Modelling the relationship between “Internet of Things”, value co-creation and innovation performance in healthcare

نمذجة العلاقة بين إنترنت الأشياء، استحداث القيمة التشاركية والآداء الإبتكاري في مجال الرعاية الصحية

by

RADWAN SALEH AL JBOUR

A thesis submitted in fulfilment

of the requirements for the degree of

DOCTOR OF PHILOSOPHY IN BUSINESS MANAGEMENT
at

The British University in Dubai

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ABSTRACT

This research aims to explore the influence of “Internet of Things” (IoT) capabilities on the value co-creation and the service innovation performance of healthcare organisations. ‘Internet of Things’ is a new phenomenon, and the impact of its capabilities on service innovation performance has not been examined in a similar healthcare domain. Therefore, this study investigates the IoT capabilities from a marketing perspective of value co-creation to draw out vital elements to constitute resource integration practices and co-creation towards obtaining service innovation outcomes and achieving a competitive advantage. Also, the study attempts to theoretically contribute to the value co-creation and IoT literature by affording an empirical establishment for IoT- enabled value co-creation and demonstrating how it underpins the interaction between actors within the healthcare ecosystem.

The study employed resource-based view (RBV) theory and service-dominant logic framework to develop a theoretical connection and empirically examine the influence of IoT capabilities on service innovation performance through the mediating effect of value co-creation practices. It also used the Orlikowski structuration model of technology to depict the relationship between technology and value co-creation. The study adopted the deductive, quantitative method following the positivism philosophical assumption. This method involved a survey questionnaire completed by healthcare givers (e.g. doctors, nurses, therapists) in Jordan’s private and public sectors hospitals. A pilot study was conducted to ensure the validity of the research design. It included a small-scale distribution of the survey questionnaire and interviews with individuals from the target population. Data were collected (n=208) using a drop-off pick-up method and analysed using multiple techniques, including exploratory factor analysis, confirmatory factor analysis and structural equation modelling (SEM).

The study’s findings confirm the influence of IoT monitoring and collaboration capabilities on the service innovation performance and support the proposition of IoT monitoring, optimisation and collaboration impact on value co-creation practices. However, IoT control capability shows no support to innovation performance. Findings also show that monitoring is an essential capability of IoT in healthcare, suggesting that successful value co-creation heavily depends on how hospitals access, observe, contact, interact and apply their technological knowledge processes.

ABSTRACT IN ARABIC

ملخص البحث

تهدف هذه الاطروحة إلى استكشاف تأثيرالقدرات التي تمتلكها تقنية انترنت الأشياء على ممارسات القيمة التشاركية والابتكار الخدمي في قطاع الرعاية الصحية، تعتبر تقنية إنترنت الأشياء هي ظاهرة حديثة في عالم التكنولوجيا ؛ لم يتم فحص تأثير قدراتها في اية دراسة سابقة على أداء ابتكار الخدمة في مجال الرعاية الصحية. تهدف هذه الدراسة إلى التحقق من قدرات تقنيات إنترنت الأشياء من منظور تسويقي لتحقيق القيمة التشاركية ، واستخلاص العناصر الحيوية لتشكيل ممارسات تكامل الموارد والإبداع المشترك نحو الحصول على نتائج الابتكار في الخدمة، وتحقيق الميزة التنافسية. كما تسعى الدراسة إلى المساهمة في تطوير أدبيات ومفهوم تحقيق القيمة التشاركية وتقنية إنترنت الأشياء من خلال توفير دراسة بحثية تجريبية للقيمة التشاركية التي تدعم إنترنت الأشياء وإثبات كيفية دعم التفاعل بين الجهات الفاعلة داخل نظام الرعاية الصحية بشكل عام.

وظّفت الدراسة النظرية القائمة على الموارد (RBV)، ومنهجية (منطق سيادة الخدمة Service-dominant logic) لتطوير المنهج النظري ودعم المنهج التجريبي للبحث من أجل فحص تأثير قدرات إنترنت الأشياء على أداء الابتكار في الخدمة من خلال التأثير الوسيط لممارسات خلق القيمة التشاركية وقدرة المنظمة على التكيف مع التغييرات الناجمة عن تطبيق التتقنية المتقدمة. كما استخدمت الدراسة نموذج هيكلة أورليكوفسكي للتكنولوجيا كتأصيل نظري لفهم العلاقة بين التكنولوجيا وتحقيق القيمة التشاركية. اعتمدت الدراسة المنهج الاستنتاجي الكمي بعد وضع الافتراض الفلسفي المناسب. تضمنت هذه الطريقة استبيانا لمقدمي الرعاية الصحية (مثل الأطباء والممرضين والمعالجين) في مستشفيات القطاعين العام والخاص في المملكة الأردنية الهاشمية. تم إجراء دراسة تجريبية للتأكد من صحة تصميم البحث من خلال توزيعًا محدوداً لاستبيان الاستقصاء والمقابلات مع أفراد من العينة المستهدفة. تم جمع البيانات (عدد العينات = 208) باستخدام طريقة التوزيع اليدوي وتحليلها باستخدام تقنيات متعددة بما في ذلك تحليل العوامل الاستكشافية وتحليل العوامل المؤكدة ونمذجة المعادلة الهيكلية (SEM) .

تؤكد نتائج الدراسة على التأثيرالمباشر الإيجابي لنوعين من قدرات إنترنت الأشياء (المراقبة والتعاون) على أداء الابتكار الخدمي. كما أكدت النتائج على صحة فرضية تأثير قدرات انترنت الاشياء (المراقبة، التحسين والتعاون) على ممارسات إيجاد القيمة التشاركية تأثيراً مباشراً وإيجابياً. في المقابل وعكس ما كان متوقعا لم تظهر القدرة الخاصة بالتحكم أي دعم للأداء الابتكاري. أظهرت النتائج أيضًا أن المراقبة هي قدرة أساسية لإنترنت الأشياء في مجال الرعاية الصحية ما يشير إلى أن القيمة التشاركية الناجحة تعتمد بشكل كبير على كيفية استخدام المنظمات للمعرفة التكنولوجية في المراقبة والاتصال والتفاعل والتطبيق.

DEDICATION

I dedicate this work to

The soul of my father who passed away before this research has been completed.

To

My children Bashar, Mohammed and Sara

ACKNOWLEDGEMENTS

Foremost, I am thankful to **Allah** who gave me the strength and patience to endure the challenges experienced during this long journey; without His favour and grace, this project would not have been completed.

I would like to express my special appreciation and thanks to my supervisors, Dr Abdel Mounem Lahrech, and Professor Halim Bousubaine, for their generous support, invaluable guidance, and encouragement throughout my PhD journey.

I am grateful to my dear mother for her endless love, care, affection and attention, that sustained me through the end of this journey. Deep gratitude is owed to my wife for her sacrifice and patience during the study, without here continuous support; this research would have been much difficult to achieve.

Utmost gratitude is owed to my brothers and sisters for their unconditional encouragement and love, which has given me enormous strength to continue until achieving the goal.

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List of Abbreviations:

AAL	Ambient Assisted Living
CGM	Continuous Glucose Monitor
D2D	Device-to-Device
EHR	Electronic Health Records
G-D	Goods Dominant
GPS	Global Positioning System
ICT	Information and Communication Technologies
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
IP	Internet Protocol
M2M	Machine to Machine
NFC	Near Field Communication
RBV	Resource-based view
RFID	Radio Frequency Identification
S-D	Service-Dominant
VCC	Value Co-Creation
Wi-Fi	Wireless Fidelity
WSAN	Wireless Sensor and Actuator Networks

Chapter 1 Introduction

1.1 Research background

Creating value is the purpose of all forms of economic exchange (Vargo et al., 2008; Vargo and Lusch, 2008). The idea of value co-creation has largely been used in the healthcare service (e.g. Lee 2019, Russo, Tartaglione and Cavacece, 2019). The concept of value co-creation emphasises the Service-Dominant (S-D) logic framework of how value created, exchanged or used. The S-D logic approach highlights the cooperative role of both caregiver and patient in co-creating value. The S-D logic framework has been widely accepted approach in marketing literature. This well-known viewpoint stems from the critical analysis presented in the seminal work of Vargo and Lusch (2004, 2008) about the role of service in the global economy (Tommasetti, Vesci and Troisi, 2015). S-D logic emerged as a substitute for the traditional goods-dominant (G-D) logic paradigm as a way to understand the concepts of economic exchange and value creation (Vargo and Akaka, 2009). It profoundly influenced marketing theory (Tommasetti, Vesci and Troisi, 2015) and proposed a theoretical foundation for service science expansion (Lusch, Vargo, and Wessels, 2008; Maglio and Spohrer, 2008).

This study draws upon social exchange theory to explore the association between value co-creation and service innovation. Social exchange theory explains that humans' actions are motivated by the returns that they expect to obtain from others (Blau, 1964). According to this theory, the principle of individual behaviour is to increase benefits and decrease costs. Social exchange theory explores how the level of mutual interaction in the transaction influences ties and commitments in the actors' relationships. Generally, exchange relations occur within structures of reciprocal dependence (Molm, 1994). This study draws upon the social exchange theory to explore exchanges of mutual resources between actors within the healthcare ecosystem. Social exchange theory seeks to describe the human behaviour during transaction process (Cropanzano and Mitchell, 2005; Molm, 1994).

Social exchange theory focuses on the social relations between actors rather than the content of interaction (Molom, 1994). Social exchange favours — care, attention, respect and kindness — lose their social value if bartered (Blau, 1964). For example, a patient sharing information about his own experience of particular disease with another patient to help him understand how to manage the situation is a social exchange. That is to say, the costs of support in time, effort and involvement that first patient causes are granted with the implied expectation of a mutual reward in the form of social benefits. Gal, Jensen and Lyytinen (2014) argue that changes in the use of ICT technology and its affordances enable multiple patterns of social exchange to emerge. ICT technology is not only what its devices feature, but it is also the affordances that they offer (Gal, Jensen and Lyytinen, 2014; Faraj and Azad, 2012). This study argues that the changes that occurred with the adoption of IoT enable new forms of social exchange that may accommodate novel service delivery.

This thesis explores the effect of technology on value co-creation and investigates the complex interactions between actors in the healthcare ecosystem in co-creating values. Technology is a cardinal idea in service and value co-creation research (Akaka and Vargo, 2013; Maglio and Spohrer, 2008). Technology is defined from a S-D logic perspective as a set of practices, procedures and symbols that achieve human demand (Akaka and Varog, 2013). It enhances human interactions in services (Immonen, Sintonen and Koivuniemi 2018). Technology has a direct impact on how value is determined (Tommasetti, Vesci and Troisi, 2015), and it represents an infrastructure that enables the interaction of resource integration and supports the co-creation of value (Colurcio et al., 2017). IoT technology combines the aspects of social and business ecosystems (Li and Li, 2017), and works as an enabler of a resource integration process or a service platform (Colurcio and Verre, 2017), which, then, facilitates the interaction among actors or resource bundles through protocols of exchange (Lusch and Nambisan, 2015; Colurcio et al., 2017)

The Internet of Things (IoT) is revolutionising all aspects of our lives and societies (Alam et al., 2016; Arshad et al., 2017; Muhammed et al., 2020) by combining the physical and digital worlds. It merges RFID technology, embedded electronics, communication techniques, sensors and actuators in one innovative solution. IoT transforms normal things (e.g. chairs, tables, dishes) into smart objects that are capable of detecting changes, continuously gather data and interact with the environment. The massive number of IoT connected devices and the estimated massive amount of generated data open the doors for new opportunities for service offerings to the society, economy and environment (Madakam, Ramaswamy, and Tripathi, 2015). IoT utilises the advanced technologies of Radio Frequency Identification (RFID), Wireless Sensor and Actuator Networks (WSAN), the rise of ubiquitous computing and the improvement of communication protocols

(Dawued and Meri, 2019; Andrade et al., 2017). IoT also makes use of the existing massive infrastructure of computing technologies and applications, communication technologies, hardware devices, laptops, mobile phones and tablets. The potential growth of mobile phones and their applications as well as the broad accessibility to wireless connectivity have significantly pushed the emergence of IoT technology forward (Sen, 2016, Ahmadi et al., 2018). Recent research studies consider IoT the most attractive technological target for investment by many industries (Khanna and Kaur, 2019; Bremner, 2017; Saha, Mandal and Sinha, 2017; Gubbi, 2013). A wide range of businesses are seizing the advantages that can be gained from using IoT to cultivate value and obtain greater efficiency as well as improvements in reliability and cost (Ahmadi, 2018).

This study employs resource-based view RBV and organisational capability theory to develop theoretical connection and empirically examine the influence of IoT capability on service innovation performance through mediating effect of value co-creation practices. The organisational capability perspective considers the organisation as a bundle of resources and capabilities to achieve competitive advantage (Grant, 1996; Rumlet, 1984). Organisational capability theory developed from the RBV of the firm (Barney, 1991; Wernerfelt, 1984).

This study draws up organisational capability theory to develop an empirical framework that focuses on the impact of IoT capabilities on value co-creation constructs in the healthcare service and, in turn, enhances the performance of service innovation. According to organisational capability theory, IoT is probably capable of integrating the organisation-customer relationship as well as the internal process across the organisation. The resource-based view seeks to explain organisational performance in terms of internal skills and resources that are valuable, inimitable, rare and non-substitutable (Barney, 1991). Organisational capability theory explains how an organisation obtains competitive advantage by the creation and allocation of resources and capabilities in a dynamic context (Teece, 2014; Rumlet, 1984).

There are multiple capabilities in the IoT that can impact the social, economic and technical sides of life. These capabilities include managerial capabilities (e.g. monitoring and collaboration) and technical capabilities (e.g. sensing and actuating). This study argues that the importance of IoT comes from its capability to identify new opportunities, and offer innovative solutions to contribute to the quality of human lives. The healthcare industry perceives IoT as influential technology with potential opportunities (Diez et al., 2018, Ahouandjinou et al., 2016; Hamrioui et al., 2014). This view explains why healthcare is recognised as one of the fastest industries to adopt IoT technologies (Hamrioui and Lorenz, 2017). The integration of IoT in medical settings significantly improves quality of life, increases efficiency and enhances patient satisfaction (Diez et al., 2018). The healthcare industry experienced several forms of innovation (Freire and Sangiorgi, 2010; Omachonu and Einspruch, 2010) targeting quality of life, life expectancy, the treatment process, administrative efficiency and operational effectiveness. This study aims to identify the changes that IoT capabilities make in healthcare ecosystems in terms of the actor-to-actor relationship within and outside the medical organisations, and explore how these new settings transform the way of co-creating value.

There are three approaches to defining and measuring service innovation: assimilation, demarcation and synthesis (Coombs and Miles, 2000). Most of research studies in innovation literature focus on assimilation perspectives (Gallouj, 2002; Witell et al., 2016). The assimilation view applies developed concepts and ideas to measure innovation in manufacturing. However, this thesis is inspired by the emerging stream of research that adopts the synthesis view of innovation. This view is coequal with the S-D logic framework that aims to extend the context of innovation to the self-motivated ecosystem of service interactions and institutions (Akaka, Vargo and Wieland, 2017).

Jordan is a leading healthcare country in the Middle East and, among Arab countries, in medical tourism (Rasmi et al., 2018). The Jordanian healthcare sector has been recently transformed with the adoption of emerging technologies to enhance its operational efficiency (Alaiad, Alsharo and Alnsour, 2019). The Jordanian healthcare industry has its own accreditation system, managed by the healthcare accreditation council, which is accredited by ISQua (an international healthcare body that accredits the accreditors) (MoH, 2019). Jordanian healthcare services are shared among three independent administrations: Ministry of Health (MoH), Royal Medical Services through Jordan Armed Forces and the private sector. Government of Jordan has adopted a nationwide health information system, focusing on electronic health records (EHR) in public and military medical organisations (Alaiad, Alsharo and Alnsour, 2019) to improve the quality of healthcare services. Jordan has an advanced infrastructure of ICT, particularly in terms of wireless telecommunication services (Alsharo, 2017). According to Jordan’s telecommunication regularity commission there are 16,746 million mobile phone subscribers, representing a 120% penetration rate (JTRC, 2020). This high rate is mostly due to availability and the inexpensiveness of wireless services in the country (Alsharo, 2017).

1.2 Research Motivation

In the recent few years the evolution of global markets and their economic and social impact has changed dramatically. ‘Health and wellness’ is one of social trends that generate significant opportunities in the market of smart and medical health applications. The synergy of knowledge sharing and potential data exchange, opens huge opportunities for IoT technologies. This new technology is far different from internet where many products, resources and management solutions have undergone with serious difficulties of high cost and poor connectivity. The new advanced technologies such as cloud computing and big data analytics enables broader range of development and applications that will drastically transform services, channels and business models. This study investigates the association between IoT, value co-creation and innovation performance. Although it has recently shown technological advancement, IoT literature still relies heavily on technicalities and anecdotes with very little empirical research.

Providing continuous, high-quality healthcare is critical for medical organisational success. The growing ageing profile in various countries across the world requires healthcare services to support this critical concern (Yuehong et al., 2016). The global population of individuals aged 80 years and more (called “oldest old”) is projected to grow significantly from 126.5 million in 2015 to 444.6 million by 2050. Simultaneously, the global life expectancy is expected to increase continually to reach 76.2 years in 2050 (U.S Census Bureau, 2015). Figure 1.1 shows the remarkable increase in the percentage of old people as part of the global population from 2015 to 2050. This demographic change will force the healthcare industry to innovate and reshape its processes, positively adapting to cope with the increasing demand for healthcare services. Literature suggest that offering advanced services require organisation to develop and maintain new capabilities which is far different from traditional capabilities that exist in most organisations today. (Story et al.,2017; Sjödin, Parida and Kohtamäki 2016; Parida et al., 2015)

People aged over 65 years need continuous healthcare monitoring (Swaroop et al., 2019). More than third of the world's population suffers from mental disorders, including 400 million suffering from depression, 36.5 million people suffer from Alzheimer's and dementia, and 21 million suffer from schizophrenia (Ivascu et al., 2015), with 60 million people suffering from bipolar disorder (Diez et al, 2018). It is expected that the number of adults aged over 65 years will reach 1200 million and developing countries will have 80% of this number (Swaroop et al., 2019).

Obtaining a clear picture of a patient's healthcare needs requires immediate health services as well as detection and monitoring systems (Wan et al., 2017). Elderly patients with chronic diseases, for example, need to periodically monitor their vital signs (e.g. blood pressure, temperature readings, respiratory rate) (Raji Jeyasheeli and Jenitha, 2016). Fatal medical errors (e.g. mix-ups in medication and mistakes in complex surgeries) come as the third cause of death in the United States (Sipherd, 2019). There are multiple reasons for medical errors, including a communication gap with patients, poor reliability of systems and protocols, exhaustion caused by long working hours, time pressures, and distractions (Rodziewicz and Hipskind, 2019; Russo et al. 2019).

Healthcare technologies are considered a key safety solution for reducing human medication errors (Michalek and Cason, 2020). Medication errors may lead to patient injury and economic cost. According to US Food and Drugs Administration (2016) medication errors lead to (minimum) one death every single day and around 1.3 million injuries every year in the United States. It is also reported that the global economic cost of medication errors is US $42 billion every year (WHO, 2017). The adoption of technological-based self-services is highly increasing in the healthcare industry (Nadia and Tam, 2016). Khosla (2012) argues that 80% of doctors could be replaced by machines by 2030.

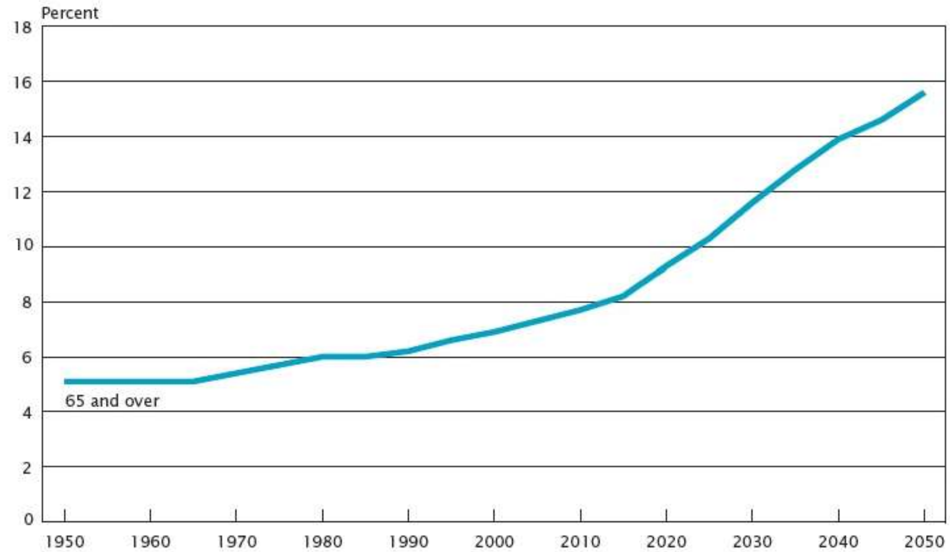

Figure 1.1 Old people as a percentage of the global population 2015-2050. Source: U.S Census Bureau, 2015

IoT has the potential to assist medication management, enhancing the efficiency of medical operations and increasing the process's reliability (e.g. RFID can manage the blood-taking process in rush-hour). IoT is able to connect the health status of the principal actor of the healthcare ecosystem (the patient) to related caregivers and other actors at hospital, home or any other location. This can be achieved with minimum effort in a way that highly and positively influences the healthcare service. Moreover, IoT influences the healthcare service ecosystem's processes by optimising daily functions, supporting fact-based decisions and enhancing big data analysis.

