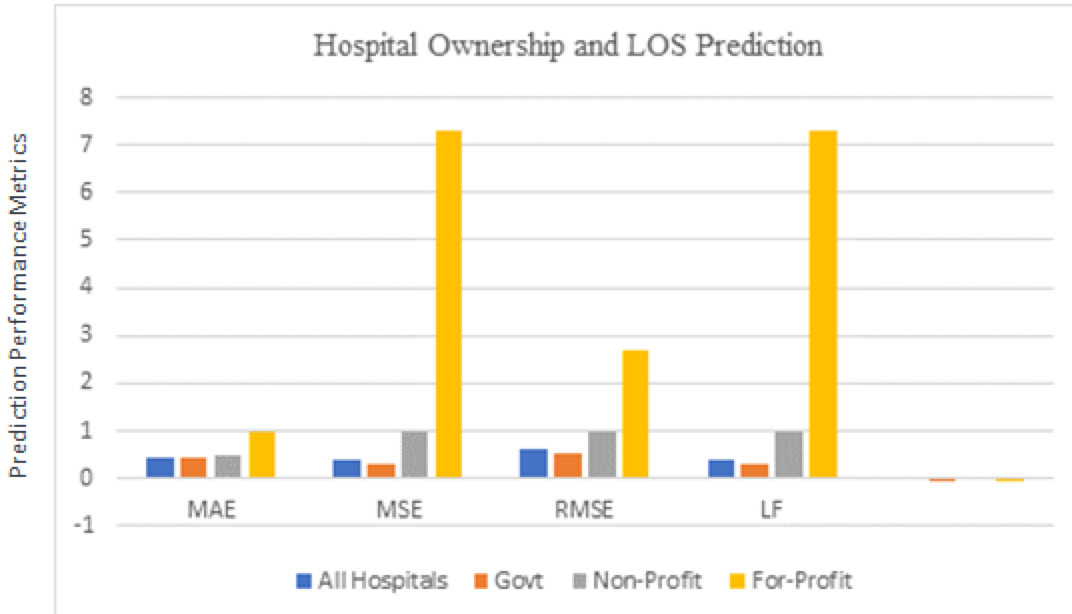

Figure 23. Hospital Ownership and LOS Prediction

Further analysis of the effect of hospital ownership when predicting hospital performance shows that the accuracy performance changes with the type of ownership suggesting moderation. With an RMSE of 1, the sample of private For-Profit hospitals had the worst prediction accuracy. This was significantly larger than all the other subsamples as well as the full sample (RMSE= 0.63). The subsample which had the best accuracy in predicting LOS was Government hospitals (RMSE = 0.53).

Compared to non-government hospitals, we observe the significant role HIT functionalities have in predicting length of stay (LOS) in government hospitals. This may be due to reimbursement pressure for government hospitals to adopt and properly integrate HIT functionalities to improve patient quality care. We observe a reduced prominence of HIT functionalities as predictors of LOS for private hospitals compared to government hospitals. While non-profit hospitals have more autonomy to use HIT their established priority to provide quality of care over profit (Tiemann et al. 2012) is likely to motivate them to use and properly integrate HIT to meet their mission. On the other hand for-profit hospitals focus on profitability hence the prominence of using and properly integrating HIT functionalities is less compared to non-profit hospitals (Adler-Milstein et al. 2014).

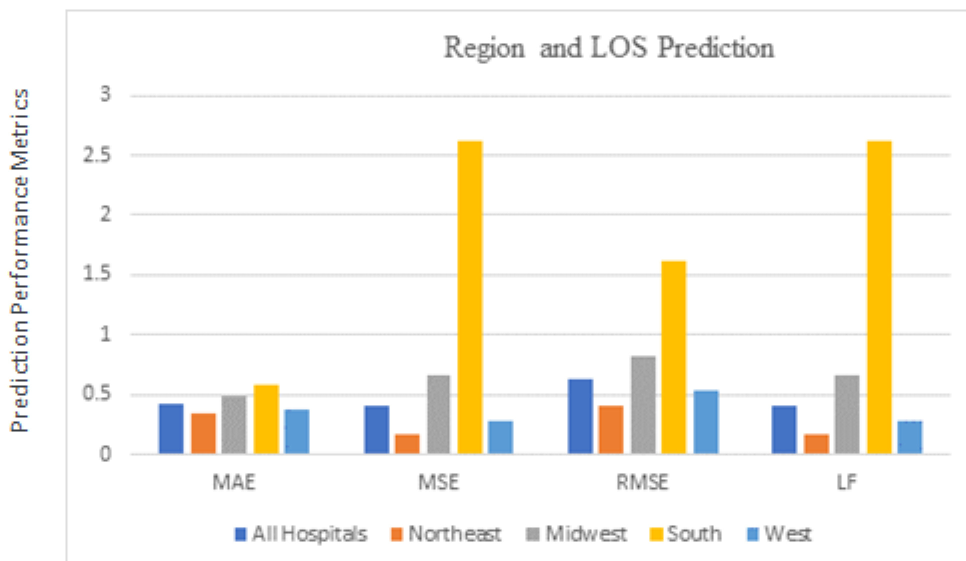

Figure 24. Region and LOS Prediction

Predicting LOS for hospitals which use HIT functionalities is further moderated by the region where hospitals are located. For this characteristic, hospitals in the south performed significantly worse (RMSE = 1.69) than the other regions. The sub sample with the best accuracy for predicting LOS was northeastern (RMSE = 0.4). This was followed by the prediction with a full sample than western hospitals (RMSE = 0.53).

The results, showing the prominence of HIT functionalities in predicting the quality of hospital care (in terms of LOS), is consistent with the level of technological and health care advancements in the various US regions. With states like Massachusetts, New York, and Pennsylvania, the Northeast with large metropolitan areas have been found to have high adoption rates of HITs in supporting the healthcare delivery of hospitals (King et al. 2013). Due to advancements in many large hospitals in this region, the role of HIT in delivering quality of service tends to be high. By the same argument Western region with states like Oregon and Washington, though having large metropolitan areas but fewer than the Northeast has less reliance on HIT functionalities for reducing LOS.

This trend is followed by the Midwest and then the South respectively. With states like Mississippi and Alabama, the South has the most rural areas compared to other states in the US. They therefore have fewer large hospitals which are reliant on HIT functionalities for delivering quality of care. Hence, the observation that HIT functionalities as predictors of hospital performance is least prominent in the South is in line with its level of advancement and metropolitan populations.

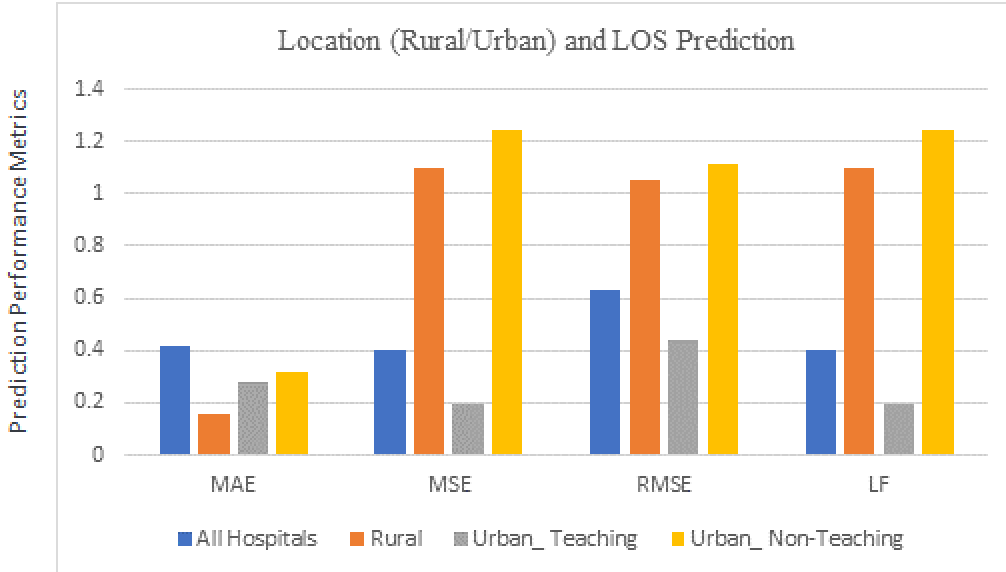

Figure 25. Location (Rural/Urban) and LOS Prediction

A prediction of LOS of hospitals using HIT functionalities showed a moderator effect of location of the hospitals. Compared to the predictive performance of the full sample (RMSE =0.63), urban non-teaching hospitals (RMSE = 1.19) which was the worst accuracy performance. This was closely followed by rural hospital subsample (RMSE = 1.04). Urban- teaching hospitals gave the most accurate prediction for hospital LOS (RMSE = 0.44).