IoT is a combination of multiple technologies including a wide range of smart devices (e.g. sensors, actuators), cloud computing, and smart objects to communicate and establish a network for the productivity and efficiency of the healthcare service ecosystem. IoT brings many benefits to a healthcare service ecosystem: it provides on-time patient care or real-time remote monitoring so that the treatment will be more efficient. In a healthcare IoT system, where the devices are connected to human bodies, the information can be transmitted to the assigned channel to provide evidence-based medication. This reduces the attention needed from doctors, improves the level of care, reduces the treatment's cost, and supports healthcare management. IoT can enhance medication control (e.g. edible IoT or smart pills), diabetes management (e.g. Continuous Glucose Monitor, CGM) and blood pressure monitor to lower the cardiac risk. The capabilities of IoT will enormously increase the productivity of healthcare services and foster big data analytics within the service ecosystem. Other uses of IoT devices include pharmaceutical inventory management, where it provides real-time monitoring and control. Despite the increasing number of research papers on IoT; the quantitative studies on its capabilities are extremely rare (Verdouw et al. 2016; de Vass, Shee and Miah 2018). So this study aims to contribute in filling this gap.

Transferring the provision of service from a human-service based system to a device-connected base system is not a natural choice. There are also challenges concerning value co-creation in this sophisticated setting — this mandates the actors within the IoT healthcare service ecosystem to effectively collaborate to achieve the goal of service exchange. One of the main challenges within the system is the communication that results from the technological challenges of device connectivity. Achieving success by affording functional solutions can be reached by overcoming these challenges. The IoT healthcare service ecosystem frequently attracts more actors as it promises a fruitful way of connecting technology and humans, aids human well-being, and provides practical solutions to patients and their families. IoT can enhance the treatment process and assist in the preventive approach of healthcare (Zois, 2016; Diez et al., 2018). IoT demonstrates its capability to support the doctor's decision by providing related information and remote monitoring of patient status. IoT also has the potential to enhance the administrative decisions within a hospital by providing and distributing the relevant information about learning: materials, clinical schedules, and updates (Metcalf et al., 2016). Likewise, it can increase quality of life and reduce the cost of healthcare service expenses.

From a marketing perspective, it is expected that the growth of the IoT healthcare market worldwide will increase from US $72.5 billion in 2020 to US $188.2 billion by 2025 at a compound annual growth rate of 21% during the five-year forecast period (Markets and Markets, 2020). The projected growth is motivated by the increased focus on patient engagement, the promotion of digital health initiatives by governments in many countries (particularly after the pandemic of COVID-19), and the increased growth of telecommunication and network technologies. The market of IoT in healthcare is expanding as it has the potential to create higher value in the service ecosystem. The rising demand for healthcare services and the shortage in professional healthcare staff (Khan et al., 2019) requires healthcare organisations and technologies to provide smart solutions to overcome such problems.

1.3 Research aim, objectives and questions:

As a new phenomenon, the IoT deployment capabilities have not been investigated in a similar healthcare domain. The outcome of this study is to investigate how the adopting of IoT technologies under the lens of the S-D logic framework and the marketing perspective contribute to value co-creation and impact the performance of service innovation in healthcare in order to draw out vital elements to constitute resource integration and value co-creation practices towards achievement of organizational competitive advantage. The study also attempts to contribute theoretically to the value co-creation and IoT literature by affording an empirical foundation for IoT technologies implementation under the lens of S-D logic framework. This study purposes to theoretically contribute and respond to the paucity of research that investigate how emerging technologies enable service innovation (Wu, Xiao and Xie 2020), in spite of service innovation literature has explored the effects of technological factors on service innovation (e.g. Ye and Kankanhalli, 2018). This study aims to explore the emergence of IoT technology in the medical service and how medical organisations can adapt their internal processes to the changes caused by this emerging technology.

In light of the aim of this study, the objectives of this research are:

1. Conceptualising the core capabilities of IoT in the healthcare service.
2. Investigating how IoT capabilities contribute to the value co-creation related practices in healthcare services.
3. Examining how both IoT capability and value co-creation influence the service innovation performance in healthcare.

Based on the research aim and objectives, the study's research questions are:

1. What are the IoT capabilities that influence healthcare co-creation practices and consequently impact service innovation performance?
2. What is the relationship between IoT, value co-creation and the performance of service innovation?

Chapter 2 Theoretical perspectives: ‘Internet of Things’

2.1 Overview of IoT technology

The concept of the Internet of things (IoT) refers to the mechanism of integrating the physical world with the virtual world, transforming inanimate things into living objects and converting them into interactive objects that can communicate with the world (Atzori, Lera and Morabito, 2010; Gubbi et al., 2013; Madakam, Ramaswamy, and Tripathi, 2015). The idea started by connecting the Radio Frequency Identification Device (RFID) with the internet to improve business operations (Suresh et al. 2014). Put simply, IoT is a combination of objects that carry identifiers and wireless connections to communicate with each other. This technology can generate a massive amount of environmental data, which can be transformed into information to help decision-makers. This new technology opens up huge opportunities for improving human life.

The MIT group define IoT as “an intelligent infrastructure linking objects, information and people through the computer networks, and where the RFID technology found the basis for its realization” (Brock, 2001). On the other hand, the Cluster of European Research Projects on the Internet of Things (CERPIoT) defines IoT as “a dynamic global network infrastructure with self-capabilities based on standard and interoperable communication protocols where physical and” virtual” things have identities, physical attributes, virtual personalities and use intelligent interfaces, and are seamlessly integrated into the information network” (Jain, Hong, and Pankanti, 2009). The first International Telecommunication Union (ITU) report on the concept of Internet of Things was published in 2005; they said IoT was “a new dimension… added to the world of information and communication technologies (ICTs): from anytime, anyplace connectivity for anyone, we will now have connectivity for anything. Connections will multiply and create an entirely new dynamic network of networks — an Internet of Things”. However, The International Telecommunication Union (ITU) proposed another definition in 2012. It defines IoT as “a global infrastructure for the information society, enabling advanced services by interconnecting physical and virtual things based on existing and evolving interoperable information and communication technologies” (The International Telecommunication Union, 2012). Ng and Wakenshaw (2017) conducted a literature review on IoT and define IoT as: “a system of uniquely identifiable objects (things) and virtual addressability that would create an Internet-like structure for remote locating, sensing, operating, and actuating of entities, which we would term internet-connected-constituents (ICCs)” (Ng and

Wakenshaw, 2017, p.3). This study adopts Ng and Wakenshaw's (2017) definition as it focuses on the IoT capabilities in terms of connecting parties.

IoT immensely utilises the significant changes that have occurred in the technological industries: the tiny size of processors and microcontrollers, the falling consumption of energy as well as the declining of prices of sensors and devices (Payne and MacDonald, 2006) are all contributing to the rise of IoT. The potential of these interactive (smart) objects comes from the embedded communication and information technology; this would have a massive impact on the way they are used. Connecting things with a microcontroller would add a new capability and enable them to communicate with people and each other (Atzori, Lera and Morabito, 2010). Access to the internet would also mean they could be used for controlling, tracking, labelling, and much more, opening new opportunities of generating significant value. Connecting objects to the internet would facilitate the remote monitoring of their state, and the gathering of up-to-date information about real-world objects and their related processes (Gubbi et al. 2013). This setting put many features of physical world under "detailed observation" at almost no cost (Mattern and Floerkemeier, 2010) and would revolutionise technological management and decision-making processes.

Opening up new horizons to solve complex problems dealing with critical situations and optimising business problems are other value-added activities for the Internet of Things (Mattern and Floerkemeier, 2010; Fleisch, 2010). The main objective of the Internet of Things is to connect anything at anytime, anywhere, with anyone, through any network and any service (Gubbi et al., 2013). The smartness of the interactive object comes from their ability to make or enhance contextual decisions when they access information collected by other things (Spoladore, 2017). Thus, this study sets out to investigate the impact of the IoT's capability for healthcare value co-creation practices to improve quality of life and well-being.

2.2 Origin and development of IoT

The idea of connected devices is not new (Pandurov et al., 2014; Thakare, Patil and Siddiqui, 2016). One of the first attempts to connect devices to the internet was by a student at Carnegie Mellon University in the early 1980s (Vetter, 1995) when he connected a coke machine indicator's light to a photo sensor linked with a software program to count how many cans remained in the machine and send the information to a website, so students could check the coke availability from any place before going to the machine. Although that was a creative idea that raised awareness of the benefits of connected devices, the technical limitations faced restrained the concept from becoming widespread (Pandurov et al., 2014). The first internet-controlled device was created in 1990 by John Romkey (Castro, 2017); it was a toaster that could be controlled through the internet. Romkey's invention was an engineering challenge at that time because connecting a device to the internet needs hardware to be built (Thakare, Patil and Siddiqui, 2016). Microsoft started to link devices with its operating system, Microsoft Windows, in 1993, by introducing the "Microsoft at Work" MaW operating system (Coopersmith, 2015). MaW is capable of communicating with conventional business devices, such as printers and fax machines, through a standard communication protocol, and users can control and obtain status information regarding the machine.

The concept of connected devices was developed by Raji (1994), when he published his article "Smart networks for control" *in IEEE Spectrum*, who described how status or command are transferred within a packet of information from one node to another or among several nodes in a control network which then opens the door to integrating and automating anything. In 1996 Bill Joy, a computer engineer and co-founder of Sun Microsystems, presented a speech at the World Economic Forum in Davos and proposed his six Webs taxonomy. One of the Webs was the "pervasive Web" or a device-to-device (D2D) technology, which explains how devices interact with each other, exchange information, manage, and control processes.

Distinct identification is essential for any device connected to the internet, so objects must have an internet protocol (IP) address number to communicate with other objects. The number of IP version 4 (IP v4) addresses was limited (4.3 billion), so introducing IP v6 in 1996 was of massive benefit to IoT. IP v6 has address of 128 bits, while IP v4 has an address of 32 bits. This address space makes the number of addresses that can be assigned to things equal to approximately 3.4×10^{38}, which enables IoT to assign addresses to anything on the Earth.

The term "Internet of Things" was first raised in 1999 by Kevin Ashton (Atzori, Lera and Morabito, 2010), when he presented the benefits of RFID technology in Proctor and Gamble, the company where he was working. Ashton also was the executive director of the Auto-ID Centre, in Massachusetts Institute of Technology (MIT). Ten years later, Ashton published a paper titled "That 'Internet of thing' thing" in *RFID Journal* (Ashton, 1999). There are two main types of IoT products: IoT for industries and IoT for consumers. Currently, IoT is used across a wide range of industries, such as smart cities, healthcare, logistics, transport, wearables, smart homes, oil and gas and connected cars.

2.3 IoT Applications

IoT technologies have been implemented in a wide range of applications across many industries such as healthcare, telematics, smart cities, home automation, security, traffic management, logistics, media entertainment, energy management, environmental management, industrial automation insurance, and many more (Antonio Jara et al., 2013; Zhao, Chaowei and Nakahira, 2014; Ahuja et al., 2016; Chen, 2014; Raji, Jeyasheeli and Jenitha, 2016; Zois, 2016; Kim and Chung, 2017; Wan et al., 2017). Although IoT technology has brought many opportunities for business, scholars argue that its technological advancement is still in its primary phase (Kim and Kim, 2016). IoT technology offers vast benefits to many businesses and societies (Nguyen and Simkin, 2017). Most of the applications of IoT are new and innovative. Scholars expect IoT devices to support nearly all industries (Ahmadi et al., 2018; Dholakia and Reyes, 2013). The enormous number of IoT-connected devices and the massive amount of collected data opens the door for new services that will positively influence the economy and society (Borgia, 2014).

Wearables are one of the clearest applications of IoT for personal use. There are a wide range of functionalities for wearables on the market including health and fitness tracking, identification, authorisation, contactless payment, and localisation. Major players in the technology industry such as Apple, Google, Microsoft, Garmin and Intel, as well as big non-technological companies like Adidas and Nike have heavily invested in wearables.

IoT also converts the traditional techniques of the agriculture sector into smart methods. The processes of weeding, spraying, irrigation, and soil moisture sensing can be accomplished by using IoT technologies (Gondchawar and Kawitkar, 2016).

Smart cities are one of main applications of IoT. IoT technology plays a principal role in enhancing the smartness of cities (Scuotto et al., 2016) through many applications including smart building (Ferrández-Pastor et al., 2018), waste management (Anagnostopoulos et al., 2017), intelligent transportation (Saarika, Sandhya and Sudha 2017), traffic congestion (Scuotto et al., 2016; Soomro et al. 2018) and smart parking (Al-Turjman and Malekloo, 2019; Khanna and Anand, 2016). Through its capability to sense and monitor, IoT can solve the major issues in big cities like pollution and road traffic. In a smart environment, there are many opportunities to apply IoT to enhance the city. IoT sensors used to monitor combustion gases can detect fires in forests (Mohamed, 2019) as well as monitoring the quality of air through detecting the CO_2 emissions of factories and other toxic gases. Sensors can also be used for monitoring the water quality and water leakages.

IoT can be used to enhance the flow of traffic by utilising both sides of the road in peak morning and evening timing. IoT can transform a road into smart one by formulating an automated movable divider, which can monitor and detect the underutilisation of available resources (ongoing and incoming lanes) and, hence, shift lanes to minimise traffic jams (Nirosha, 2017).

In the retail industry, IoT technologies enable retailers improve the customer experience, simplify the shopping process and reduce the cost (Balaji and Roy, 2017). The use of RFID tags enables management to identify and track automatically a huge number of objects. IoT technology plays a significant role in the retail industry; it allows greater customer data management to enable marketers to predict customer behaviour and raise customer satisfaction.

The aviation industry has implemented IoT to improve maintenance efficiency, passenger experience and cockpit connectivity. The increased number of sensors embedded in the airplane enables engineers and mechanics to diagnose problems immediately and prescribe the right course of maintenance accordingly. Airlines use IoT applications through smartphones for alerts, baggage tracking and other personalised services. In the hospitality industry, IoT technologies are used to transform business delivery. Hotels, resorts, cruise ships and restaurants utilise the potential capabilities of IoT to gather data, interact with users and automate processes to enhance the customer experience. IoT provides many solutions for hospitality, such as eliminating the cost of energy in guests' rooms, sensors can automatically recognise whether the room is occupied and adjust the temperature accordingly, preventing energy consumption in vacant rooms.

In the supply chain, IoT technology allows the tracking of shipments, authentication of products, and monitoring of inventories. Using IoT technology, inventory is tracked and traced worldwide based on item-level and users are informed immediately about any deviation from schedule. This offers full inventory visibility, correct information about availability and an estimated arrival time, all of which enables decision makers to optimise supply management processes and reduce costs.

2.3.1 IoT Applications in Healthcare:

The applications of IoT in medicine and healthcare are massive. They include patient remote monitoring (Ivascu et al., 2015; Torre Diez et al., 2019), medical treatment management (Torre Diez et al., 2019; Zois, 2016), mental health (Diez et al., 2018), telemedicine (Raji, Jeyasheeli and Jenitha, 2016), product authentication (Rajagopalan et al., 2018), data computing (Chen, 2014) and many more. IoT technology is also penetrating inventory management in hospitals and medical centres, healthcare building facilities and the pharmaceutical industry.

IoT uses biosensors to gather information on patients' vital signs and send them through a network to the caregiver and relevant medical staff so they can take it into account when making their decisions. As an example, IoT employs gyroscope and accelerometer sensors to prevent unwanted motion in elderly or Alzheimer's patients (Laplante and Laplante, 2016). Biosensors are used to detect hypertension and body temperature in homecare settings. Another example is introducing IoT to the portable infusion pumps (Han-soo, 2018) to send the status and location of the device, saving the nurses' time and, consequently, enhancing efficiency. IoT has become an innovative choice for home healthcare solutions. It takes the advantages of wireless sensors networks, big data and cloud computing to introduce an innovative system to track, locate and detect when elderly people fall (Yacchirema et al., 2018).

IoT technologies are capable of enhancing the processes of other medical tools, such as bionics, magnetic resonance imaging and epigenetics (Suha and Sharma, 2016). By using the advancements in big data analysis, IoT sensors enhance bionics and the treatment of psychiatric diseases (Stellbrink and Meisenzahl, 2017). Data mining algorithms use the big data generated by IoT sensors to help medical staff with diagnosis techniques and enhanced treatment methods. The models generated by data mining techniques enable patients to know about their health based on their vital signs. (Raji, Jeyasheeli and Jenitha, 2016). IoT provides innovative solutions to promote effective methods in the field of healthcare such as mental health (Deiez et al., 2018; Suha and Sharma, 2016; Glenn and Monteith, 2014), ambient assisted living (Alam et al., 2016; Wan et al., 2016), elderly healthcare (Pinto, Cabral and Gomes, 2017) chronic disease (Raji, Jeyasheeli and Jenitha, 2016), kidney disease (Vijayarani and Dhayanand, 2015) and rehabilitation (Fan et al. , 2014).

A smart solution offered by AT&T shows how IoT technology enhances the value co-creation process in healthcare service provision. The solution called the Medical imaging and information Management solution (MiiM) enables physicians and other medical staff to collaborate through a web-enabled platform and conduct a concurrent diagnosis of a patient immediately from anywhere, saving more time when doctors need to see other patients and greatly enhancing patient health management (Tyagi, Agarwal and Maheshwari, 2017). Yuehong et al. (2016) introduce a framework of a “one-stop” IoT smart rehabilitation system that serves many residents in a smart city instead of going to the hospital. The patients share the flexible service within their area, which leads to an increase in the utilisation of rehabilitation systems. IoT technology deployment in healthcare organisations is based on big data gathered from sensors installed in relevant areas and an effective smart algorithm needs to be developed to remove unwanted data.

Clinical professionals use data mining techniques to generate knowledge by following the treatment programme of a specific disease or health condition to verify the most reliable applied strategy. They also use data mining to detect fraud and misuse through determining uncommon patterns and the inconsistent referral of medical claims by hospitals, laboratories and doctors (Kaur, 2019). However, having efficient approaches to data mining in healthcare information systems is still far away due to the complications in applying it to the healthcare service. (Yuehong et al, 2016). This study focuses on portable smart devices such as mobile phones, wearables, ingestible sensors, connected inhalers, glucose monitoring devices, as well as IoT automation systems for healthcare facilities.

2.4 ‘Internet of Things’ capabilities:

The organisational approach to technology is a strategic decision that should be adopted through organisational choices including its employees, structure and processes (White and Bruton 2010). Technological capabilities are fundamental for organisations to obtain a competitive advantage (Burgelmn, Maidique and Wheelwright, 2004). The literature identified various forms of organisational capabilities. Kusunoki, Nonaka and Nagata (1988) propose three types of capabilities in organisations: local capability, architectural capability and process capability. Wade and Hulland (2004) identify organisational capability in terms of core and dynamic capabilities. The organisational capability is defined as the “ability to perform repeatedly a productive task which relates either directly or indirectly to a firm’s capacity for creating value through effecting the transformation of inputs into outputs” (Grant, 1996). Huo (2012, p.5) define core capability as the “distinctive individual units of competencies in relatively stable environments” and dynamic capability as “the ability to integrate, build, structure, and reconfigure internal and external competencies to meet the requirements of changing environments to generate multiple sustained competitive capabilities simultaneously in dynamic, unstable, or volatile environments” (Huo, 2012).