Our observations show that urban teaching hospitals are more likely to use and properly integrate HIT functionalities to support their care delivery. This could be due to their academic affiliation and awareness of best practices through increased research activities. Adopting HIT functionalities and properly integrating them would facilitate communication and processes hence decrease the LOS of patients. On the other hand, non- teaching hospitals might be the proportion of urban hospitals which are smaller and less likely to rely on HIT functionalities for delivering care. We observe that HIT has higher prominence in rural hospitals than non-teaching urban hospitals because the subsample of rural hospitals may be a good mix of smaller and large hospitals which gives more prominence of HIT as predictors of their LOS performance than the subsample with mostly smaller urban non-teaching hospitals.

Similar to the predictions of LOS of hospitals using HIT functionalities, we carried out prediction tests of the cost of patients care. A repeat of the investigation of the moderator effect of the hospital characteristics under study revealed very insightful results as detailed below.

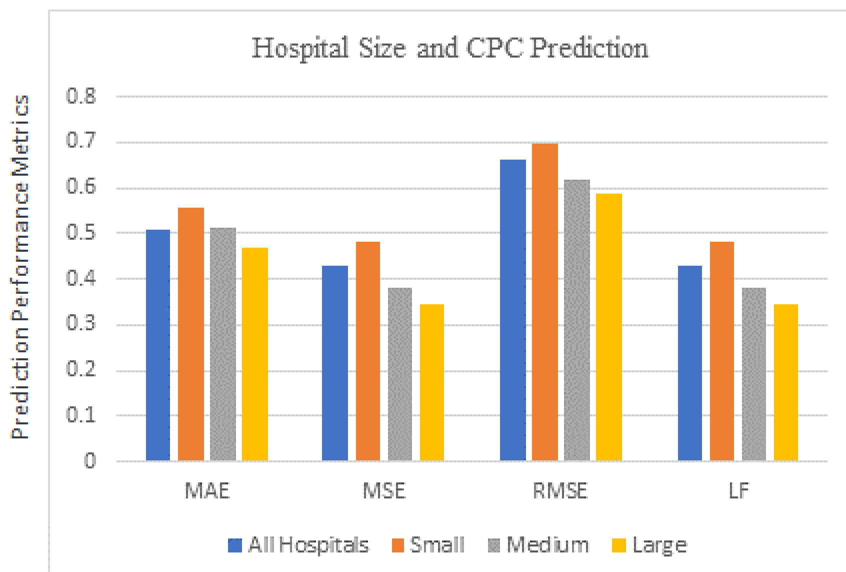

Figure 26. Hospital Size and CPC Prediction

First, the results showed that the subsample with small hospitals (≤ 199 beds) had the lowest accuracy for predicting CPC (RMSE = 0.695). This was followed by the predictive performance of the full sample (RMSE = 0.66). The subsample with large hospitals (≥ 400 beds) had the best accuracy for predicting CPC of hospitals with HIT functionalities (RMSE = 0.587).

When reducing patient cost of care, we observe that the impact of hospital size is minimal when HIT functionalities are used as predictors. Though the prominence of HIT functionalities with care delivery processes may change with the size of hospitals, we do not see big differences with their effect on cost of care as observed for LOS prediction. Since a patient's length of stay impacts their cost, we see a similar trend of prominence of HIT functionalities as predictors where large hospitals have the highest prediction accuracy followed by medium and small hospitals respectively though the differences are not that much.

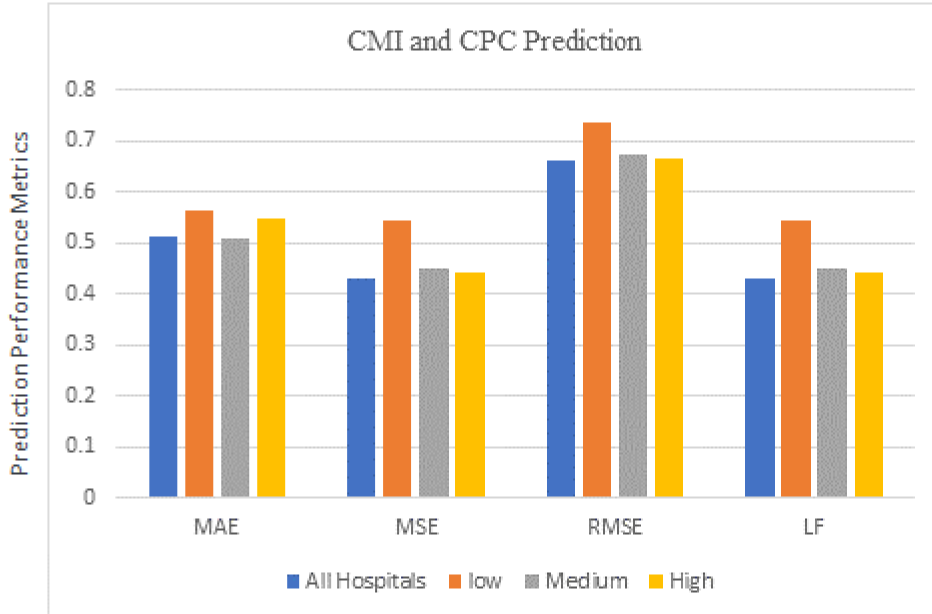

Figure 27. CMI and CPC Prediction

Our analysis further showed that the complexity of cases handled by the various hospitals (measured by the CMI) had a significant effect on the predictability of CPC. Hospitals with low CMI (≤ 1.5) had the worst performance (RMSE= 0.737) in the prediction of CPC while their counterparts with medium (>1.5 to 2) and high (> 2) CMI had similarly higher levels of prediction accuracy (RMSE= 0.672 and 0.665 respectively).

As predictors of cost of care, HIT functionalities had the most prominence when cases were of medium CMI followed closely by high CMI. Compared to low CMI hospitals with predominantly non-complex cases, medium and high CMI hospitals are more likely to rely on HIT functionalities to deliver quality of care and achieve efficiency. This would often require the use and proper integration of resources such as HIT functionalities to facilitate information processing to avoid costly mistakes. On the other hand, having relatively easy cases may reduce the need for HIT functionalities to get decisions and information processing right without costly mistakes in hospitals with low CMI.

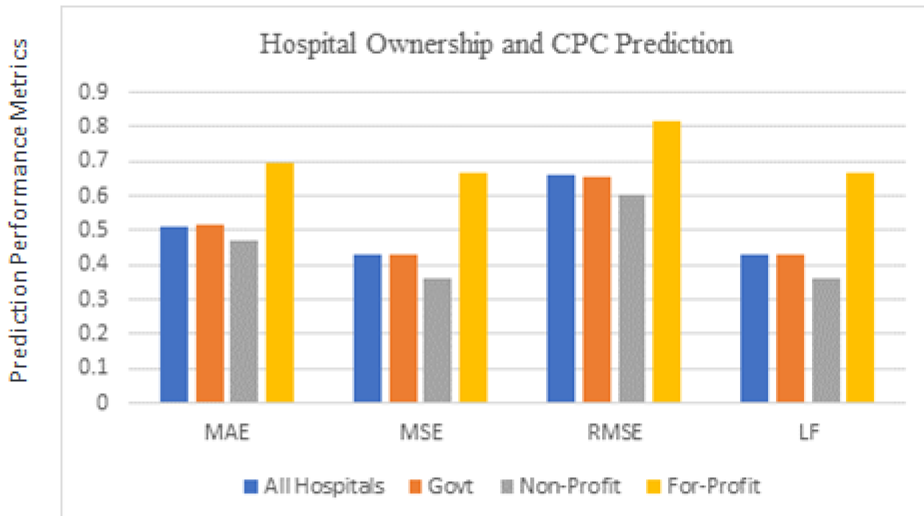

Figure 28. Hospital Ownership and CPC Prediction

Also, we observed that hospital ownership had a significant moderator effect on the accuracy of predicting CPC. Private for-profit hospitals showed the lowest accuracy for predicting CPC (RMSE = 0.815). This was followed closely by government owned hospitals (RMSE = 0.656), the full sample (RMSE = 0.66), and private not-for-profit hospitals (RMSE = 0.601) respectively.