Smart service literature suggest that digital capability is a key capability that organisation should develop to provide advance service offerings for their customers (Sjödin, Parida and Kohtamäki 2016; Porter and Heppelmann 2014) Digital capability explains an advanced ability to implement and use smart digital technologies and data analytics to offer high value of service delivery (Sjödin, Parida and Kohtamäki 2016). This study conceptualises IoT as an advanced phase of Information and Communication Technology (ICT) (Borgia, 2014). IoT is not a working-alone technology, but a set of complementary technological techniques working together to generate capabilities for the organisation (Atzori et al., 2010; Lee and Lee, 2015). This research conceptualises IoT technology as an additional capability with organisational functions and operations that can help organisations to acquire a competitive advantage. This study considers IoT capability comparable to ICT capability as discussed in literature (e.g. Peng, Schroeder and Shah, 2008; Parida, Oghazi and Cedergren, 2016). ICT capability refers to “a firm’s ability to strategically use a wide array of technologies for business purposes, ranging from basic to very sophisticated” Parida, Oghazi and Cedergren, 2016). Table 2.1 shows an overview of IoT capabilities in literature.

Table 2.1 IoT capabilities in healthcare

Capability	Example	Reference
Ad hoc networking	A connection between mobile phone and wearable device on the patient’s body to enhance the monitoring process (no assistance from other networks)	Varshney and Sneha, 2006; Chen, 2014
Ambient Assisted Living (AAL)	Gathering and sending necessary medical data about elderly patients to monitor health status by using a combination of smartphone RFID and NFC	Raji, Jeyasheeli and Jenitha, 2016; Zois, 2016; Kim and Chung, 2017; Wan et al., 2017

Authentication	Medical image encryption in telemedicine and healthcare applications	Atzori, Lera and Morabito 2010; Rajagopalan et al., 2018
Auto data collection	Using RFID in medical inventory management to collect and transfer data.	Vilamovska et al., 2009; Atzori, Lera and Morabito, 2010
Communication	A network that facilitates a connection between individuals and things.	Antonio Jara et al., 2013; Chen, 2014
Computing	Supporting medical data applications by cloud computing.	Chen, 2014
Control	Using software to control the physical state of the patient by analysing the collected data of vital signs.	Raji, Jeyasheeli and Jenitha 2016; Qi et al. 2017
Decision-making support	Using data mining techniques to identify critical vital signs data using a classification model, the doctor can remotely access the information and make the decision.	Raji, Jeyasheeli and Jenitha, 2016; Zois, 2016; Kim and Chung, 2017;
Detection	Investigate drugs to detect an adverse drugs reaction or any harmful effects.	Pappas et al., 2001; Zhao, Chaowei and Nakahira, 2013; Ahuja et al., 2016, Jara et al., 2010; Torre Diez et al., 2019; Ukil et al., 2016
Environmental sensing	Monitoring the pathogens in air, water, soil, or food	Patel, Nanda and Sahoo 2016; Chen 2014;
Identification	RFID tags implanted in the patient's hand	Antonio Jara et al., 2013; Chen, 2014; Ahuja et al., 2016; Atzori, 2010
Information platform management	Big data management through IoT platforms	Zhao, Chaowei and Nakahira, 2011; Ahuja et al., 2016,

Location sensing and sharing	The geographical position information from GPS	Chen, 2014
Monitoring	Monitoring the treatment effects of drugs	Torre Diez et al., 2019; Ivascu et al., 2015; Hayati and Suryanegara, 2017; Bui and Zorzi, 2012; Qi et al., 2017; Patel, Nanda and Sahoo, 2016
Monitoring of disease progress	Monitoring elderly patients using the accelerometer sensors on smartphones.	Ivascu et al., 2015; Torre Diez et al., 2019
Prediction	Psychiatric Emergency State Prediction in Smart Home Service Platform for ambient assistance living	Alam et al., 2016; Hadjem, Salem and Naït-Abdesselam, 2014
Prevention	Assistance in cardiac disease prevention	Zhao, Chaowei and Nakahira, 2011; Ukil et al., 2016
Preventive health support	Implementing the Diabetes Prevention Program through IoT to change behaviours in prediabetes people.	Dimitrov, 2016; Zois, 2016;
Real-time monitoring	Blood glucose monitoring	Raji, Jeyasheeli and Jenitha, 2016; Cosma et al., 2017; Babar et al., 2017; McWhorter et al., 2017
Remote controlling	The lab-on-a-chip device can control cells at the single-cell level simultaneously.	Patel, Nanda and Sahoo, 2016; Chen, 2014;
Remote Diagnoses	Using data transmission via Electronic Health Records (EHR) allows for quicker and more accurate diagnosis and treatment of a large number of conditions.	
Remote monitoring	Medical data collected by wearable devices and connected sensors and sent via Wi-Fi to	Zhao, Chaowei and Nakahira, 2011

	the patient's Electronic Health Record (EHR).	
Remote surgery	The collaboration between surgeon and robot through a high-speed data connection to perform surgery on a patient, the robot translates the movement of the surgeon's hands into precise movement inside the patient's body.	Qi et al., 2017
Remote-less infrastructure	Using a single control device to control several machines instead of using remote controls for all of them individually.	Ahuja et al., 2016
Secure communication	Sending the authenticated physiological data from the patient's body to Azure IoT Hub through GSM module	Chen, 2014; El Zouka and Hosni, 2019
Sensing	Biosensors used to sense the real-time signals such as the production of biomolecules.	Patel, Nanda and Sahoo, 2016; Atzori, Lera and Morabito, 2010;
Telemedicine	The surgeon performs remote operations using "5G" technology	Raji, Jeyasheeli and Jenitha, 2016
Tracking (People and Objects)	Track the physical assets of the hospital's inventory to avoid damage, damage, demurrage, loss and repair. Tracking people: the case of patient flow monitoring to improve workflow in hospitals.	Atzori, Lera and Morabito, 2010; Hayati and Suryanegara, 2017

Source: researcher synthesis.

A smart device can sense, communicate and interact with the surrounding environment (Kortuem and Kawsar, 2010). The automatic collection of data using RFID in medical inventory management can support the decision-making process in a hospital (Vilamovska et al., 2009; Atzori, Lera and Morabito, 2010). Hospitals and medical centres take advantage of the ability of

IoT technology to monitor the patient in real time, such as blood glucose monitoring (Raji, Jeyasheeli and Jenitha, 2016; Cosma et al., 2017; Babar et al., 2017; McWhorter et al., 2017). Enhancing the accuracy of diagnosis and the treatment of a large number of conditions by sending data via Electronic Health Records (EHR) is another capability of IoT technology (Zhao, Chaowei and Nakahira, 2011). Moreover, remote surgery (telesurgery) has become more comfortable as IoT facilitates the collaboration between surgeon and robot through a high-speed data connection (Qi et al., 2017). The interactive characteristic of IoT systems enables the technology to guide people toward more sustainable behaviours (Bocken, Ingemarsdotter and Gonzalez, 2019). Consequently, this study seeks to discover the effects of IoT capabilities on value co-creation that can ultimately improve quality of life and enhance organisational performance outcomes. One of the literature gaps identified in this study is that the role of IoT capabilities and their managerial and operational potential have not been fully explored (Whitmore, Agarwal and Da Xu 2014).

IoT capabilities explained in Table 2.1 can be grouped under managerial capabilities or higher-level capabilities as shown in Table 2.2

Table 2.2 Levels of IoT capabilities in healthcare

“Level 1” Capabilities	“Level 2” Capabilities	Reference
Monitoring	Real-time monitoring, Ambient Assisted Living, detection, environment sensing, identification, location sensing and sharing, monitoring of disease progress, prediction, remote monitoring, telemedicine, tracking people and objects.	Atzori, Lera and Morabito, 2010; Porter and Heppelmann, 2014; Wolf, Stumpf-Wollersheim, and Schott, 2019; Dauwed and Meri, 2019
Control	Ambient Assisted Living, authentication, identification, prevention, preventive health support, remote control, remote surgery, remote-less infrastructure, telemedicine.	Porter and Heppelmann, 2014; Wolf, Stumpf-Wollersheim and Schott, 2019; Suppatvetch Godsell and Day, 2019
Optimisation	Auto data collection, computing, decision-making support, information management, remote diagnoses, remote surgery, telemedicine.	Porter and Heppelmann, 2014; Wolf, Stumpf-Wollersheim and Schott, 2019; Schweizer, 2018

Collaboration	Auto data collection, communication, decision-making support, location sensing and sharing, remote diagnoses, remote monitoring, remote surgery, secure communication, telemedicine.	Porter and Heppelmann, 2014; Wolf, Stumpf-Wollersheim and Schott, 2019; Bedwell et al., 2012

Source: researcher synthesis.

Chapter 3 Value co-creation and innovation

3.1 The definition of value

The concept of value has been studied in business literature from different viewpoints but only with vague meaning (Parasuraman, 1997). According to Graf and Maas (2008), the notion of value has always come with little consensus. Likewise, Hilton, Hugehes and Chalcraft (2012) argue that the meaning of value is complex and subjective. The concept of value is one of the most overused and misused terms in social sciences (Khalifa, 2004, Sanchez-Fernandez and Iniesta-Bonilo, 2007). The nature of ambiguity in the literature comes from the absence of agreement among researchers about the conceptualisation and measuring of the concept of value. Scholars describe "value" as "subjective" (Zeithaml, 1988), "dynamic" (Parasuraman and Grewal 2000), "multifaceted" (Babin, Darden and Griffin, 1994) and "complex" (Lapierre, 2000). Woodall (2003), suggests five distinct concepts of value: net value, marketing value, derived value, sale value and rational value.

The literature shows that there are two fundamental approaches to defining the concept of value. The first approach proposes value as a solo concept; it called the *one-dimensional* approach (Sanchez-Fernandez and Iniesta-Bonilo, 2007, Sweeney and Soutar, 2001). The second approach is *multi-dimensional*, where value constitutes things such as benefits, quality and cost (Hoolbrook, 1996; Babin and James, 2010).

The one-dimensional approach refers to the neoclassical economy. The traditional perception of the market believes that customer choices and market options are motivated by utilitarian value (Chiu, Hsieh, Li and Lee, 2005). So, the value perceived by customers is based on what they take and what they give (Bowman and Ambrosini, 2000). Based on this view, value is a single idea that can be evaluated by self-reported item(s) that assess the consumer perception of value (Brady and Robertson, 1999, Kerin et al., 1992; Sweeney et al., 1999). Similarly, this stream puts the price and income as the determinants for customers' decision-making, so a low price means more value. In line with this view, Zeithaml (1988) defines value as "the customer's overall assessment of the utility of a product, based on the perception of what is received and what is given." Thus, the primary assumption is that the customer pays sacrifices (e.g. money, time, and efforts) to get the value that they believe is embedded within the product.

The multi-dimensional approach perceives value as a concept consisting of different interrelated characteristics or dimensions that shape a complex phenomenon (e.g. Holbrook, 1996, Babin et al., 1994; Sweeney and Soutar, 2001). According to Holbrook (2006), the value can be defined as "interactive, relativistic, preference and experience." Similarly, Ramaswamy (2009) proposes that value is in the experiences. On the other hand, Grönroos and Voima (2013) suggest that value is created in interactions between parties. Based on this view, value entails an interaction between actors, it is personal, context-related and characterises a preference judgment. Recent literature shows an increase in discussing value as a multi-dimensional concept. Scholars distinguish between value and values; Sanchez-Fernandez and Iniesta-Bonilo (2007) propose a clear distinction between the two terms. Value refers to the "trade-off" between benefits and sacrifices while the term "values" refers to the goals, standards, norms, procedures, and rules that serve as a basis for individual judgment (Holbrook, 1996; Sanchez-Fernandez and Iniesta-Bonilo 2007). Creation of value is the goal behind all types of economic exchange (Vargo et al., 2008; Vargo and Lusch, 2008). Graeber (2001) classifies four critical approaches to the definition of value: (1) value in business domain, as a consumer's willingness to pay cash as a price of goods to obtain such benefits, (2) value as a concept representing what is useful in human life, (3) value as meaning and meaningful difference (4) value as an action. On the other hand, Boztepe (2007) outlines three main approaches to define value: (1) value as experience, (2) value as exchange and use and (3) value as a sign. This study adopts the last conceptualisation of value as this formulation comes under the view of S-D logic framework, which guides the objectives of this study.

3.2 Conceptualisation of value and value co-creation

Customer-centric views on value provide insights into how value is derived through the use of an offering. The idea of the customer at the centre of resource interaction provides a deep understanding of how propositions can be used to derive value (Vargo, Akaka, and Vaughan, 2017), However, Grönroos and Gummerus (2014) suggest that moving the attention regarding value creation from a firm to a customer changes the balanced view of value and restricts the understanding of the value creation process. The value creation process works as a joint process that is motivated by resource integration and exchange between several actors (Prahalad and Ramaswamy, 2004a; Vargo and Lusch, 2004). So, the value is created through mutual actions and practices, not through isolated efforts. Introducing the idea of the value network (Normann and Ramirez, 1993) resulted in thinking of value creation concept in more depth. In other words, as more than a dyadic relationship of interaction to the interrelated web of exchange (Vargo et al. 2017). To extend the value creation process further, it is essential to revise and reconsider the meaning of value. This idea involves understanding value within multiple actors and actions that includes the value in use and also value in exchange (Vargo, Akaka, and Vaughan, 2017). Value is created by the interaction of market actors (organisation, supplier, distributor, manufacturer and others) during this process; actors exchange “resources” in order to get the benefit from the value creation process. Organisation can influence the value creation process even though it does not offer ready-made value within the product. How firms and customers interact with each other is influencing the value creation process (Grönroos and Gummerus, 2014). Although, customers contribute to the process of creating value; there are other players collaborate to create the value (Vargo, 2008; Vargo and Lusch, 2016; Akaka, Vargo and Lusch, 2012). The players (actors) are considered as resource integrators (Vargo and Lusch, 2016). Customers are considered not only as active contributors but as critical players in the value creation process (Akaka, Vargo and Lusch, 2012; Vargo and Lusch, 2008).

Grönroos and Gummerus (2014) define value creation as “the customer’s process of extracting value from the usage of resources.” This definition converts the view of the customer from a passive element, who perceives or receives value, to an active contributor in the business process. Therefore, a firm’s role has been changed from the producer of goods and services to a service provider of processes for customer usage. In this view, all actors — firm, supplier, manufacturer, distributor and others — collaborate with the customer to create value by offering goods and services. Hence, all actors in the market are considered value creators (Lusch and Vargo, 2006; Vargo, 2009). Customers adds meaning to the goods or services through their experience during the process of usage (Grönroos and Gummerus, 2014; Anker et al., 2015), and fulfil their needs by accepting the firm’s offerings (goods or services) then applying their own experiences onto them. (Vargo and Lusch, 2008; Grönroos and Voima, 2013). There are several terms used in literature to indicate that value is created when a customer applies their own experience during the usage process: *value-in-use* (Vargo, 2008; Lusch, Vargo and O’Brien, 2007; Sandström et al., 2008), *value-in-experience* (Turnbull, 2009), and *value-in-context* (Vargo et al., 2008; Vargo, 2008).

3.3 Service ecosystems

The word “ecosystem” originated from biology. It refers to “the complex of living organisms, their physical environment, and all their interrelationships in a particular unit of space” (Encyclopaedia Britannica, 2020). Lately, the phrase has been used in the social sciences such as marketing (Zhang and Watson, 2020), innovation management and ICT management (Pellikka and Ali-Vehmas, 2016). Other terms related to the concept of the “ecosystem” — such as service ecosystem, organisational ecosystem, business ecosystem, and innovation ecosystem — are frequently used in academia and practice (Pop et al., 2018). Firms are collaborating and competing with each other to achieve customer satisfaction through new products and to finally fit in the next level of innovation (Moore 1993). In line with this view Zhou et al. (2011) suggest that a product ecosystem shows the arrangements of several related products in a cohesive process different than the view of the traditional and isolated product. The service ecosystem can be defined as “a relatively self-contained, self-adjusting system of resource-integrating actors connected by shared institutional arrangements and mutual value creation through service exchange” (Vargo and Lusch, 2016). The service ecosystem is a customer-oriented view, so the customer is contributing to the desired outcome by being part of the resources of the service ecosystem. According to Ng et al. (2011), business organisations should consider the competencies of the customer and create new methods to engage their skills in the service ecosystem. The service ecosystem implies that the value co-creation process in motivated collectively by interactions and the customer is included in these activities (Vargo et al., 2015)

3.4 The process and dimensions of value Co-creation

Value co-creation is a multi-dimensional concept. It has many interrelated facets through several disciplines and has no unified definition (Galvagno and Dalli, 2014; Ranjan and Read, 2016). Grönroos (2008) defined value co-creation as a process “adopting a service logic makes it possible for firms to get involved with their customers’ value-generating processes, and to actively take part in value fulfilment for customers.” On the other hand, Cova and Salle (2008) described value co-creation as a process connecting the customer and service provider in the service network. Similarly, Grönroos (2011) defined the value co-creation process as: “joint collaborative activities by parties involved in direct interactions, aiming to contribute to the value that emerges for one or both parties." (Randall, Gravier and Prybutok, 2011) described value co-creation as an actor's connection, trust and commitment. Value co-creation can be defined as "benefit realised from integration of resources through activities and interactions with collaborators in the customer's service network." (McColl-Kennedy et al., 2012). Lee (2019), however, defined it as a benefit resulting from the experiences accumulated during patients' interactions with medical staff, which help maximise the quality of their care.

Co-creation concept connects with several disciplines such as management, service science, marketing, tourism, innovation, technology, healthcare and social services (Leclercq et al., 2017). Value co-creation is an interactive process that connects two or more resource integrators (actors) through a specific type of reciprocally valuable collaboration (Frow, McColl-Kennedy and Payne, 2016). See Figure 3.1.

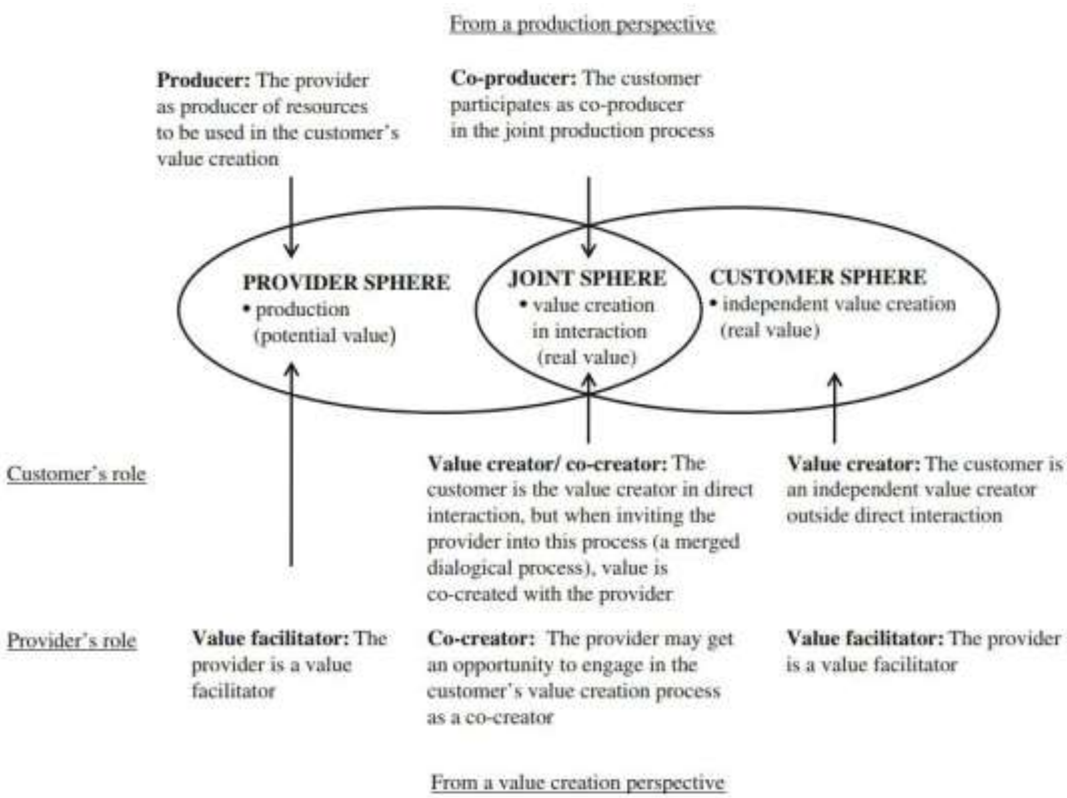

Figure 3.1 Value co-creation spheres (Grönroos and Voima, 2013)

As Figure 3.1 shows Grönroos and Voima (2013) propose a framework to analyse the outcome of value co-creation through three forms of spheres: the customer's sphere, the organisation's sphere and the joint sphere. Payne, Storbacka and Frow (2008) as well as Skaržauskaitė (2013) proposed a similar approach of value co-creation that consists of three elements: customer value creation process, supplier value creation process and encounter process.