When comparing the prominence of HIT functionalities as predictors of patient cost performance to predicting LOS, we observe a difference in trend. While government hospitals had higher reliance on HIT for achieving LOS compared to private hospitals, we observed that HIT use in non-profit have a higher prominence in predicting cost of patient care. While both government hospitals and private non-profit prioritize quality of patient care (e.g., LOS) over profits, private non-profits may be forced to focus more on using HIT functionalities to reduce cost rather than care quality metrics like LOS. This is because, they are not funded by the government and have less room to be wasteful in order to stay in business. On the other hand, for profit hospitals prioritize profit, hence their focus may be relying on branding and attracting top physicians to attract customers. The proper integration of HIT functionalities to minimize cost to patients may be lacking as they prioritize their reputation to deliver results rather than save in the cost of patient care.

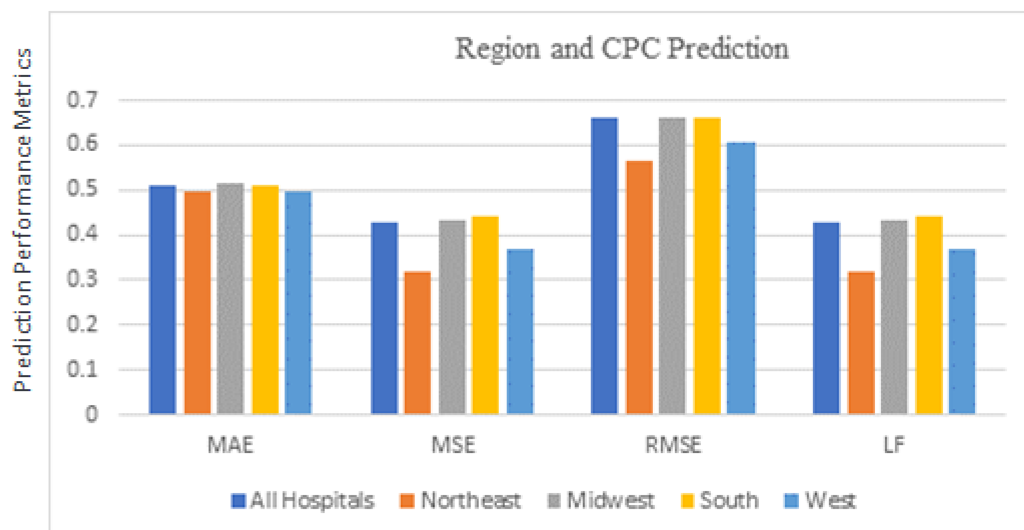

Figure 29. Region and CPC Prediction

Our results further showed that the region where a hospital is located has some moderator effect (though minimal) on the accuracy of predicting CPC. The subsample of Northeastern hospitals gave the best prediction performance (RMSE = 0.563). The second-best prediction was observed for Western regional hospitals. This was followed by the predictive performance of Midwestern hospitals (RMSE = 0.659), then the full sample (RMSE = 0.66) Southern hospitals had the worst predictive accuracy (RMSE = 0.663).

Similar to the trends observed for predicting LOS, the prominence of HIT functionalities as predictors of cost of patient care was highest for Northeast hospitals. The Northeast has a large a significantly high level of advancements in technological integration in their hospitals which tend to be large and located in large metropolitan areas. The larger the hospitals are, the greater their need for HIT functionalities to facilitate communication and streamline processes to avoid costly mistakes which can contribute to cost of patient care. Following a similar trend for LOS predictions, the West, Midwest and South respectively had lower reliance on HIT functionalities for CPC performance.

Compared to the Northeastern region, hospitals in the South, which is less developed, are more likely to be smaller. This means closer proximity and stronger social ties among medical staff and patients. This is likely to require less prominence for HIT use in completing care processes and sharing information without costly mistakes. Also, since LOS could directly affect the cost of patient care, we observe similar trend in the prominence of HIT as predictors of LOS and CPCs in the various regions.

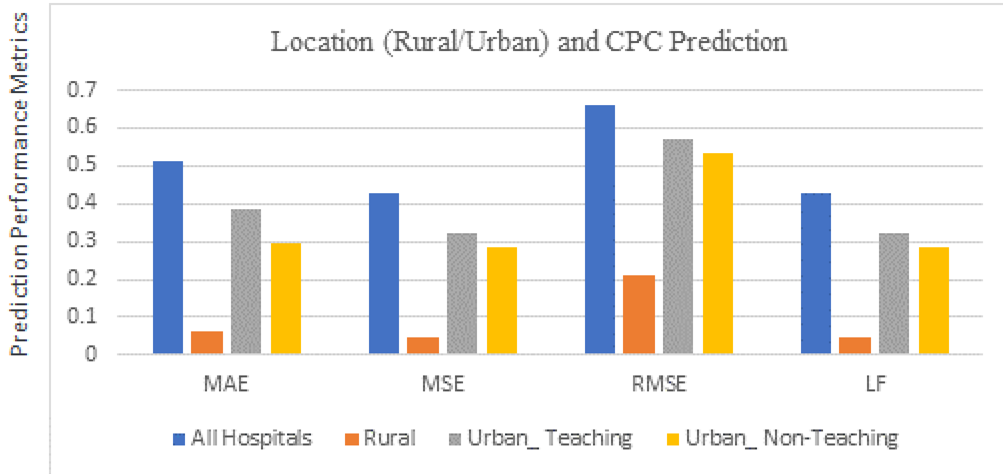

Figure 30. Location (Rural/Urban) and CPC Prediction

When predicting CPC with our proposed smart decision support system, a significant moderator effect was observed for the location (rural/urban). Prediction with the rural subsample gave the best accuracy (RMSE= 0.211). The urban sub samples performed better than the full sample. The teaching hospitals (RMSE= 0.57) had better accuracy in predicting CPC than the non-teaching hospitals (RMSE = 0.534).

As predictors of patient cost of care, HIT functionalities show the highest prominence in rural teaching hospitals. This was different for the prediction of LOS where urban teaching hospitals relied more on HIT functionalities than the other types of hospitals. Though often smaller in size than typical hospitals in urban areas, HIT functionalities when used could be significant in streamlining processes and supporting decision making to avoid costly mistakes leading to reduced cost of care. This is important because the typical patient in rural areas may not be able to afford high service costs. Hence hospitals may priority HIT functionalities that enable them to significantly reduce cost of service. On the other hand, typical patients in urban hospitals may be more likely to afford higher costs of service. This may lead hospitals to mostly rely on HIT functionalities to enhance communication and speed up care process without emphasis on saving patients cost of care.

4.5 Discussion

The factors which affect the performance of hospitals have important implications for stakeholders like hospital administrators, shareholders, policy makers, and the government. The ability to predict performance, knowing the impact of hospitals' sources of variations will further enhance effective decision making. Based on findings from essay 2, this study assesses the impact of hospitals' heterogeneity on the accuracy of predicting performance. We measured performance as patients' length of stay (LOS) and cost of patient care (CPC). We focus on the disparities among hospitals in their sizes, complexity of cases, location (urban/rural), region and ownership. We utilize US hospital data from AHA IT supplement and RAND for our analysis. The findings give interesting insights on how hospitals can use our proposed smart decision support system (discussed in essay 2) based on their unique characteristics. Additionally, our results emphasize the importance of effective integration of HIT functionalities in hospitals to be used as prominent predictors of hospital performance.

The results of the study show that, when predicting the performance of hospitals that use HIT functionalities, the size of the hospitals significantly influences the accuracy of the prediction. When predicting LOS and CPC, the large hospitals gave the best performance for accurate predictions with small hospitals having the worst prediction.

This suggests that different hospitals must take into account their size when making decisions based on predictions and role of HIT functionalities in their specific hospital scenarios. For example, while large hospitals can have a high degree of confidence in their predictions for making decisions, small hospitals must apply more caution doing same and take into consideration their unique culture and role of strong ties among doctors, nurses, staff and patients which allow for complex and deep knowledge to be shared between person to person rather than thorough HIT functionalities implanted via computer systems.