All participants in the framework within spheres are equally important (Sharma, Conduit and Hill 2014). The sequence of spheres is not linear, and it can take any order (Grönroos and Voima, 2013). Value co-creation is activated through an encounter between supplier and customer in the joint sphere. The organisation uses its sphere to create value as well as to manage the relationship with customers and other actors (Uhrich, 2014). Value is facilitated only in the provider's sphere by offering related resources for customer use without interaction (Anker et al., 2015). In this sphere the customer exchanges the product with money and gets the embedded value within the product, so *value-in-exchange* is created (Grönroos and Voima, 2013).

Customers manage their activities by using resources, processes and practices in the customer's sphere (Mickelsson, 2013). The customer is the user and value creator who assesses the value. *Value-in-use* is created in the customer's sphere (Grönroos and Voima, 2013). The customer creates and evaluates the value of usage both longitudinally and experientially (Moeller et al., 2013). The interaction within the customer's sphere occurs between customers or with the direct involvement of service provider providing support (Moeller et al., 2013). The encounter process occurs in the joint sphere, with the interaction between customer and service provider producing the value for both, so they are co-producers of the service and co-creators of value (Holmqvist, Guest and Grönroos, 2015). Actors in the joint sphere can be individuals, intelligent systems or products (Grönroos and Gummerus, 2014).

During the interaction process, the service provider can take the opportunity to affect the value co-creation process of the customer (Skaržauskaitė, 2013). The organisation and customer can co-create value at various interaction events (Hsieh and Hsieh, 2015). The mutual impact between organisation and customer enables a dialogical process and then co-creation (Grönroos and Voima, 2013; Hsieh and Hsieh, 2015). Interaction with the customer offers an opportunity for the organisation to expand its capacity for service customisation (Hsieh and Hsieh, 2015). The result of the direct interaction between both sides is a combination of all value-creating processes into one integrated dialogical process (Skaržauskaitė, 2013). Organisation and customer are operating inside each other's domains (spheres) and are able to coordinate practices, integrate resources, build knowledge, and directly affect each other (Skaržauskaitė, 2013). This study focuses on the joint sphere and the interaction process where customer and organisation can collaborate to co-create value (Holmqvist, Guest and Grönroos, 2015; Grönroos and Gummerus, 2014; Grönroos and Voima, 2013).

Recent literature of digital and smart technologies has provided new views on joint sphere of value co-creation and explored the factors that may influence it (e.g. Lenka, Parida, and Wincent, 2017; Schüritz et al.2019). There are various methods of interaction between patient and caregiver through IoT applications, one of them is the data flow through several types of IoT applications (e.g. wearables, m-health), where the vital signs of patient transmitted to the caregiver domain. This way of interaction would influence the joint sphere of value co-creation. Lenka, Parida, and Wincent, (2017) suggest that two VCC's mechanisms perspective and responsive which enabled by digitalization capabilities can improve the breadth and depth interaction hence, extending the joint sphere of value co-creation. Smart technological services can expand the joint sphere based on the type of information shared between actors and how it enables them to co-create more value (Schüritz et al. 2019).

Value co-creation interactions are concurrent processes to generate a new value materially and symbolically (Galvagno and Dalli, 2014). The co-creation process integrates value through real usage of services or value-in-use, rather than through marketing or value-in-exchange (Alves, Fernandes, and Raposo, 2016). Ranjan and Read (2014) have comprehensively analysed value co-creation. They focus on two primary constructs *co-production* and *value-in-use* as shown in Figure 3.2. Co-production represents the actor's level of engagement and has three dimensions: interaction, equity and knowledge sharing (Ranjan and Read, 2014). In contrast, value-in-use refers to the forms of experiences that are affected by cognitive, emotional, and behavioural characteristics and can be captured through three dimensions: experience, personalisation and relationship (Ranjan and Read, 2014; Payne, Storbacka, and Frow, 2008; Frow, McColl-Kennedy and Payne, 2016). This study adopts the co-creation construct that is derived from Ranjan and Read (2014) and Frow, McColl-Kennedy and Payne (2016), as shown in Figure 3.2 The co-production practices consist of three factors: knowledge sharing, equity and interaction. On the other hand, value-in-use activities are captured through three factors: experience, personalisation and relationship.

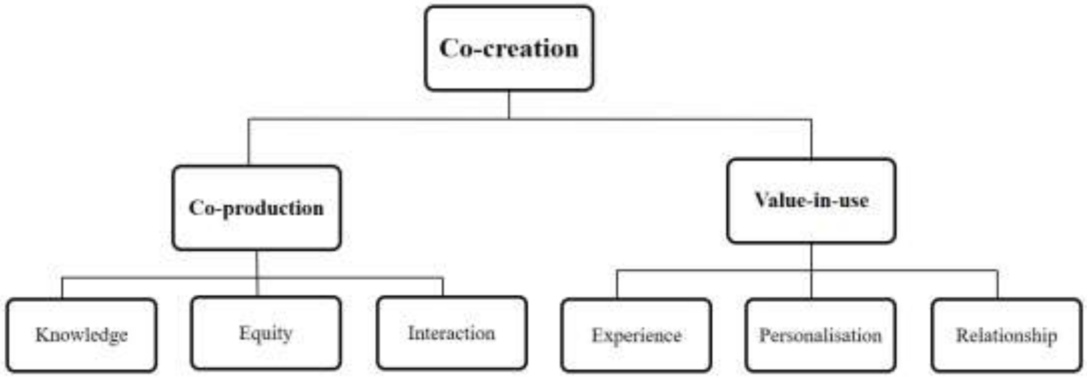

Figure 3.2 Co-creation practices and dimensions. Adapted from Ranjan and Read (2014)

Prahald and Ramaswamy (2004) proposed the DART model, a conceptual framework that emphasises the interaction activities of the co-creation process. It consists of four co-creation structures: *dialogue, access, risk-benefits and transparency*. Sorrentino, Badr and De Marco (2017) conducted a qualitative study in the healthcare context using the DART model to interpret the role of caregivers and expand the debate on value co-creation in healthcare. Schiavone, Metallo and Agrifoglio (2014) extended the DART model by adding a new measure. They argue that the spread of new technologies and the need for innovation made the DART framework incomplete so they added technology management as a fifth dimension to the model.

Some scholars focus on how various characteristics of organisational capabilities increase value for customers and the performance of a firm (e.g. Wang et al., 2015). Martelo, Barroso and Cepeda (2013) examined the impact of market orientation capability on the outcome of value co-creation. Cepeda and Vera (2007) studied the influence of knowledge management capability on value co-creation. However, these studies do not explain how organisational capabilities underpin specific co-creation practices. This study focuses on the IoT capabilities that support related healthcare value co-creation practices with the purpose of proposing a framework for co-creation practices within the healthcare service and examining the impact of value co-creation activities through IoT technology on improving performance in the healthcare service. This study suggests that developing the orientation of strategic co-creation and building an internal competency through utilising advanced technology are both critical for organisations to facilitate value co-creation and expand their competitive advantage.

3.5 Value co-creation in healthcare services

One of the fundamental goals of a healthcare organisation is to provide patients with a high quality of care with minimal medical errors at the lowest cost. The concept of value co-creation in healthcare has received considerable attention recently, like the idea of value co-creation in business (Ramaswamy, 2011; Sweeney, Danaher and McColl-Kennedy, 2015). The process of healthcare value co-creation requires participation from many actors such as patients, caregivers, hospitals, insurance firms and governmental authorities. According to Sweeney, Danaher and McColl-Kennedy (2015), healthcare value co-creation can be achieved through three types of activities: activities in the hospital, outside hospital activities and self-generated activities. Patients are active co-creators of care services; they are no longer passive receivers of healthcare services (Sweeney, Danaher and McColl-Kennedy, 2015; Grönroos and Voima, 2013). Patients must participate in value co-creation to achieve the expected results of the treatment programme. This setting leads to positive outcomes for the service, such as an improvement in quality of life (Lee, 2018; Auh et al., 2007).

Healthcare service delivery represents a typical example of the value co-creation process between the patient and the healthcare organisation (Nambisan and Nambisan, 2009). Some scholars have studied value co-creation through resource integration and actor's interactions (e.g. Gummesson and Mele, 2010). Interaction between patients and hospitals or among actors is required during healthcare service delivery. Lee (2018) argues that it is critical to determine the impact of different types of interactions on value co-creation and to design an effective process for quality of life.

The primary purpose of interaction between actors is to obtain value. Lee (2018) viewed value in healthcare as "the benefit to patients' quality of life resulting from healthcare resources (e.g. medical staff, advanced technology and information, treatment"). Value co-creation takes place when a patient uses his experience effectively through an interaction with the healthcare organisation. Value resulted from co-creation produces a personalised experience for the patient (Roser et al., 2009).

McColl-Kennedy et al. (2012) conducted a study on individuals who have experience with cancer treatments to figure out the key practices of healthcare co-creation that contribute to the treatment programme. Their research revealed eight forms of activities include cooperating, collating information, combining complementary therapies, co-learning, changing ways of doing things, connecting with people, co-production and cerebral activities. McColl-Kennedy and her colleagues categorised these activities into five practice styles including team management, passive compliance, insular controlling, partnering and pragmatic adapting. Sweeney et al. (2015) extended the arguments of healthcare co-creation practices and examined the hierarchy of co-creation activities for patients. Their study focuses on value co-creation that occurs beyond service interactions between the patient and the organisation and shows how the patient involves themselves in co-creation activities outside the healthcare organisation that eventually contribute to their quality of life and well-being. Sweeney, Danaher and McColl-Kennedy (2015) divide value co-creation activities in different levels of difficulty and argue that linking these activities would lead to a better quality of life and improved patient satisfaction. These include compliance regarding medical requirements, seeking information, interactions with medical staff, involvement in decision-making, positive thinking, sharing information, healthy diet, managing the practicalities of life, diversionary activities, emotional regulation, connecting with others who suffer from the same illness, and relationships with family and friends. Table (3.1) shows these activities.

Table 3.1 Value co-creation activities in healthcare services

Activity	Description	Reference
Cooperating	Compliance with necessary accepted information from the service provider	Badcott, 2005
Collating information	Sorting and classifying information	Badcott, 2005 ; Elg et al., 2012; Gill et al., 2010
Co-learning	Seeking and sharing information with others	Badcott, 2005; Elg et al., 2012
Connecting	Build and maintain a relationship	Elg et al. 2012, Gill et al. 2010
Co-production	Participation in the service process	Frow, McColl-Kennedy and Payne, 2016; McColl-Kennedy, 2012; Hardyman et al., 2015; Chen et al., 2011
Cerebral activity	Maintaining a positive attitude	McColl-Kennedy, 2012
Changing the way of doing things	Managing adaptive change	McColl-Kennedy, 2012
Collaboration	Self-administration of drugs	Frow, McColl-Kennedy and Payne, 2016, Badcott, 2005, Elg et al., 2012; Gill et al., 2010
Knowledge sharing	Interact with online forums	Frow, McColl-Kennedy and Payne, 2016; Badcott, 2005; Elg et al., 2012, Gill et al., 2010

Co-design	Medical staff collaborate to design a new healthcare system	Sanders and Stappers, 2008; Freire and Sangiorgi, 2010
Co-learning (shared learning)	Participation in open online courses	Diaz-Meneses, 2019
Treatment decision involvement	Participation in treatment course customisation	Chen et al., 2011; Sweeney et al., 2015
Participation	Taking part in an error prevention programme	Hardyman et al., 2015
Pre-encounter information search	Getting online information prior to clinical encounter	Osei-Frimpong et al., 2016
Compliance	Commitment to instructions regarding taking medicine	Houseman, 2004 ; Dellande et al., 2004; Sweeney et al., 2015
Participate in decision making	Sharing detailed information with the patient and allowing them to select the preferred treatment method	Osei-Frimpong et al., 2016
Relationship with family and friend	Maintaining and building new relationships during the treatment course	Sweeney et al., 2015
Sharing information	Exchange illness information with others	Sweeney et al., 2015
Connecting with others with the same illness	Discuss and exchange experiences with patients	Sweeney et al., 2015
Positive thinking	Maintain an optimistic attitude against illness	Sweeney et al., 2015

Source: researcher synthesis

3.6 Value co-creation practices

Value co-creation is the process that shows how resource integration occurs when actors interact with each other through practices within the service ecosystem. This concept of co-creation highlights the key role of practices (McColl-Kennedy, Cheung and Ferrier, 2015), the importance of resource integration (Vargo and Lusch, 2002, 2008), and the collaboration of actors (Maglio and Spohrer, 2008). According to Normann (2001), the goal of practices is to use resources, altering deficiencies in resources and enhancing the density of resources. These practices are called "co-creation practices" because they involve co-creation activities and the interaction process in a particular context (McColl-Kennedy et al., 2012). Practices are defined as "routinised ways in which bodies are moved, objects are handled, subjects are treated, things are described, and the world is understood" (Reckwitz, 2002).

The co-creation practices are activities where actors participate collectively through interactions within a specific context (Frow, McColl-Kennedy and Payne, 2016). The literature shows remarkable benefits from co-creation including fostering innovation performance (Namibian and

Baron, 2009), encouraging the active involvement of participation (Prahalad and Ramaswamy, 2000), supporting knowledge sharing (Walter, 2003), and improving well-being (Ostrom et al., 2010).

Several scholars question what customers do when they engage with the co-creation of value (Arnould et al., 2006; Payne, Storbacka, and Frow, 2008; McColl-Kennedy et al., 2016). There are several studies attempting to answer this question. They found customers engage in activities including *cooperating* (Badcott, 2005), *co-learning* (Diaz-Meneses, 2019; Elg et al., 2012; Badcott, 2005), *connecting* (Gill et al., 2010, Elg et al., 2012), *co-production* (Frow, McColl-Kennedy and Payne, 2016; Hardyman et al., 2015; Chen et al., 2011), *collaboration* (Badcott, 2005; Elg, 2012; Frow, McColl-Kennedy and Payne, 2016), *knowledge sharing* (Badcott, 2005; Gill et al., 2010; Elg, 2012; Frow McColl-Kennedy and Payne, 2016), *compliance* (Osei-Frimpong et al., 2016; Housman, 2004; Sweeney, Danaher and McColl-Kennedy, 2015), *engagement* (Hardyman et al., 2015), *spiritual relationship* (Sweeney, Danaher and McColl-Kennedy, 2015), *participation in decision making* (Sweeney, Danaher and McColl-Kennedy, 2015; Osei-Frimpong et al., 2016;), and *positive thinking* (Sweeney et al., 2015). Table (3.1) shows more forms of co-creation activities.

The domain of value co-creation extends beyond the dyadic relationship between customer and firm; it includes other actors in the customer's service ecosystem. Vargo and Luch (2008) describe customer and firm as resource integrators. A customer can also integrate resources from other sources. Vargo and Lusch (2011) categorise sources into (1) private sources (e.g. family, friends, and colleagues), (2) market-facing sources (e.g. organisations, other business entities), (3) public sources (e.g. government).

The activities of customer value co-creation occurred within a social system (McColl-Kennedy et al., 2012). This setting provides opportunities for the actors to learn, connect, share information, and make decisions based on their perception of the social environment. In the resource integration process, the efforts of the actors on the activities varied based on the nature of their actions. Some activities needed a natural effort (e.g. cooperating), others need more efforts (e.g. co-design). Sweeney et al. (2015, p.1) define customer efforts in value co-creation activities as *"the degree of effort that customers exert to integrate resources, through a range of activities of varying levels of perceived difficulty."* In line with the above definitions, this study defines value co-creation practices as “a collaborative effort of two or more actors in a purpose to generate a value (idea, solution, product and service).”

3.7 Technology-enabled value co-creation

Technology is a fundamental concept in service and value co-creation studies (Akaka and Vargo, 2013; Maglio and Spohrer, 2008). Akaka and Varog (2013) define technology through the lens of S-D logic as *“a combination of practices, processes and symbols that fulfil a human purpose.”* Technology reduces human interaction in services (Immonen, Sintonen and Koivuniemi, 2018; Walker and Johnson, 2004). The recent technological advancements have reformed service delivery, innovation and management (Borgia, 2014; Khanna and Kaur, 2019). This view highlights the importance of technology in the co-creation of value by facilitating knowledge and information sharing among actors within the service system. Technology impacts and is impacted by institutions and the actions of social and economic actors within the service ecosystem (Orlikowski, 1992). Thereby, technology influences how value is determined (Akaka and Vargo, 2013). It is a critical element of service systems, and the essential driver of co-creation of value and service innovation (Orlikowski, 1992).

This study draws on Orlikowski’s structurational model of technology (Orlikowski, 1992) to understand the role and scope of technology in value co-creation processes and to conceptualise the interplay between technology and human actions. Service science is the study of service systems (Akaka and Vargo, 2013). Service systems can be defined as the configuration of value co-creation of individuals, technology and value propositions that combine service systems (internal and external) with shared information about procedures and methods (Maglio and Spohrer, 2008).

This study uses Orlikowski’s structurational model of technology to clarify the relationship between technology and value co-creation. The structurational model of technology is one of the most influential frameworks used in technology research to depict the interplay between technology and humans or institutions (Thompson, 2012). The model is derived from Giddens’s theory of structuration. It incorporates two dimensions: technology is seen as an “objective external factor” and “socially constructed artefact” (Orlikowski,1992). The model entails three components: human agent (e.g. actors, customers, workers), technology (e.g. software, cloud computing, IoT) and institutional properties (e.g. culture, norms, structure). These elements and their relationship are shown in Figure 3.3.

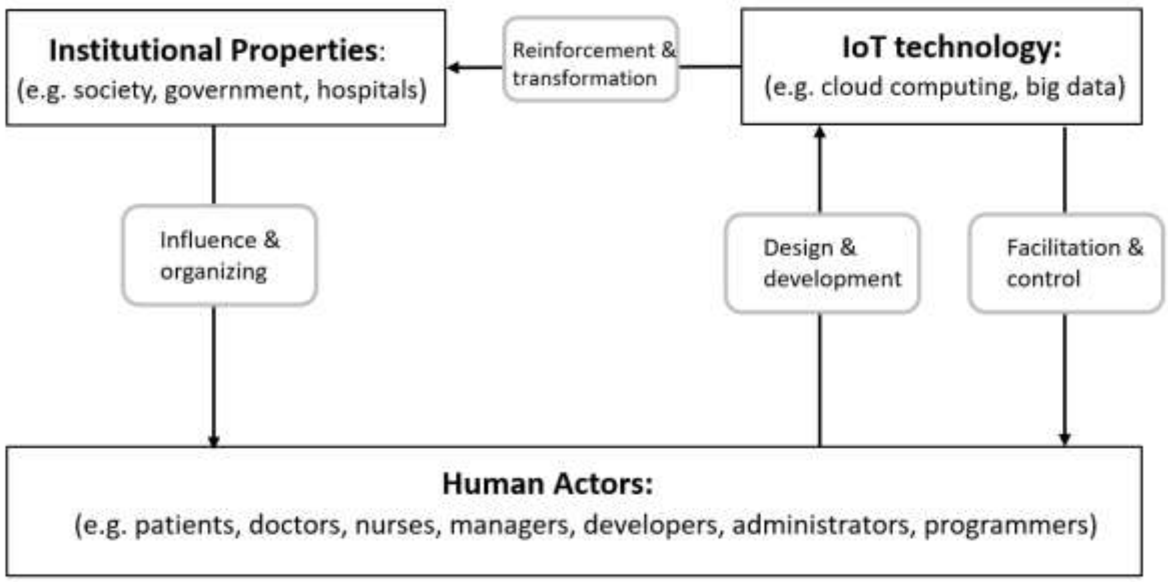

Figure 3.3 Structurational model of technology (adapted from Orlikowski, 1992; de Waal, Outvorst and Ravesteyn, 2016)

In contrast to Orlikowski's structurational model of technology, Arthur (2009) suggests that technologies are recognised not merely as a product or an outcome but also as a process and practice. He proposes that technology should be conceptualised as three forms (1) means to satisfy human need, or (2) a collection of actions and components or (3) a complete assembly of devices and engineering practices within the culture. From the S-D logic perspective, technology is recognised as either operand (e.g. outcome of human action, design, hardware, software) or operant resources (e.g. facilitating the interaction among actors) (Arthur, 2009; Vargo and Lusch, 2004). The technological inventions in the past decades have resulted in human-computer interaction and technology-generated self-service (Kolbe and Brenner 2006), such as online shopping and telemedicine. Technological advancement of information and communication makes the physical locations of actors in the co-creation process less important, thereby the way of interaction between the service provider and customer has been changed. Figure 3.4 shows the shift toward IoT-enabled value creation.

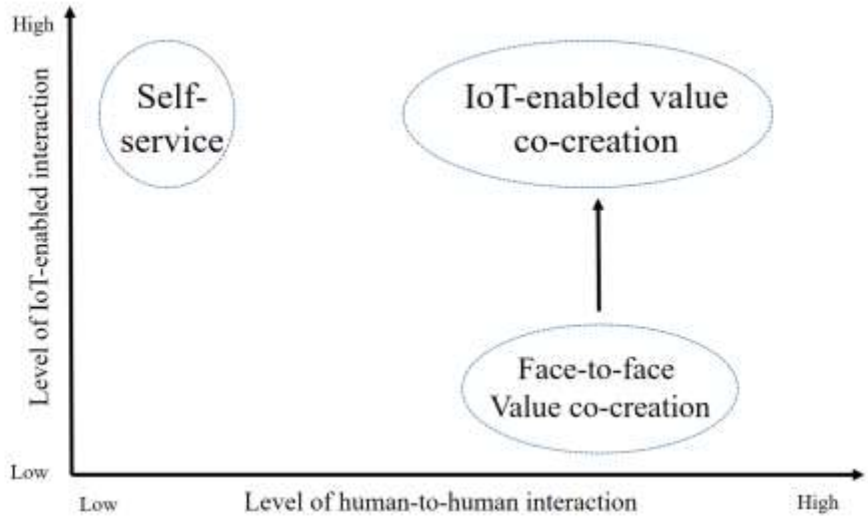

Figure 3.4 Technology-Interaction-Service Matrix. Adapted from Wunderlich (2009) and Breidbach, Kolb and Srinivasan (2013)

3.8 IoT-enabled healthcare value co-creation

The deployment of IoT in healthcare settings will soon spread out (Ahmadi et al., 2018), and the dependence of healthcare industry on IoT technology will be increased (Kulkarni and Sathe, 2014), because the healthcare service sector usually seeks new technologies that positively influence service delivery, enhance quality of life, and reduce operational cost (Akaka and Vargo, 2013). IoT technologies are promising solutions for many issues related to the healthcare services. IoT technologies (e.g. wearables and mobile applications) empower patients and enable them to expand their productivity during their treatment course. They also open up more opportunities for connecting them with hospitals, leading to an effective contribution in the value co-creation process, satisfaction, and better quality of life.

As mentioned earlier, the S-D logic approach has changed the view on which resources are used to create value and the view of the role of the customer in the value creation process (Vargo, 2009; Vargo and Akaka, 2009). S-D logic is different from G-D logic as it focuses on value-in-use or value-in-context. There is no value without using the offering, so experience and perception are critical factors to determine the value. Vargo, Maglio and Akaka (2008) suggest that value co-creation is achieved through integration and application of resources so it requires the contribution of several service systems.

IoT technology is operant resources because it affects how value is determined (Akaka and Vargo 2013). According to Tommasetti, Vesci and Troisi (2016, p.5) operant resources are *"dynamic and capable of acting on operand and other operant resources to contribute to value."* IoT is a technology that brings people together, connects people with things (objects) and connects objects with each other. This opens the door for a higher level of collaboration and cooperation within the healthcare service. When integration between IoT applications and any form of resources occurs "value is uniquely and phenomenologically determined and as technologies are repeatedly combined or integrated with other resources innovation occurs and new social norms form" (Akaka and Vargo 2013 p. 13). IoT technology facilitates value co-creation by enabling resource integration through offerings and opportunities provided to patients (e.g. using mobile apps to send vital body signs from home), which leads to personalised interaction and better-quality healthcare service.

Actors within healthcare agree that the system could utilise the superior benefits of IoT technologies during the resource integration process and value co-creation. IoT supports multiple practices of value co-creation such as decision-making involvement (McColl-Kennedy et al., 2012), sharing information (Sweeney, Danaher and McColl-Kennedy, 2015), and connecting with others who are ill (Liu et al., 2020).

3.9 Views on innovation

Although the concept of innovation emerged in literature many years ago, there is no one agreed definition for the term. Scholars view innovation either as a consequence or as a process. The researchers who conceptualise innovation as a consequence attempt to understand how organisations innovate by examining the context, structure and internal process within the organisation (Jiménez-Jiménez and Sanz-Valle, 2011; Damanpour and Gopalakrishnan, 1998). On the other hand, researchers who define innovation as a process try to comprehend how organisations cultivate innovation by looking at the way it emerges and develops within their daily business activities (Rogers, 2010; Damanpour and Gopalakrishnan, 1998; Van de Ven et al., 1989). The concept of innovation was initially introduced in literature by the work of Shumpeter (1934) who defined innovation as the creation of a new idea for a new product or service, a new process or method of manufacturing, or new way of doing things (Drejer, 2004). Other researchers defined innovation as the implementation of new ideas, products, systems, programs, behaviours, and procedures that are considered new to the organisation. (Daft, 1978; Herkema, 2003; Palangkaraya et al., 2010). Likewise, Vaccaro et al. (2010) defined innovation as a product, process, or distribution method considered to be new to the firm. OECD (2005) defined innovation as: "the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations." Another comprehensive definition of innovation proposed by Liao et al. (2008) defined innovation as the creation or implementation of a new idea and behaviour related to product, service, production, procedure, or management strategy. A more inclusive definition was argued by Kim et al. (2012), who recognised the importance of knowledge application, personal skills, and capabilities. Therefore, Kim et al. (2012) defined innovation as a new application of knowledge, ideas, methods, and skills that can generate unique capabilities and increase an organisation's competitiveness.

There are multiple definitions of "innovation" in the literature, Assink (2006) defined innovation as the implementation of ideas which are new to the organisation, or as the process succeeds of what it is created for and has significant value to the organisation. Hobday (2005) explained that innovation is a product or process that is new to the organisation, not necessarily to the market or the world. Similarly, White and Glickman (2007) suggested that innovation is the introduction of new ideas, methods and devices. Albury (2005) indicated that innovation is about generating and adopting novel products, services, processes and methods for the purpose of improving the organisation's effectiveness. According to Van de Ven (1986), innovation is a process that involves the creation, adoption, and implementation of novel ideas and practices. Gault (2018) defined innovation as "the implementation of a new or significantly changed product or process." Kamaşak and Bulutlar (2010) defined innovation as developing, generating, adopting, and implementing new ideas, methods, programs, and policies to attain organisational objectives. Nusair et al. (2012) proposed a similar definition: innovation is creating, developing, and implementing new ideas, methods, programs, and procedures to achieve organisational goals effectively. Tushman and Nadler (1986) defined innovation as producing a product, service or process that is new to a business unit. Du Plessis (2007) defined innovation as creating new ideas, knowledge and thoughts to obtain the desired outcome for the organisation. Likewise, Oddane (2008) perceived innovation as a cooperative, open-ended activity intended to create and adopt a new product or process to obtain financial and other types of values. According to Grawe et al. (2009), innovation is developing a new service that seems to be novel and useful to a particular audience. In line with this definition, Fruhling and Siau (2007) defined innovation as a new idea, practice, or object that was novel to people and wherever it was applicable in the organisation. Chen and Tsou (2007) suggest that innovation is adopting and implementing new ideas or practices to develop products, services or business activities.

3.10 Innovation diffusion and adoption

The diffusion of innovation (DOI) is an old social science theory proposed by Everett Roger in 1962. It describes how the new idea or product is disseminated and spread over time through the social ecosystem. DOI explains how different types of customers perceive the novel idea and accept it. Adoption of the new idea, service product or behaviour is the result of the diffusion. DOI is interested in the speed innovation is adopted (Corsaro, Sebastiani and Mele, 2017).

Roger (2010) proposes five phases of the adoption process: the first phase is the knowledge or awareness about innovation, where the targeted individual does not have enough information to become engaged with innovation. The second phase is persuasion, where the targeted individual pays attention to innovation and tries to obtain more detail. Third is the decision phase, where the individual decides to accept or reject the innovation based on their usage assessment. Fourth is the implementation phase where the adopter measures the value and benefits of the innovation. The final phase is the confirmation or continuation where the adopter makes their final decision about whether to continue to employ the innovation.

IoT symbolises the advanced technological innovation of telecommunication, ubiquitous computing and embedded electronics. The adoption of IoT is quickly gaining momentum as the pressure of competition encourages businesses to innovate and transform (Lee and Lee, 2015). However, there is a lack of understanding about how organisations can utilise and deploy IoT. The anticipated fast diffusion of IoT technology and adoption has not occurred (Hwang, Kim and Rho 2015). In line with this study, Luthra et al. (2018) conducted a study on the diffusion and adoption of IoT in the Indian context, they found that IoT technology's diffusion and adoption remain a challenge. This status requests researchers, practitioners, and policymakers to make an effort to fix factors that unfavourably influence the adoption of IoT technology and to raise awareness among the authorities and in the community about the benefits and values that IoT can bring to the ecosystem. Hwang, Kim and Rho (2015) suggest that value configuration analysis of IoT can decrease the reluctance and hesitation of potential adopters. This can be achieved by responding to their concerns such as where and how businesses can benefit from IoT technologies and which form of IoT should be considered for deployment in different types of industries.

3.11 Types of innovation

Generally, most of the studies on innovation focus on industrial innovation. There are different ways to classify innovation. Some scholars categorise innovation into two forms: product innovation and process innovation (e.g. Abernathy and Clark, 1985; Utterback and Suarez, 1993; Damanpour, 2009; Rujirawanich, Addison and Smallman, 2011; Higón, 2011). Other scholars divide innovation into radical and incremental innovation (e.g. Freeman and Soete, 1997; Schilling, 2010; Marqués et al., 2006; Wu et al., 2008; Zhou and Li, 2012). According to Freeman and Soete (1997), the later form of classification depends on the *"radicalness"* of innovation compared to technological advancement.

Radical innovation can be defined as: "A successfully exploited radical new product, process, or concept that significantly transforms the demand and needs of an existing market or industry, disrupts its former key players and creates whole new business practices or markets with significant societal impact" (Assink, 2006). It is also defined by Jha et al. (1996) as: "a collection of activities that constitute a process intended to achieve performance improvement." Radical innovation refers to the newness of the idea and the degree of change. Tidd and Bessant (2011) describe radical innovation as non-linear and discontinuous innovation and one that is involved in the latest advancement of technologies.

On the other hand, incremental innovation focuses mainly on improvement and modification. It involves modifications to the existing components rather than breakthrough changes (Goffin and Mitchell, 2010). Incremental innovation does not need high investment or significant changes in organisational skills and capabilities (Garcia-Sabater et al., 2011). Bessant and Tidd (2011) argue that incremental innovation enables the organisation to acquire competitive advantage.

The Oslo Manual (OECD, 2005) sorted innovation into four categories: *product innovation, process innovation, marketing innovation* and *organisational innovation.* Usually, the word "product" refers to goods and services. Some forms of product innovation in services are creating a new service entirely or modifying an existing service by changing its features or substantially changing an existing service. *Process innovation* in service focuses on the exploitation of substantially improved or new methods to offer services. *Marketing innovation* is concerned with the implementation of new methods for products such as pricing, placement, promotion and design. *Organisational innovation* refers to the creation and application of new organisational approaches in daily business practices inside and outside the firm, such as developing a new method for product delivery or designing a new approach to evaluate external suppliers.

In addition to product and process innovation, Tidd and Bessant (2011) added two more forms: *position innovation* and *paradigm innovation*. They conceptualise position innovation as an innovation that involves changes in the product's context. Paradigm innovation, on the other hand, focuses on changes in the essential mental models related to the organisational work. Other researchers proposed administrative innovation (Walker, 2007; Birkinshaw et al., 2008; Schilling, 2010; Jaskyte, 2011). *Administration innovation* refers to the creation and development of the practices, activities, structure, processes, procedures, social systems and management systems of the organisation (Walker, 2007; Damanpour and Aravind, 2012; Trott, 2008). However, Jiménez-Jiménez and Sanz-Valle (2011) and Damanpour and Schneider (2006) conceptualise product, process, and administrative innovation as part of organisational innovation. Another type of innovation is *technological innovation* (Damanpour and Schneider, 2006; Jaskyte, 2011), it refers to the adoption by businesses of tools — new equipment, techniques, equipment, concepts, systems and methods — that improve organisation.

Some researchers argue that an organisation can obtain innovation either by exploitation or exploration (e.g. He and Wong, 2004). Exploitation is a short-term approach with means improvement, adoption, efficacy, and production. In contrast, exploration is a long-term approach, achieved by conducting research, experimentation, discovery, and it is viewed as a risky strategy (He and Wong, 2004).

Most of the research on innovation after the work of Schumpeter focused on manufacturing and technological innovation in the view of the fact that the manufacturing industry was the main contributor to the economy (Drejer, 2004). However, several later studies highlighted the concept of "service economy" when the manufacturing of goods was no longer the leading source of employment (Fuchs, 1965). The complication of service innovation research refers to the *"fuzzy"* nature of service output, which carries difficulties in measuring and identifying service innovation (Gallouj and Weinstein, 1997). Although service firms are shown in literature as innovative businesses, they are less innovative than businesses in manufacturing industries (Sundbo 1997; Gallouj, 2002).

3.13.1 Service Innovation:

3.13.1.1 Service innovation approaches:

Coombs and Miles (2000) propose that there are three main perspectives when defining and measuring service innovation:

- Assimilation: this concept means that service innovation is primarily similar to manufacturing innovation. Consequently, researchers can apply methods and concepts developed for traditional product innovation.
- Demarcation: this approach, on the other hand, considers service innovation as very different, so it pursues dynamics and shows characteristics that need new theories and instruments.
- Synthesis: this perspective has to be developed further, but it argues theories and methods of service innovation should be broad enough to involve both service and manufacturing innovation.

Witell et al. (2016) conducted a literature review of service innovation. They identified how the definition of "service innovation" has been developed across the three approaches — assimilation, demarcation and synthesis — and found that there is much diversity in definitions, which they believe deters the development of service innovation. Their research also found that the meaning of service innovation is changing. The mainstream research in service innovation literature adopted the assimilation approach (Gallouj, 2002; Witell et al., 2016), whereas a lower number of studies examine service innovation from a demarcation perspective (Vink et al., 2018; Witell et al., 2016).

This difference in focus relates to the idea that assimilation applies existing concepts to measure innovation in manufacturing. In contrast, demarcation requires the application of a new ideas and measurements (Witell et al., 2016).

The demarcation approach argues that studies on innovation have failed to identify the specific features of the service industry and have missed the key contribution of services in production manufacturing (Gadrey, Gallouj, and Weinstein, 1995; Droege, Hildebrand, and Forcada, 2009). On the other hand, the synthesis or integrative approach focuses on the need to have an integrative approach of innovation that combines both technological and non-technological perspectives (Carlborg, Kindström and Kowalkowski, 2014). It emphasises creating the insights that can be gained from studying both assimilation-oriented (e.g. manufacturing) innovation research and demarcation-oriented research to create a common framework (Gallouj and Windrum, 2009; Carlborg, Kindström and Kowalkowski, 2014).

This study follows the literature that is moving towards a more profound comprehension of the "dynamic, systemic and service-driven nature" of innovation (Akaka, Vargo and Wieland, 2017; Vink et al., 2018). Therefore, this study adopts the synthesis view of innovation (Coombs and Miles, 2000). It is in line with the innovation approach of service ecosystem and its S-D logic framework that expands the context of innovation to the self-motivated ecosystem of service interactions and institutions, which are usually reshaped as numerous actors integrate resources to co-create value (Akaka, Vargo and Wieland, 2017).

There is a lack of common understanding related to the meaning of service innovation, which has caused the problems regarding its definition (Flikkema, Jansen, and Van Der Sluis, 2007; Toivonen and Tuominen, 2009). Even though literature is reflecting a growing focus on service innovation (Ordanini and Parasuraman, 2010; Dotzel, Shankar, and Berry, 2013), the service innovation concept is generic, broadly defined, and needs more research (Ostrom et al., 2010). The literature usually used the term "service innovation" to indicate the new or improved services and to describe the processes that create a new service product by using new knowledge and technology (Bettencourt, 2013).

According to Den Hertog et al. (2010), the experience of a new service obtained by organisation leads to a new system of service or process that enable an organisation to create value for the customer, and the customer-organisation interaction determines the degree of a novelty for the service innovation. They also define service innovation as: “a new service experience or service solution that consists of one or several of the following dimensions: new service concept, new customer interaction, new value system or business partners, new revenue model, new organisational or technological service delivery system” (Den Hertog et al., 2010). Agrawal and Selen (2009) proposed a definition that considers the innovation outcome, they define service innovation as “process, product, and organisational innovation and even performance and productivity improvements culminating from proactive creation, development, and maintenance of relationships with partners, customers, suppliers, or other stakeholders, resulting in a multidimensional service innovation capability.” (Agrawal and Selen, 2009). Berry et al. (2006) define service innovation as “an idea for a performance enhancement that customers perceive as offering the new benefit of sufficient appeal that it dramatically influences their behaviour, as well as the behaviour of competing companies.” Berry and his colleagues’ definition emphasises the role of the customer in service innovation, his involvement in new service development and the collaboration between the organisation and potential customers.

Lusch and Nambisan (2015) argue that “the distinction between “service innovation” and “product (goods) innovation” is no longer relevant since from the S-D perspective all product innovations are service innovations (products being only a mechanism, medium, or vehicle for delivering service).” This study draws on the S-D logic framework and selects service innovation as the most appropriate type of innovation to fit with the aim and objectives of the study. In light of the above discussions, and based on the objectives of the research, this study defines service innovation as “a novel idea that incorporates a service solution that offers benefit to the customer and adds value to the ecosystem.”

3.12 Innovation and user involvement

The idea of user involvement in product and service innovation is not new (von Hippel, 1976; Urban and von Hippel, 1988). The focus in this study is on the patient who is the end consumer of a particular healthcare service.

Scholars emphasised the importance of user participation in the innovation process (e.g. Magnusson, Wästlund and Netz, 2016). Other studies demonstrate that users were the source of innovation for some market products before they were adopted and sold by firms (von Hippel, 2005; Baldwin, Hienerth and von Hippel, 2006). The literature shows that the involvement of the customer in the innovation process can lead to benefits for firms, such as a common understanding of customer needs (Bogers, Afuah and Bastina, 2010), cutting the cost of product development (Kujala, 2008), decreasing the development time (Bogers, Afuah and Bastina, 2010), increasing the process development efficiency of product and service (Damodaran, 1996), and reducing the time to market (Morrison, Lynch and Jones, 2004).

There are two different views on user involvement in the literature: the *traditional approach* and the *customer-as-innovator approach* (Thomke and von Hippel, 2002; Bogers, Afuah and Bastina, 2010). The traditional approach refers to the passive view that the customer is not able to participate in idea generation of the products and services; they can only evaluate the idea after product development (Rothwell, 1992; Fuchs et al., 2013). Scholars who adopted this approach argue that user involvement is a complicated process and it is the firm's responsibility to know what customers need through conducting research (Damodaran, 1996; Kujala, 2003). The other view, however, believes in the active role of customer, it suggests that firm-customer interaction is a key source for generating new ideas and new methods of doing business (Prahalad and Ramaswamy, 2004b; Kujala, 2008; Ansari and Munir, 2010).

In this approach, the customer is perceived as co-innovator. The supplier offers the proper tools for the customer to design and develop a part of the product to fulfil his need (Franke and Shah, 2003; Ansari and Munir, 2010). Getting users involved in the design of technology-based services is a beneficial strategy for firms (de Jong and von Hippel, 2009). von Hippel (2009) argues that lead customers have created and developed many products in different industries. However, Trott et al. (2013) suggest that identifying lead customers is a challenge and their participation can possibly be exaggerated.

The efficiency of the customer role is the determinant factor in deciding the form of practice (Szymańska, 2017). According to Damodaran (1996), user involvement takes multiple forms: (1) *informative*, where the user provides information related to the service, (2) *consultative*, where a user shares an opinion with a firm about the predefined service, (3) *participative*, where the user takes a vital role and influences decisions concerning the big picture of the system. User involvement is considered in this study since it emphasises the co-creation practices and the role of the customer as the main actor who actively interacts in the process of value co-creation.

3.13 Research Gap:

This section outlines the analysis processes of the literature review to identify major gaps in the existing body of knowledge on RBV, IoT and value co-creation fields and to discover paths for future research.