When predicting LOS, a significant moderator effect of the complexity of cases (measured by the CMI) on accuracy is observed. While CMI is found to moderate the accuracy of predicting CPC, it has a much lower effect than LOS. For both types of hospital performance predictions, the subsample with the low case complexity (≤ 1.5 CMI) had significantly lower accuracy than the other types of hospitals. This could be due to the fact that low case complexity means patients with easier diagnosis and treatment and thus the role of HIT predictors is low. On the other hand, more complex patient cases may require more and complex information and tests and wider sharing compared with low complexity patients.

Hence a patient with seasonal flu with low complexity for example, will require less knowledge and information flow compared to a cancer patient with lots of complexity and deep and complex knowledge and information flow where HIT functionality has a better predictive power. This has decision making implications for managers. It is important that, when using a smart decision support to predict performance, hospitals with low CMI must be cautious about basing critical decisions on their predictions. Also, prediction of performance based on CPC does not change much with using full sample or medium and high CMI samples. However, when predicting LOS, decision makers must know that, the accuracy of their results would be significantly impacted by how well they have stratified the hospitals in their database.

Our observations also show that the type of ownership of a hospital moderates the accuracy of predicting performance with our proposed smart decision support system. Stakeholders must therefore make decisions knowing that the type of ownership of hospitals can result in more accurate or less accurate results and factor this in their measures to mitigate errors. Also, for the prediction of both CPC and LOS, private non-profit hospitals gave significantly lower levels of accuracy compared to the other types of ownership. The possible explanation is that not-for profit is not driven by profit motivation and so is not beholden by the market performance. So HIT functionalities are not seen or needed as much as in for-profit where efficiency is rewarded by the market. It is therefore important especially for non-profit hospitals to take measures in mitigating the uncertainty that may affect their decisions with our Smart DSS performance predictions.

When making decisions based on predictions with our proposed smart decision support system, the region of the hospital matters. Stakeholders must therefore bear in mind the region of hospitals before making critical decisions based on performance predictions using our proposed smart system. Especially for hospitals in the south, the predictions recorded had very low accuracy. This could be attributable to hospitals in

Northeastern states having more efficiency and being more market driven compared to hospitals in the South. Hence the level of use and appropriate integration of HIT functionalities could be much higher in Northeastern and Western region hospitals than those found in Midwest and the South. Hence, using data from hospitals in different locations for predictions could significantly impact the accuracy of results one may get. This poses a high risk to adequate decision making.

While predicting LOS with urban teaching hospitals gave the best accuracy. On the other hand the rural subsample had the best accuracy performance for predicting CPC. This could be due to urban teaching hospitals focusing on using HIT functionalities to enhance quality of care without prioritising the cost of service. The typical patient in rural areas may not be able to afford high cost of care. Hence, the prominence of HIT functionalities in helping to reduce patients cost of care becomes higher in rural areas. Hence, stakeholders must make decsions based on predictions of hospital performance by first factoring the location of the hospital (urban/rural) due to the significant moderator effect on prediction accuracy.

4.6 Limitations and Future Directions

Like any other study, we had limitations with this study. First, the use of secondary data limited us to the source of hospital variations we could investigate for this study. In future studies, it would be interesting to explore how other sources of hospital heterogeneity impact the accuracy of predicting performance. Second, we investigated the prominence of HIT functionalities as predictors of performance without considering then individual types of HIT functionalities. Future studies can explore the prominence of different types of HIT functionalities as predictors of performance and the role of hospital heterogeneity.

4.7 Conclusion

In this essay, we have successfully investigated the impact of hospital heterogeneity on the accuracy of predicting patient length of stay and the cost of patient care. We find that various sources of hospital variation have a significant moderator effect on predictions. From the trends observed we found that the use of HIT functionalities is as important as their effective integration in order to enhance hospital performance. The prominence of HIT functionalities as predictors of performance significantly changed with how much hospitals depended on them for effective communication and completing care processes. We hope that this study will provide a foundation for further studies in this emerging and important area of research in the information systems discipline.

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