Prior research proposes that despite the rapid advancement of digital technologies, the academic research in the field of IoT systems is still limited (Liu and Gao 2014; Shin 2015; Ng and Wakenshaw, 2017; Ahmadi et al. 2018). Recent studies have emphasised the importance of IoT capabilities (Dunaway, Sullivan and Wamba 2018; de Vass, Shee and Miah 2018; Verdouw et al. 2016; Ahmadi et al. 2018; Whitmore, Agarwal and Da Xu 2014). Research has focused on different types of capabilities such as sensing, seizing, reconfiguring, monitoring, control, optimisation, automation, and communication. However, insights into the dynamics of the types of capabilities show that they have been fragmented with inconsistent results. Also, the role of IoT capabilities and their managerial and operational roles have not been fully explored (Dunaway, Sullivan and Wamba 2018; Whitmore, Agarwal and Da Xu 2014). Thus, scholars argue that there is a need for more research studies on the operations and capabilities of IoT technologies (Ahmadi et al. 2018; Verdouw et al. 2016; de Vass, Shee and Miah 2018; Lee, Choi and Kim 2017).

Studies digitalisation and value co-creation indicate that research on IoT-enabled value co-creation is extremely limited (Balaji and Roy 2017, Ng and Wakenshaw, 2017; Lee, Choi and Kim 2017). Balaji and Roy (2017) conducted an empirical study using structural equation modelling to examine the relationship between customer interaction with IoT technologies and value co-creation; they found that a high level of IoT technologies leads to a greater perceived degree of value and usefulness. Their study was one of the first studies in the literature of IoT retail technology.

The academic literature does not offer enough evidence on the relationship between IoT capabilities and value co-creation practices (Ng and Wakenshaw, 2017, Breidbach and Maglio, 2016).) Also, the empirical insights in the technology-enabled value co-creation area are extremely limited. Abdi, Witte and Hawley (2020) identified a knowledge gap in IoT and emerging technologies in the social life and care domain. They highlighted the necessities for further exploration of the healthcare benefits of these technologies to meet the needs of patients, particularly older people. Lee, Choi and Kim (2017) conducted a literature analysis in IoT technologies from a social science perspective; they analysed 300 papers and concluded that IoT technologies in healthcare services have not yet been sufficiently investigated.

The research studies that empirically investigate the antecedents and the consequences of value co-creation within the organisation are rare (Peña, Jamilena and Molina 2014; Verma, Rajagopal and Mercado 2013). Furthermore, although the effects of technological factors have been explored in service innovation literature (Ye and Kankanhalli, 2018), there is a paucity of studies investigate how emerging technologies enable service innovation (Wu, Xiao and Xie 2020).

In the same vein, recent studies report that research on social benefits and the business value of the IoT is not fully explored (Nicolescu et al. 2018; Brous, Janssen and Herder 2020). Responding to the user requirement is the key factor impacting the broad adoption of IoT technologies (Ahmadi et al., 2018). There are various benefits of value co-creation through medical technologies such as decision-making involvement (McColl-Kennedy et al., 2012), sharing information (Sweeney, Danaher and McColl-Kennedy, 2015), collaboration (Frow, McColl-Kennedy and Payne, 2016; Badcott, 2005), Knowledge sharing (Frow, McColl-Kennedy and Payne, 2016; Badcott, 2005; Elg et al., 2012, Gill et al., 2010) and connecting with others who are ill (Liu et al., 2020). However, literature so far has focused on the benefits of value co-creation of patients and service providers in isolation (Pappas et al., 2018). So, research studies have viewed the value co-creation of medical technologies from two different standpoints: patients' and caregiver's perspectives. In real life, actors do not work in isolation; instead, they interact together.

Thus, this work attempts to advance the literature with an in-depth analysis of value co-creation through IoT medical technologies and enhance our understanding of actors' interactions and interrelationships that lead to value co-creation and innovation. Additionally, the academic literature does not offer enough evidence on the relationship between IoT capabilities and value co-creation practices (Ng and Wakenshaw, 2017). Also, the empirical insights in the technology-enabled value co-creation area are extremely limited (Balaji and Roy 2017; Breidbach and Maglio, 2016).

Chapter 4: Conceptual Framework

4.1 Introduction

This chapter essentially describes the conceptual framework, the constructs and their inter-relationships. The conceptual framework is proposed to define the main research elements. This step came after conducting the literature review and defining the research aim, objectives, and questions.

The conceptual framework emerged from the literature review and is supported by social exchange theory, organisational capability theory, and S-D logic framework. In this chapter, the focus will be directed towards the research questions of this study. The chapter also describes the conceptual framework and its interrelated elements for this research. It highlights the underlying factors in the relationship between IoT and value co-creation and the impact of this relationship on the performance of service innovation. The chapter ends with a brief summary of the study's hypothesis.

4.2 Theoretical foundation

This section outlines the main theories underpinning this study. Discussions of this section include resource-based view (RBV), value co-creation and SD logic frame work and how they relate to each other and to this research

4.2.1 Resource-based view theory (RBV)

The resource-based view RBV of the firm is one of the most influential and broadly accepted theories in the management field (Barney, 1986,1991,2001; Peteraf, 1993; Wernerfelt, 1984). Since then, RBV earned huge attention among researchers. The concept of RBV revolves around Conceptualising a firm as a bundle of resources, and adequate resources are the critical determinant of performance and sustainable competitive advantage (Grant 1991, Penrose 1959; Barney, 1991; Wernerfelt 1984). RBV derived from the theory of firm growth (Penrose 1959), presented by Wernerfelt (1984) and extended by Jay Barney (1991). Barney 1991) argues that a firm can achieve a sustained competitive advantage from resources that are valuable, rare, imperfectly imitable and non-substitutable. These four conditions are known as (VRIN) (Barney 1991). These resources can be seen as a bundle of tangible and intangible assets, such as a firm's capabilities, firm's infrastructure, managerial skills, knowledge, organisational processes and technical know-how skills controlled by a firm (Barney 1991; Bharadwaj 2000).

When resources are valuable, they have the potential to lead to exceptional profits if a firm can manage them better than competitors (Barney 1991). On the other hand, the paucity of resources makes firms own rare resources generate superior revenues compared with competitors (Bowman and Ambrosini, 2003). According to Barney (1991), firms can achieve a competitive advantage in the short term if they hold valuable and rare resources. However, firms should also ensure that these resources are imperfectly imitable and non-substitutable to maintain a sustainable advantage in the long run. The imperfectly imitable resource means that it is hard for competitors to replicate a resource (Bowman and Ambrosini, 2003). Inimitability comes from different sources (1) unique historical circumstances led to bundle creation, (2) causal ambiguity of connection between the resources and the achieved competitive advantage and (3) social complexity of resources (Lippman and Rumelt 1982; Bowman and Ambrosini, 2003). Non-substitutability of a resource means that another resource cannot reproduce the resource that has the same impact. (Barney,1991). Evaluating the substitutability of resources entails a thorough understanding of the value behind the resource (Bowman and Ambrosini, 2003). So, understanding the role of the resource in the value creation process is fundamental.

RBV proposers that internal endogenous factors determine a firm's performance (Boyd, Bergh and Ketchen 2010). These internal resources include tangible assets, competencies, capabilities, knowledge, policies, processes, and organisational characteristics controlled by the firm. Prior literature has differentiated between tangible assets (physical structure, land, buildings, factories, offices, technological materials, raw material, workforce) intangible assets (competencies, capabilities, knowledge, experience, intellectual property) (Kamasak, 2017; Day, 1994), organisational (planning, culture, formal reporting, relations, coordinating systems and controlling) (Barney 2001). Capability is the ability to deploy resources in connection with other processes to attain the desired outcome (Lee, 2008; Amit and Schoemaker, 1993). Both resources and capabilities are the basis for a sustained competitive advantage when owned and controlled by a firm. (Barney 2001). Capability is a key factor in forming firm heterogeneity by enabling cooperation and coordination among resources.

However, RBV does not clearly define the connection between capabilities and resources from one side and the competitive advantage from the other side (Akio 2005). It also does not draw an explanation of how the source of value create or exist (Wojcik 2015). Prior studies criticise RBV for its entire focus on a single firm with no consideration to the context under which the firm exists. (Alberto and Stefano 2003). The research on RBV needs to explicitly define the way a firm generate and sustain value, whether it is capable, a specific feature, network, benefit or a skill. This study employs a rarely considered perspective by connecting the concepts of RBV of organisational capabilities with value co-creation theory to understand how resource integration occurs through the implementation of IoT technologies to attain competitive advantage.

4.2.2 Value co-creation

Value co-creation is a new concept in management and marketing literature that enables organisations and actors within the contextual ecosystem to create value through interaction (Grönroos, 2011; Hsieh and Hsieh, 2015). Value co-creation is the key idea when trying to understand the service science and service system (Maglio, Kieliszewski and Spohrer, 2010). S-D logic presumes that value is always co-created through exchange and interaction and it views co-creation as a mutually beneficial relationship. Actors build the relationship with each other, interact and integrate by applying their resources. They exchange a service for another service to get the benefits for their own and other actors. The service system interacts and exchanges with different service systems in order to enhance its situation by improving the conditions of others (Vargo and Akaka, 2013). Value is co-created with a variety of social entities not only with firms and customers (Ostrom, 2010). Value co-creation comprises more than the interaction between two service systems (Akaka et al., 2012). The availability of resources, as well as the associated relationship, is critical to value co-creation. The service ecosystem and other necessary elements in S-D logic philosophy are dependent on each other through the value co-creation cyclic process (Vargo and Lusch, 2016). Although actors fundamentally resemble each other, they are profoundly different in operant resources (i.e. knowledge, skills and abilities), they increase the viability of the ecosystem by exchanging services to fulfil their needs by helping other actors (Fujita, Vaughan and Vargo, 2018).

According to RBV views, value co-creation is an outcome of combining complementary resources and capabilities through collaboration (Lavie 2006). The value creation process is a key process motivated by resource integration and exchange between multiple actors (Prahalad and Ramaswamy, 2004a; Vargo and Lusch, 2004). Value is created through mutual actions and practices, not through isolated efforts. Sharing knowledge and a skills governance structure that formulates collaboration is essential for value co-creation (Grover and Kohli, 2012). RBV conceptualise IoT capabilities as a resource that produce competitive value only when they enable pre-existing organisational resources, assets and skills (Bareny 2001, Bharadwaj 2000).

Prior research focuses on how various characteristics of organisational capabilities increase value for customers and a firm's performance (e.g. Wang et al., 2015). Martelo, Barroso and Cepeda (2013) examined the impact of market orientation capability on the outcome of value co-creation. Cepeda and Vera (2007) studied the influence of knowledge management capability on value co-creation. However, these studies do not explain how organisational capabilities underpin specific co-creation practices. This study focuses on the IoT capabilities from RBV point of view that support related healthcare value co-creation practices to propose a framework for co-creation practices within the healthcare service and examine the impact of value co-creation activities through IoT technology on improving performance in the healthcare service.

To extend the value creation process further, it is essential to revise and reconsider the meaning of value. This involves understanding value within multiple actors and actions that include the value in use and value in exchange (Vargo, Akaka, and Vaughan, 2017). Value is created by the interaction of market actors (organisation, supplier, distributor, manufacturer and others) during this process; actors exchange “resources” to benefit from the value creation process. An organisation can influence the value creation process even though it does not offer ready-made value within the product. How firms and customers interact with each other influences the value creation process (Grönroos and Gummerus, 2014).

4.2.4 Service-dominant (S-D) logic framework

The service-dominant (S-D) logic framework presents a theoretical understanding of the value co-creation process when several actors collaborate to create the value (Vargo and Lusch, 2004, 2008; Akaka and Vargo, 2013). Value co-creation is the heart of the S-D logic approach. Under the lens of the S-D logic framework, the roles of customers and firms have been changed. The firm is no longer the value provider, and the customer is recognised as a critical player in the co-creation process, so they become a value co-creator (Vargo and Lusch, 2004). S-D logic divides resources into two types: operant (intangible resources such as knowledge, skills, competencies) and operand resources (tangible resources such as buildings, machines, infrastructure) (Vargo and Lusch, 2004). G-D logic focuses on the tangible resources, transaction, and embedded value (Vargo and Lusch, 2004, 2008), whereas S-D logic focuses on operant resources and value-in-use (Vargo and Lusch, 2008).

Exchanging goods for profit generation was the primary purpose of the market for a long time ago. The traditional idea of marketing focuses on goods, representing an important relationship between the firm and customer. Firms do not know how the customer consumes or uses the product (Grönroos, 1998). However, in the past few decades, marketing has been viewed as a collaborative activity encompassing multiple actors, stressing building and maintaining a continuous relationship (Brodie et al. 1997). This view transforms the relationship between firm and customer to a higher level of collaboration, which leads to extending this idea in market literature by introducing "Service-Dominant logic" (Vargo and Lusch, 2004), which presents an alternative concept to Goods-Dominant logic (G-D logic). The new view of the market offers a service-based lens to show the exchange process between actors. The fundamental emphasis of S-D logic is on the service, not on goods or services as it is in the G-D logic approach. The seminal work of Stephen Vargo and Robert Lusch (Vargo and Lusch, 2004) became the structure for service marketing literature. The idea of S-D logic has gained exceptional attention among researchers; it views the service as the basis of exchange, which highlights the resource integration process and the collaborative co-creation of value (Akaka and Vargo, 2013). S-D logic opened the door for the evolution of the new logic of marketing and changed the basis of marketing practices and principles. It also focused away from the traditional way of doing business, where attention was emphasised on the exchange process and its economic side.

S-D logic has changed the perception about the value. In past decades, the understanding was that value is produced in the provider's domain, then offered to the consumer who receives the value embedded in the purchased product. According to this view, product design within the firm's domain determines how value is presented to the customer (Smith and Colgate, 2007; Vargo and

Lusch, 2004). Customers' perceived value depends on their perception about what they take and what they give (Bowman and Ambrosini, 2000, Vargo and Lush, 2008). For that reason, the firm was perceived as the producer of value and customer as the consumer. However, viewing value from the customers' perspective has been the focus of many studies in literature. According to this research, value is not produced and offered by the provider anymore. Instead, the customer creates the value while using the product. So, these products do not have embedded value, but they enable customers to interact with them and obtain value (Vargo and Lusch, 2004, 2008; Grönroos and Voima, 2013). In other words, the customer does not receive value inherent in the product, but they get the value based on the way they use the product (Grönroos, 2009). The experience of how the customer uses the product plays a critical role in the manner they perceive its value. Value is influenced by the experience of the customer (Sandström et al., 2008; Heinonen et al., 2010). It is the customer, not the firm, who perceives and determines the value (Vargo and Lusch, 2008; Ellway and Dean, 2016; Grönroos, 2011).

4.3 The conceptual framework and hypothesis development

The ultimate goal of this research is to investigate the emergence of the IoT service ecosystem in the medical service industry from a S-D logic perspective. The aim is to examine how this would influence service innovation performance and how medical service organisations would be able to expand their innovation capacity through the adoption of IoT technologies. This study attempts to understand how the new technology of IoT could disrupt the medical service ecosystem and reshape the relationship among actors. Figure 4.1 shows the conceptual framework of the study.

4.3.1 IoT capabilities and value co-creation practices

Studies on IoT capabilities in the literature identified capabilities from technological characteristics (Borgia, 2014), applications (Chen et al. 2014) and ethical design (Baladini, 2016). Borgia (2014) identified IoT capabilities based on their characteristics, and he classified them according to the form of technology deployed: (a) *capabilities of RFID technology* include identification, storing and communication, (b) *capabilities of sensors* are sensing, storing, processing and communication (c) *capability of Near Field Communication (NFC)* is communication. Chen et al. (2014), on the other hand, identified five capabilities for IoT: sensing and sharing location, collecting and processing information, remotely controlling terminals and executing functions, self-organised networking and secure communication. Likewise, Baladini (2016) argues that IoT should have four capabilities: (a) capability of agency control, awareness and flexibility in collecting and distributing data, (b) capability of implementing various regulation over time and space (c) capability to support dynamic context (d) capability to underpin ethics.

RBV theory promotes the unique firm's capability which would lead to organisational competitive advantage (Prahalad and Hamel, 1990; Grant, 1991; Hayes et al., 1996). RBV suggests that a firm consists of bundles of tangibles and intangibles assets, resources and capabilities (Barney, 1991; Peteraf, 1993; Grant 1996). This study uses RBV and organisational capability theory to investigate the impact of IoT capabilities on VCC and service innovation performance in healthcare. The study conceptualises IoT capabilities as a special type of organisational resources (Makadok, 2001) that incorporate intangible assets (e.g. technical skills, analytics) which embedded within firm-specific resources to enhance the performance of the other resources owned by organisation.

This study conceptualises IoT as an extension of Information and Communication Technology ICT (Borgia 2014). The study also conceptualises IoT technology as an additional capability for organisational functions and operations to support the goal of acquiring a competitive advantage. This study considers that IoT capability is comparable to ICT capability (Bharadwaj, 2000; Peng, Schroeder and Shah, 2008; Parida, Oghazi and Cedergren, 2016). Various capabilities identified in ICT literature include technical skills (McKenney, 1995; Ross, Beath et al., 1996; Fichman, 2000), ICT management skills (Ross, Beath et al., 1996; Feeny and Willcocks, 1998, Bharadwaj, 2000) and relationship asset capability (Ross, Beath et al., 1996; Feeny and Willcocks, 1998).

IoT capabilities refer to the capacity of the organisations to set up, install and deploy IoT resources, in combination with other internal and external resources. This study incorporates the definition of the Cluster of European Research Projects on the Internet of Things (CERPIoT) of IoT. As mentioned in Chapter 2, IoT is "a dynamic global network infrastructure with self-capabilities based on standard and interoperable communication protocols where physical and "virtual" things have identities, physical attributes, virtual personalities and use intelligent interfaces, and are seamlessly integrated into the information network" (Jain, Hong, and Pankanti, 2009). IoT infrastructure is tangible resources, including hardware and software. IoT resources include networks, platforms, cloud servers, sensors, data, applications, actuators, and architecture. This study defines IoT infrastructure capability as the ability of IoT infrastructure to enable the operation of IoT applications and support their deployment as well as the ability to upgrade to fulfil the organisational need.

IoT management refers to the organisational selection, deployment, operations, customisation and utilisation of IoT technology towards achieving competitive advantage. Technical now-how refers to intangible assets and the personal skills to choose, install, operate and use IoT component technology. Grant (1995) described intangible IT-enabled resources as knowledge assets, customer orientation and synergy. Similarly, the IoT technical “know-how” capability enables the organisation to develop and integrate IoT systems with other organisational technologies and business functions. It also allows them to analyse, interpret and benefit from collected data. IoT technology needs highly qualified and competent personnel to deploy, install and maintain the technology. One of the knowledge gaps identified in this study is that the academic literature does not offer enough evidence on the relationship between IoT capabilities and the value co-creation practices (Ng and Wakenshaw, 2017). Also, the empirical insights in technology-enabled value co-creation area are extremely limited (Balaji and Roy 2017; Breidbach and Maglio, 2016). Although the literature has various studies discussing the adoption of ICT and its impact on innovation (e.g. Álvarez, 2016; Higon, 2011), there is a paucity of empirical research investigating the adoption of IoT technology and innovation outcomes (Liu and Gao, 2014, Breidbach and Maglio, 2016). The role of technology deployment in service innovation performance has also not been thoroughly examined (Akaka and Vargo, 2013).

The organisation should be able to get the benefits and obtain the value of IoT. This value is dependent on the effective integration of IoT characteristics (Wolf, Stumpf-Wollersheim, and Schott, 2019). Scholars recognise essential functions of applications deployed by IoT technology; these include trigger functions, security, validation and customer feedback (Wolf, Stumpf-Wollersheim and Schott, 2019; Lee and Lee, 2015; Porter and Heppelmann, 2014; Fleisch, 2010). Porter and Heppelmann (2014) identified four capabilities for smart technologies: monitoring, control, optimisation, and automation. This study focuses on these four capabilities of IoT monitoring, control, optimisation, and collaboration (Wolf, Stumpf-Wollersheim and Schott 2019).

4.3.2 The hypotheses relating to IoT capabilities and service innovation

4.3.2.1 IoT Monitoring and service innovation

The rapid development of the technological industry requests organisational management to adapt to market and environmental change. Implementing the IoT technologies has potentially improved the effectiveness of the decision-making approach, the efficiency of operational processes, and employees' involvement (Rot and Sobinska, 2018). Information is a key resource in service systems. Possession the timely access to information is critical for achieving active co-creation with the customer (Bucherer and Uckelmann, 2011; Briedbach and Maglio, 2016; Wolf, Stumpf-Wollersheim and Schott, 2019). IoT enables the organisation to monitor its processes, collect information and gain an insight into the customers' usage and product usage performance (Kumar et al., 2016; Bressanelli et al., 2018; Suppatvetch, Godsell and Day, 2019). This setting allows organisations to improve their resource utilisation and get more flexibility while responding to dynamic changes.

Health monitoring systems are now widely used in healthcare (Atzori, Lera and Morabito, 2010). IoT-monitoring based technologies offer a wide range of innovative solutions to medical organisations, such as performing sensing tasks, exchanging information between systems, and significantly facilitating managerial duties and processes. Through using sensors and embedded electronics, the domain for IoT health monitoring technologies has become broad. IoT monitoring became a critical part of today's advanced technology, namely telemedicine and patient compliance. It also provides real-time information on key health indicators, vital signs monitoring, alerts regarding patient well-being and chronic disease monitoring (Raji, Jeyasheeli and Jenitha, 2016).

Providing better healthcare services to the growing number of patients with limited economic and human resources revealed the importance of adopting IoT technologies that have the capability through remote monitoring to provide solutions for these demands (Varshney and Sneha, 2006). The monitoring capability of IoT has brought various innovative solutions to healthcare services. For example, IoT-based monitoring has transformed the relationship between patient and physician by reducing the number of visits to a hospital and enabled specialists to collaborate and discuss the patient case regardless of time and location (Dauwed and Meri, 2019).

H1a: IoT monitoring capability has a direct and positive impact on service innovation performance

4.3.2.2 IoT Control and service innovation

Control is a management function to govern organisational aspects, roles, and responsibilities such as operations, processes, activities, and resources. Management control is defined as the process of directing organisations through environments in which they operate to accomplish both short-term and long-term goals (Otley and Soin, 2014). Usually, management control works in two forms: formal and informal (Chenhall, 2003). Formal controls include performance evaluation processes, accounting-based controls, defined rules and standard operating procedures (Chenhall et al., 2010). Informal controls have unwritten policies, norms, values and beliefs.

IoT control technology work with collected data on many situations such as wearable applications, mobile applications, equipment performance, environmental circumstances and energy usage and allow users and automated systems to track performance in real-time regardless of time and locations constantly. Smart grid and smart metering are good examples where IoT monitoring and control technologies can identify the patterns of operations and areas of potential improvements and optimise operational processes to lower costs and increase productivity. There are various innovative solutions of IoT control applications in many fields; in car renting services, the IoT monitoring and control capability have transformed the delivery of value proposition. For example, in free-floating car-sharing schemes (Suppatvetch, Godsell and Day, 2019), the IoT monitoring and control capabilities enable the providers to track the car's identification number and location and exchange information with their customers through mobile applications. This solution leads to a new business model in car renting services.

IoT monitoring and control support the idea of smart home technology through using wireless communication to control the application in home automation remotely. The new and innovative smart devices of IoT monitoring and control technology transform the way home applications operate. The deployment of IoT technology supports medical organisations in significantly controlling their resources. RFID has been used in access control for buildings and facilities to avoid product duplications and recover missing components (Sharma and Siddiqui, 2010). IoT control-based technologies facilitate a platform for accessing patient information through granting access authority (Laranjoa, Macedo, and Santos, 2012). Ajami and Rajabzadeh (2013) conclude that RFID facilitates processes and highly reduces medications and diagnosis errors when used with EHRs and clinical decisions support systems. Medical errors include patient monitoring, poor decision making, poor patient tracking, lack of quick response, poor communications, patient misidentification (Chao et al. 2007). Hospitals are seeking technological innovations to overcome these challenges (Ajami and Rajabzadeh 2013). They need to deliver high quality, accurate and timely information to increase patient safety performance (Verdu-Jover et al., 2005). IoT monitoring and control capability can collect and share data, leading to efficient operations and better innovation performance. Chao et al. (2007) find that IoT technologies improve patient safety by reducing medical errors through monitoring and control. These studies indicate that IoT control contributes to medical errors reduction and patient safety improvement, leading to increasing service innovation performance. Thus, the study proposes that:

H1b: *IoT control capability is positively associated with service innovation performance*

4.3.2.3 IoT optimisation and service innovation

Organisations focus on optimisation to achieve various benefits, such as improving overall efficiency, reducing costs, and improving quality. Optimisation is defined as "a process of selecting a better or the best solution out of existing alternatives" (Gosh, Surjadjaja and Antony, 2004). Optimisation enables an organisation to streamline its business processes to reduce the time taken for tasks and decrease human errors, leading to higher efficiency.

Smart devices using IoT can sense, measure, record, and share temperature, humidity, pressure, speed, and time (Lee 2019, Haddud et al. 2018; Hwang, Kim and Rho 2016). This capability provides insightful information on assets, equipment and machines. When the information collected from devices and properly analysed, organisations obtain valuable information that can optimise operations and enable them to make better fact-based decisions. IoT has the potential capacity to improve processes, reduce maintenance costs and increase uptime. This capability empowers organisations to optimise their asset management. IoT technology supports the operation of healthcare services by optimising how the system can deploy heavy machines and expensive equipment leading to cost reduction, enhancing efficiency, and maximising return on investment.

Data gathered from IoT applications provides healthcare givers with information to optimise their operations and identify the best treatment for patients, which lead to innovative service and greater patient's satisfaction. In Building Management System (BMS) IoT technology, cloud-based applications and building analytics systems empower hospitals to the level that can optimise options, apply predictive maintenance, proprieties requirements and identify savings (Chin 2020) Through collaboration with big data, IoT provides demand-sensing information. This is achieved based on historical data from multiple locations and different timings to enable IoT systems to predict the demand. The forecasting information is used to identify the customers' patterns and plan for future needs. In line with the above discussion, the following hypothesis is proposed:
H1c: *IoT optimisation capability is positively associated with service innovation performance.*

4.3.2.4 IoT collaboration and service innovation

Most of today's businesses have recognised the benefits and values of collaboration. Collaboration is defined as: "An evolving process whereby two or more social entities actively and reciprocally engage in joint activities aimed at achieving at least one shared goal" (Bedwell et al., 2012 p.9). From SD logic, integration of resources is not a unidirectional process (Vargo 2008), but it is multidirectional in a many-to-many view (Gummesson 2008). Accordingly, IoT collaboration is a critical instrument that brings many-to-many to co-create value through resource integration. IoT technologies bring networks of humans and devices closer together and ensure all systems are working collectively to improve efficiency and productivity. The value of IoT technology goes beyond connected devices; it also enhances inter and intra-organisational collaboration. (Pennec and Raufflet 2016). Collaboration begins to arise when people and objects work together through Cloud communication and IoT, so organisations can improve business processes and take quick decisions based on real-time information. Deploying IoT enables people and smart objects to work more seamlessly towards achieving organisational objectives as an advantage of quickly accessing data, enhanced efficiency and increased automation. DeBlois and Millefoglie (2015) conducted a study on Home Health Visiting Nurses (HHVN) in Southern Maine who travel more than 1.6 million miles annually to provide medical services to over 8,500 patients in their homes. HHV also deploy telehealth technologies. Results showed a substantial reduction in hospitalisation rates, improved medication compliance, patient self-management and a significant increase in patient satisfaction.

Prior research has noticed that collaboration positively impacts innovation practices (e.g. Chen, Tsou and Ching, 2011; Schilling and Phelps, 2007). Others report that innovation is one of the main drivers for collaboration (Holmes and Moir 2007). In the same vein, Agrawal and Selen (2009) conclude that service innovation is an outcome of collaboration and cannot occur through individual efforts (Agrawal and Selen, 2009). Telemedicine is one of the IoT technologies that enable patients to get remote healthcare and allows hospitals to exchange information and deliver medical services despite the distance. This technological advancement has significantly transformed the hospital relationship with the patient and enhanced the decision-making process. Telemedicine systems have influenced the treatment process and the responsibilities of actors within the healthcare ecosystem (Kamsu-Foguem et al., 2015). Telehealth systems transfer vital sign histories and summary data to e-healthcare records that profoundly improved the collaboration and communication among all actors in the healthcare ecosystem, leading to new opportunities to pave the way for novel strategies in health care services. Prior studies conclude that collaboration positively impacts innovation practices (Hagedoorn 2002; Deeds and Rothaermel 2003; Schilling and Phelps 2007). Accordingly, this study proposes that IoT collaboration improves service innovation practices. In light of the above discussion, the following hypothesis is proposed:

H1d: *IoT collaboration capability is positively associated with service innovation performance*

4.3.3 The hypotheses related to IoT capabilities and value co-creation

4.3.3.1 IoT Monitoring and co-production

The increasing pace of technological advancement leads to a broad range of new collaborative solutions and new channels of sharing information. IoT technology can recognise objects remotely and automatically, which improve the process of knowledge sharing and exchanging (Vilamovska et al., 2009; Atzori, Lera and Morabito 2010; Jara et al. 2013). For example, the IoT health monitoring systems have revolutionised traditional healthcare services by providing insights into the patients' health and medical condition. (Hassanalieragh et al., 2015). Giant aviation manufacturers such as General Electric (GE) and Rolls Royce use the monitoring capability of IoT to co-create value through their operations by implementing IoT to monitor, collect, and analyse the data on the aeroplane's engines, providing customers with the required information about their aircraft systems' performance and predictive maintenance (Shim et al. 2019; DuBravac and Ratti, 2015). IoT has offered a better tracking opportunity for airline companies to take the right decision at the right time, which significantly increases the efficiency of flight operations. Monitoring an aircraft's engine performance using IoT technologies enables aviation manufacturers to build a strong relationship with their customers, involve them in their processes, and provide more safety measures for flight operations.

Implementing medical IoT provides medical organisations with opportunities to monitor the patient in real-time, such as blood glucose monitoring, tracking people and objects, and monitoring of disease progress (Raji, Jeyasheeli and Jenitha, 2016; Cosma et al., 2017; Babar et al., 2017; McWhorter et al., 2017, Dauwed and Meri, 2019). Moreover, remote surgery (telesurgery) has become more comfortable as IoT facilitates the collaboration between surgeon and robot through a high-speed data connection (Qi et al., 2017). Lee et al. (2018) investigated the impact of telemedicine in monitoring the treatment for post-liver transplantation patients. They found telemedicine maintains the patient-doctor interaction and keeps the valuable relationship between patient and hospital. It also represents the monetary value (e.g. cost saving) and convenience value (reduced length of stay in hospital), improving value-in-use activities for the patients. Another finding was that telemedicine patients were highly satisfied with the interaction and communication approach compared to clinic patients who receive standard care. IoT technology devices can sense, communicate and interact with the surrounding environment (Kortuem and Kawsar, 2010). The interactive characteristic of IoT systems enables medical centres to co-create value with their patients and guide them toward more sustainable behaviours (Bocken, Ingemarsdotter and Gonzalez, 2019). Therefore, medical organisations can enhance the patient's engagement and effectively co-produce value. In light of the above discussion, the following hypothesis is proposed:

H2a: IoT monitoring capability is positively associated with co-production practices

4.3.3.2 IoT Monitoring and value-in-use

IoT technology paved the way for new opportunities for value co-creation. Sharing information with customers through IoT applications would help them manage their processes more efficiently and lead to a reduction in operating costs (Suppatvetch, Godsell and Day, 2019). IoT monitoring technologies improves the value proposition through promoting business service offerings by monitoring business processes at the customer's location and providing insightful information on the product at any given time. Monitoring capability represents the basis for other IoT capabilities: control, optimisation (Porter and Hepplemenn, 2014) and collaboration. Monitoring systems collect data from multi-source points such as equipment performance, customer behaviour, energy usage, and environmental conditions (Lee and Lee, 2015) and share it with stakeholders for effective engagement. This ability enables decision-makers and automated systems to track performance and status on a real-time basis at any time and in any place.

IoT systems can monitor, sense, and exchange information internally and over medical networks, which significantly facilitates management tasks. The Wireless Body Area Networks (WBANs), the mobile-health (m-Health), and the advanced embedded devices are all health technologies that enable real-time monitoring of critical parameters of the human body such as blood pressure temperature, cholesterol level, and motion. They significantly help with patient participation and interaction in value co-creation processes. Mobile applications, for example, enable patients to access information and integrate their skills in an accumulative process of value-in-use. In light of the above discussion, the following hypothesis is proposed:

H2b: IoT monitoring capability is positively associated with value-in-use practices

4.3.3.3 IoT Control and co-production

In their study, Mc-Coll Kennedy et al. (2012) conceptualises value co-production as a series of activities performed by the patient as part of a broad multiplay of actions to achieve the desired outcome. As an example based on this conceptualisation, IoT control capability enhances co-production value, which is co-created for the patient through using wearables to overcome the challenge of non-compliance in chronic diseases. In contrast, non-compliance is a known challenge for chronic disease patients (Prakash, He and Zhong, 2019).

Russo et al. 2019 conclude that patient control through self-monitoring of several health parameters and telemedicine technology which allows the distance treatment of the patient and provide health services, would result in a higher value to the organisation (cost reduction, less dependence on clinicians) and community (well-being and quality of life). During the value co-creation process, the customer (patient) became an active participant in relational exchanges and co-production (Vargo and Lusch 2004). As hospitals offer value propositions through wearables and mobile applications, patients determine the value and participate in creating it through the co-production process. IoT is a key player in this offer; in other words, patients empowered by a new window of self-controlling and self-managing actions and decisions concerning their health. Based on the above discussion, the following hypothesis is proposed.

H2c: *IoT control capability is positively associated with co-production practices*

4.3.3.4 IoT Control and value-in-use

With the increasing usage of IoT technologies, chronic diseases become more manageable by medical organisations (Raji, Jeyasheeli and Jenitha 2016). The invention of the new generation of wearable devices (wearable 2.0) represents significant potential benefits for patients with chronic diseases to manage their lives themselves. Wearables are capable of helping patients raise their compliance and follow medical instructions to delay the progression of their condition. Non-compliance is a common issue for chronic disease patients (Prakash, He and Zhong, 2019). In diabetes management, it is critical for the patient to control self-management to reduce the costs and achieve effective treatment. IoT can underpin self-management of diabetes by monitoring blood pressure, glucose levels, and calories. This technology signifies a new experience where the patient can benefit and obtain value while practising a new and efficient process. AbuDagga et al. (2010) conclude that compliance among patients with telemonitoring is favourable. In light of the discussion above, the following hypothesis is proposed:

H2d: *IoT control capability is positively associated with value-in-use practices*

4.3.3.5 IoT optimisation and value co-production

Tracking the performance of medical equipment and assets and monitoring their maintenance schedule through IoT systems enables the administration to optimise daily function and staff availability. The IoT collects information about the time and frequency of medical equipment usage, allows management to reconfigure maintenance programmes, and make fact-based decisions to improve patient care and optimise operations processes. The Building Management

System (BMS) is a smart solution used in healthcare organisations (Chin, 2020). BMS utilises IoT technologies to connect key systems — such as lighting and access control — so the organisation can collect, analyse, and optimise operational performance, energy, and other assets. It also integrates with other essential building systems (e.g. power and data centres) and third-party external data. This smart solution significantly contributes to improved satisfaction for patients, staff, and visitors. In addition, it can influence the patient's perception of organisational innovativeness and impacting their psychological and behavioural responses.

As mentioned in section 1.2 of chapter one, population ageing is more vulnerable to chronic diseases and disabilities (Ahmadi et al., 2018). Researchers argue that healthcare services will be transformed into home healthcare services in be next decade (Pranger and Pang 2015). IoT technologies are among promising solutions to overcome ageing challenges. IoT and other advanced communication technologies such as NFC, WSN and RFID are among technologies used heavily in-home care operations. Such systems can monitor and track patient's situations, namely fall detection (Hsu et al. 2017) and seizure detection (Zhuang 2017) and sleep pattern detection (Ahmadi et al. 2018). Implementing these techniques enables hospitals to respond to the population shift and patient demand through interaction and knowledge sharing with patients, opening opportunities for new lanes of value co-production. In light of the above discussion, the study proposes the following hypothesis:

H2e: *IoT optimisation capability is positively associated with co-production practices*

4.3.3.6 IoT optimisation and value-in-use

The smart devices of IoT enhance inventory management optimisation and control through real-time material tracking. In addition, IoT technology supports optimising treatment and appointments in the healthcare service, which opens a new opportunity for organisations to build better relationships with stakeholders to maintain high-quality care and patient satisfaction.

IoT increases healthcare service reliability. Hence, the capabilities of monitoring, tracking, and optimisation of given parameters over time enable doctors to prescribe medication and a treatment course based on the status of the patient e-file and digital records stored in the Cloud. In addition, this technology opens the relationship between patient and hospital and allows doctors to optimise routine check-ups, re-admission and hospital stays.

M-Health is one of the IoT technologies that enable hospitals to improve patient access and experience. M-health can be a solution for primary patient care and adjustable to patient status and disease and frequent interaction with patients (Yu and Dong 2020). Telemedicine healthcare expands the capability of healthcare services to reduce risks and improve interactions with patients. Big data analytics are an important application of IoT technologies. The huge amount of data generated by IoT devices provide real-time information. The analysis of medical data from health care systems can help offer novel strategies for healthcare services. Dash et al. (2019) concluded that big data analysis could be used for patient service optimisation. In light of the above discussion, the study proposes the following hypothesis:

H2f: *IoT optimisation capability is positively associated with value-in-use practices*

4.3.3.7 IoT collaboration and co-production

Collaboration refers to "' the actor's capability to build and manage network relationships based on mutual trust, communication and commitment" Blomqvist and Levy (2006, P. 31). Scholars conceptualise collaboration capability as a subset of dynamic (Teece et al. 1997) and a set of combinative capabilities (Kogut and Zander 1993). From the perspective of RBV, IoT collaboration capability can be viewed as a source of competitive advantage as it is valuable, rare, difficult to imitate and socially complex (Barney 1991). Healthcare services identify patients and family engagement as a crucial factor in service improvement (McCannon and Berwick 2011). IoT capability can respond to healthcare demands towards the goal of patient care when facilitating the collaborative work of medical practitioners and engage them to accomplish their complementary tasks. Co-production in healthcare service occurs when patients are involved in service development aiming to ensure quality and enhance value (Grönroos 2013). IoT collaboration capability can transform healthcare service at a level where patients and healthcare professionals highly engage as co-productive partners and create a novel structure for shared activities that reach expected outcomes (Batalden et al., 2015).

Scholars conceptualised value co-creation as one characteristic of service innovation (den Hertog, 200; Bettencourt et al., 2002). Holman and Lorig (2000) conclude that achieving success in managing chronic diseases such as cancer is relevant to the collaborative interaction between patient and healthcare giver and active involvement of the patient to co-produce value. Value co-production occurs when patients can personalise their own experience while utilising the hospital's services and, in return, undertake specific activities required by a hospital (Piligrimienė, Dovalienė and Virvilaitė, 2015). Co-creation transforms an organisation from traditional goods-logic to an emerging SD-logic (Vargo and Lusch 2004). Thus, organisations having superior collaboration capability can willingly realise changes in the environment, improvement in service delivery and a process of co-creation. IoT collaboration capability can assist hospitals in developing new ways to motivate patient participation and successfully manage the co-creation activities.

H2g: *IoT collaboration capability is positively associated with co-production practices*

4.3.3.8 IoT collaboration and value-in-use

Collaboration refers to parties (patients and healthcare giver) working together "to create mutually beneficial outcomes for all participants" (Jap, 2001, p. 87). On the other hand, value-in-use practices recognised as consisting of activities in which "actors engage in value-creating activities utilising other actors' resources, without these actors being actively present" (Storbacka et al., 2016, p. 3013). Hospitals need to create collaboration capability to capture any opportunity of value for their patients and improve service performance. Scholars have argued that organisations engaged in collaborative activities create value (Pennec and Raufflet 2016). Competence on how to integrate and utilise resources to create value is a critical factor for achieving competitive advantage through high organisational performance and patient value, in particular in the patient sphere of value co-creation where direct interaction is not intense (Martelo-Landroguez, and Martin-Ruiz 2016).

From RBV and SD logic perspectives, intangible resources such as competencies and skills are the primary driver for the value co-creation to the customer and organisation (Wang et al., 2015; Grover and Kohli, 2012**)**. IoT is about connected devices and appliances; but brings people, objects networks together to ensure they work seamlessly and efficiently and improve collaboration in operations. Through IoT technology implementation, clinical processes are automatically enhanced so that management can make quick decisions based on insights from communication and real-time data. An example where IoT collaboration capability can transform the value and immensely improved the service is chronic diseases. Chronic conditions place a high financial burden on the healthcare system, represents 86% of overall healthcare cost (Agnihothri et al. 2020). In addition, many chronic diseases can be attributed to patient behaviours (Kang et al., 2016). IoT technology can improve outcomes by expanding data availability to doctors by engaging patients in self-management activities and strengthening their relationship with the hospital.

Liang et al. (2007) suggest that organisations are encouraged to compete based on their knowledge of customer needs and processes of production as an alternative of relying only upon managing tangible resources. Accordingly, Agnihothri et al. (2020) report that the main advantage of adopting m-health applications arises from enabling high opportunities for intervention by the caregiver with low office visits while maintaining the care continuity. Hence, collaboration capability is a key capability to improve value-in-use practices while improving patient value. In light of the above discussion, the following hypothesis is proposed:

H2h: *IoT collaboration capability is positively associated with value-in-use practices.*

4.3.4 Hypothesis relating to the value co-creation dimensions' relationship

Prior research report that co-creation has two dimensions: co-production and value-in-use (Ranjan and Read, 2016; Prahalad and Ramaswamy 2004a; Frow, McColl-Kennedy and Payne, 2016; Galvagno and Dalli, 2014). Co-production refers to the degree to which an organisation includes the customer in service delivery or the production process (Lehrer et al., 2012). The co-production factors are knowledge sharing, equity and interaction (Ranjan and Read, 2014; Frow, McColl-Kennedy and Payne, 2016). The critical elements of co-production are customer engagement and customer participation (Ranjan and Read, 2016). Co-production enables the customer to engage actively in shared production activity and services offers by the business (Chen Tsou and Ching, 2011). Therefore, organisations need to develop competencies for customers that shape, sustain, and boost the profitable relationship, encouraging involvement in a co-producer role. (Chen Tsou and Ching, 2011). Notwithstanding, value-in-use refers to the activities that occur in the customer sphere (Grönroos and Voima, 2013; Alves, Fernandes and Raposo, 2016). The customer creates value in this sphere through service consumption or product use outside the firm's sphere, integrating with other resources (Sharma, Conduit and Hill, 2014). The value obtained in this case is generated by the experiences developed by service encounter processes (Ballantyne and Varey, 2006). value-in-use factors are experience, personalisation and relationship (Ranjan and Read, 2014; Frow, McColl-Kennedy and Payne, 2016).

Various studies discuss the practices of value co-creation (e.g. McColl-Kennedy et al., 2012; Sweeney, Danaher and McColl-Kennedy, 2015). Scholars raised the question: "What are individuals doing to co-create value?" Several studies tried to answer this question from different angles. As an example in the healthcare ecosystem, literature revealed some activities to co-create value include cooperating, co-learning, co-production, co-design, connecting with people, participating in decision-making and changing ways of doing things (McColl-Kennedy et al., 2012; Sweeney, Danaher and McColl-Kennedy, 2015; Sanders and Stappers, 2008, Freire and Sangiorgi, 2010; Diaz-Meneses, 2019; Zainuddin, Russell-Bennett and Previte, 2013). Co-production is one of the most frequent activities mentioned in the literature (Prahalad and Ramaswamy, 2004; Chen Tsou and Ching, 2011; Frow, McColl-Kennedy and Payne, 2016; Galvagno and Dalli, 2014; Ranjan and Read, 2016). Co-production can be defined as the customer's participation in the performance activities within multiple production processes, and it involves all forms of contribution with a service provider (Etgar, 2008). Several research studies highlight the active role of the customer in co-production processes (e.g. Chen, Tsou and Ching, 2011; Roy et al., 2009).

Recently, co-creation with the customer and other stakeholders has become well-known (Nambisan and Baron, 2009). Actors are engaged in co-creation through collaborative platforms and tools like online communities, communication channels and face-to-face interactions (Frow, McColl-Kennedy and Payne 2016). The intense level of interaction offers a unique experience for customers, supporting the organisation's competitive advantage (Prahalad and Ramaswamy, 2004; Gemser and Perks, 2015). Although beneficial outcomes of co-creation exist, there is a lack of consensus on the forms and the methods of how an organisation can facilitate co-creation. The interaction is not the only source of value creation; the consumption process is another source of creating value independently from the organisation's intervention (Ranjan and Read, 2014; Frow, McColl-Kennedy and Payne, 2016). Value-in-use activities explain how actors learn to use, understand how to repair and know how to maintain the value proposition (Grönroos and Voima, 2013; Grönroos and Gummerus, 2014). So, this study suggests that these factors of value-in-use enhance the co-production processes. In light of the above discussion, the following hypothesis is proposed:

H3: *Value-in-use related practices have a direct and positive impact on co-production related practices*

4.3.5 Hypotheses relating to the value co-creation IoT and innovation relationship

4.3.5.1 Co-production, IoT and service innovation:

Co-production has been perceived as a driver for a firm's competitive advantage (Prahalad and Ramaswamy, 2004a). And become the primary concept of the S-D logic approach for marketing services (Vargo and Lusch, 2004). This setting mandates organisations to be aware of customer empowerment in terms of service offerings and their effects on their production to enhance co-production. Customers can decide the form and service they want to produce for themselves (Auh et al., 2007). Increasingly, the product has transformed from a realised object into a process, where a customer can participate and provide input in the production process (Kelley, Donnelly and Skinner, 1990; Auh et al., 2007). One of the benefits of co-production is that it enables firms to offer customisation to provide the customer with various choices that fit their needs.

Scholars differentiate service innovation from product innovation through its service characteristics, including intangibility, heterogeneity, inseparability and perishability (e.g. Wolak, Kalafatis and Harris 1998). Service innovation is viewed as a set of innovations in a service process of existing organisational services (Chen et., 2011). Moreover, service innovation is regarded as a customer-oriented process that absorbs the development of the service offerings and the methods established to develop new customer services (Eisingerich et al., 2009). Kellogg and Chase (1995) conceptualise healthcare as a "high-contact" service that requires a high degree of connection, the richness of information exchanged between parties and the interdependence of customer and organisation inputs.

Literature suggests that motivation, capability and job clarity are all determinants of co-production (e.g. Bettencourt et al., 2002; Auh et al., 2007). Customer motivation and willingness to get involved is fundamental for high contribution and effective co-production (Lengnick-Hall, Claycomb and Inks, 2000, Auh et al., 2007). The customer became a key player in the development of service innovation when the organisation offered a new service and developed a new method or process (Eisingerich, Rubera and Seifer, 2009; Chen, Tsou and Ching 2011). From an SD-logic perspective, service systems develop a new value proposition and assist a new value co-creation through resource integration (Akaka and Vargo, 2013; Maglio and Spohrer, 2008). This setting emphasising the novelty in value co-creation as a critical feature of the innovation process (Mele, Spena and Colurcio 2010). Through the deployment of IoT systems and under the lens of SD-logic, patients and medical staff become effective co-innovators through continuous interaction, exchange, resource integration and co-creation of value. This study proposes that co-production practices enhance service innovation performance, as the actor's interaction is critical to new products and service development, and they also improve the relationship between IoT collaboration capability and service innovation. In light of the above discussion, the following hypothesis is proposed:

H4a: *Co-production related practices have a direct and positive impact on service innovation performance*

H5a: *Co-production practices mediate the relationship between IoT collaboration capability and service innovation performance.*

4.3.5.2 Value in use, IoT and service innovation.

Value-in-use is the customer value in which the customer is the one who defines the value (Webster, 1994). Customers assess value based on their perception of what they get and what they give. The customer viewpoint of value is appropriate since the success of the organisational strategy in creating value for a customer is heavily dependent on its ability to understand their needs (DeSarbo, Jedidi and Sinha, 2001). Value-in-use captured through three human characteristics: experience, personalisation and relationship (Ranjan and Read, 2014; Payne, Storbacka, and Frow, 2008). Innovation empowers organisations to realise opportunities and achieve competitive advantage through generating innovative ideas from their stakeholders and customers (Kazadi et al., 2016; Hamidi and Ghaneh 2017).

The synthesis view of innovation (Coombs and Miles, 2000) is consistent with the innovative approach of service systems and its S-D logic approach. This approach expands the context of innovation to the self-motivated ecosystem of service interactions and institutions, which are usually reshaped as numerous actors integrate resources to co-create value (Akaka, Vargo and Wieland, 2017). IoT technology can entirely transform how an organisation interacts with their customers and performs its resource integration processes. IoT facilitates a new method of communication to improve customer experiences and offer customers' data to enable the organisation to provide personalised service. IoT technology can catch customer feedback and detect trends to offer a new loop of service re-design. The world is becoming increasingly connected, generating new opportunities to elevate customer engagement to cultivate higher business profits. Organisations look for innovative methods to differentiate their customer experiences and find new ways to integrate resources. IoT systems can generate a massive amount of data that organisations can use to transform service delivery models to become highly dynamic, productive, and responsive to market demands and patient needs. This setting open novel paths for resource integration practices.

Collaboration capability is regarded as the outcome of the accumulated capabilities of monitoring, control and optimisation (Wolf, Stumpf-Wollersheim, and Schott 2019). In a similar vein, Porter and Heppelmann (2014) state that autonomy results from a combination of monitor, control and optimisation capabilities of smart technologies. This study adopts the view that IoT collaboration capability symbolises the outcome of the other IoT capabilities. Whenever IoT technology applications integrate with any form of resources occurs, "value is uniquely and phenomenologically determined and as technologies are repeatedly combined or integrated with other resources innovation occurs and new social norms form" (Akaka and Vargo 2013 p. 13). Therefore, IoT technology promotes value co-creation by enabling resource integration through offerings and opportunities provided to patients, which results in a personalised interaction and a high-performance healthcare service. In light of the above discussion, the study proposes the following hypotheses:

H4b: *Value-in-use related practices have a direct and positive impact on service innovation performance*

H5b*: Value-in-use practices mediate the relationship between IoT collaboration capability and service innovation performance.*

Figure 4.1 shows the conceptual framework with hypotheses of the research. All hypotheses are summarised in table 4.1

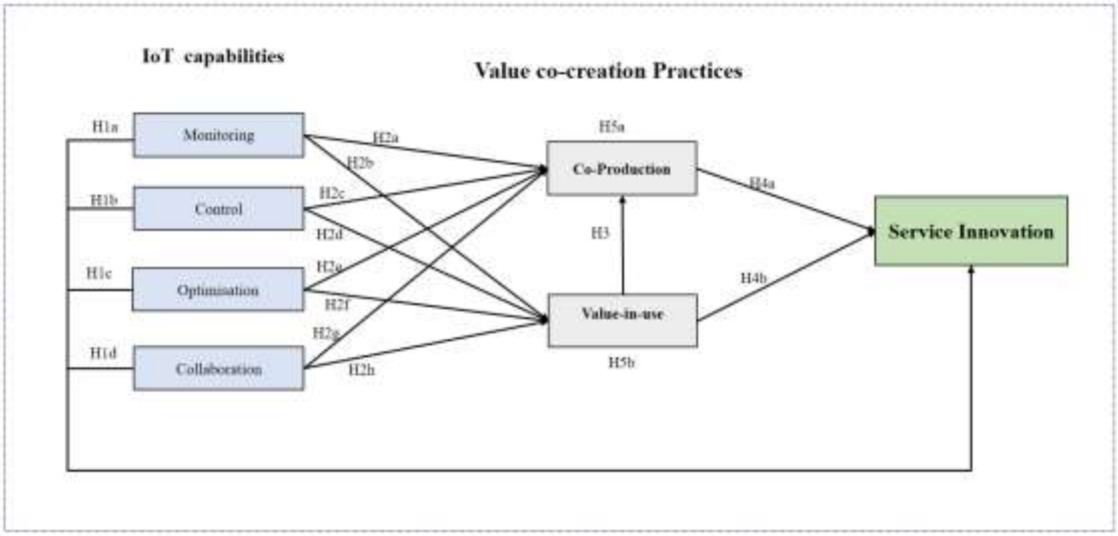

Figure 4.1 The conceptual framework

Table 4.1 Summary of hypotheses

No	Hypothesis
H1	**IoT capabilities have a direct and positive impact on service innovation performance;** this leads to the following sub-hypothesis: *H1a: IoT monitoring capability has a direct and positive impact on service innovation performance* H1b: *IoT control capability is positively associated with service innovation performance* H1c: *IoT optimisation capability is positively associated with service innovation performance* H1d: *IoT collaboration capability is positively associated with service innovation performance*
H2	**IoT capabilities have a direct and positive impact on value co-creation practices;** this leads to the following sub-hypothesis: *H2a: IoT monitoring capability has a direct and positive impact on co-production practices.* *H2b: IoT monitoring capability is positively associated with value-in-use practices.* H2c: *IoT control capability is positively associated with co-production practices*

	H2d: *IoT control capability is positively associated with value-in-use practices.* H2e: *IoT optimisation capability is positively associated with co-production practices* H2f: *IoT optimisation capability is positively associated with value-in-use practices.* H2g: *IoT collaboration capability is positively associated with co-production practices* H2h: *IoT collaboration capability is positively associated with value-in-use practices.*
H3	**Value in use practices have a direct and positive impact on value co-production practices.**
H4	**Value co-creation practices have a direct and positive impact on service innovation performance,** this leads to the following sub-hypothesis: H4a: C*o-production related practices have a direct and positive impact on service innovation performance* H4b: V*alue-in-use related practices have a direct and positive impact on service innovation performance*
H5	**Value co-creation mediate the relationship between IoT capabilities and service innovation performance;** this leads to the following sub-hypothesis: *H5a: Co-production practices mediate the relationship between IoT collaboration capabilities and service innovation performance.* *H5b: Value-in-use practices mediate the relationship between IoT collaboration capabilities and service innovation performance.*

Chapter 5 Research Methodology

5.1 Introduction:

This chapter provides in-depth information about the research design and the research approaches applied to pursue the objectives of this study. It also highlights the different approaches of the research philosophy, the development of the questionnaire, the sampling strategy, and ethical considerations. The research method was selected carefully to achieve the aim and objectives of the study and to answer the research questions. This chapter starts by explaining the purpose of the study which is investigating the effect of the IoT and value co-creation relationship on service innovation performance in the healthcare context. Furthermore, this chapter discusses the sampling techniques and population. The chapter concludes with a description of analytical techniques, statistical methods and some ethical considerations.

5.2 Research Philosophy

The research philosophy is at the heart of any research project. It is a faith in the method in which information about a phenomenon should be selected, analysed and implemented (Dawson 2009). It emphasises a set of beliefs, assumptions and rationale about how the researcher views the world and how knowledge is developed in a given context (Saunders et al. 2016). Philosophy is "a set or system of beliefs stemming from the study of the fundamental nature of knowledge, reality, and existence" (Waite and Hawker 2009, p.685). Adopting the appropriate philosophical stance is essential to research. Research philosophy revolves around the beliefs of how knowledge is developed, its nature and its sources.

The research paradigm is "a worldview, together with the philosophical assumptions associated with that point of view" (Teddlie and Tashakkori 2009, p.84). The fundamental beliefs of the research paradigm are ontology, epistemology and methodology (Teddlie and Tashakkori 2009; Guba and Lincoln 1994), these three terms are working together as a one set of assumptions, so the ontological position decides the epistemological research position which determines the choice of the methodology. To examine the phenomena of the research interest, this study has adopted the realist ontological approach and the positivist epistemological approach. The following paragraphs tackle the assumptions of the research ontology and epistemology, and the rationale behind choosing these philosophies in this thesis.

Ontology is the nature of reality and existence (Easterby-Smith et al. 2012). In social sciences, the focus of ontology is on the nature of reality (Duberle et al. 2012). The paradigms and assumptions about existing things are independent of what is already known (Blaikie 2007). Positivists believe that social reality is objective and independent of the researcher, and that there is only one reality, whereas interpretivists believe that social reality is subjective as it is socially constructed and each individual has his own sense of reality (Collis and Hussey 2009). Ontology can be categorised into idealist and realist. According to Blaikie (2007, p.8) "idealist theory assumes that what we regard as the external world is just appearances and has no independent existence separated from human thoughts", while realist theory considers that there is an existence which is independent of what we know (Duberley et al. 2012).

The epistemology is concerned with what can be known about reality (Johnson and Onwuegbuzie 2004). It focuses on the method used by the researcher to decide what can be considered as valid knowledge (Duberley et al. 2012). Epistemology explains what specifies the truth, and the means the researcher uses to obtain evidence-based truth. The methodology describes the methods the researcher used to produce knowledge (Johnson and Onwuegbuzie, 2004). It focuses on procedures and steps used to yield credible information (Rawnsley 1998). The main question of methodology is the precise path that the researcher pursues to find out what can be known based on his beliefs. This view is purely related to the ontological and epistemological assumptions of the research (Leech and Onwuegbuzie 2009). According to Guba and Lincoln (1994), the selection of the adopted research paradigm is influenced by providing answers to questions relating to the three fundamental assumptions of ontology, epistemology and methodology. The two dominant paradigms in the social sciences are interpretivism and positivism (Walsham 1995).

The philosophy of interpretivism emphasises that social science, mainly management research, is too complicated to lend itself to theorising in the same manner as natural sciences (Saunders, Lewis and Thornhil 2016). Interpretivism believes that all meanings are contextual, so they focus on the importance of comprehending the phenomenon through the meanings of human life (Brand 2009; Blaikie 2007). They also believe that it is hard to separate the subjectivity of the interpretation of reality before starting knowledge development (Duberley et al. 2012). Under the interpretivism philosophy, reality incorporates the subjective experience of the researcher, so the reality is not defined objectively but socially constructed (Walsham 1995; Bryant 2011). So interpretivists believe that the interpretation of reality is not unique, but there are many interpretations which themselves are part of scientific knowledge in the social world (Bryant 2011). Critical realism has recently grabbed attention as a viable philosophical paradigm in management and organisation research (Ackroyd and Fleetwood 2004). Critical realism believes in the existence of a reality independent of human perception, and it acknowledges the causal powers to social settings and personal powers (Blaikie 2007; Yeung 1997).

Understanding the philosophical assumptions before conducting a research study is critical for researchers to obtain a satisfactory outcome. It also enhances the researcher's position to design the research in a manner that offers accurate answers to the research questions (Easterby-Smith, Thorpe and Lowe 2002). This study is categorised under social science research (particularly organisational and management research) within a field of technology and value co-creation.

In this study, the researcher adopts the positivist philosophical assumption. This decision responds to the research aim and objectives; to investigate the influence of adopting the internet of thing technology under the lens of service-dominant logic approach to service innovation performance. Therefore, the nature of research is to examine a causal relationship in the social science field (Saunders et al. 2016; Easterby-Smith, Thorpe and Lowe 2002). Additionally, researching the philosophical assumption of positivism enables the researcher to work with real data gathered by using questionnaires. Moreover, the researcher is capable of conducting the study objectively as he is not part of the instruments or tools of the research, so the researcher is external to the data collection techniques. The results of research conducted suing positivism philosophy depend on the quantitative approach and statistical data.

5.3 Research Methods

Research methods are the strategies, processes, action plans and designs used when selecting and implementing specific methods to obtain the desired outcome (Crotty 1998). Generally, the research methods come under three main categories: qualitative, quantitative and mixed methods. According to Tsang (2014), the quantitative method is related to the research works with large samples and using statistical techniques to investigates the relationship between the given variables. Qualitative research, on the other hand, aims to investigate human experience in the real ways it emerges in people's lives (Polkinghorne 2005). Furthermore, qualitative methods focus on how, why and what; to understand why respondents believe or behave in such a manner (Barnham 2015). The mixed-method approach utilises both the quantitative and qualitative approach in one research. Mixed method approach aims to develop deep insight and comprehensive understanding about several phenomena under study which cannot be wholly comprehended using only quantitative or qualitative methods (Venkatesh, Brown and Bala 2013; Johnson et al. 2007)

In this thesis, the researcher decided to adopt a quantitative research method. In this work, it is critical to have quantified data to find out if there is a relationship between IoT technology adoption and co-creation practices and under S-D logic approach and service innovation performance. Generating quantified data is essential for statistical analysis; this can be achieved by handing out a questionnaire or structured interviews. Collis and Hussey (2003) proposed two paradigms of research: positivist or quantitative and phenomenological or qualitative philosophy. Conducting positivist research suggests that elements of the study are not influenced by research activities, while in qualitative research, the researcher comes to know the reality through subjective reasoning and insights.

5.4 Research Approach

Based on the ontological philosophy; there are two research approaches: field studies and case studies (Yin 2013). Field studies attempt to generalise from a large number of observed events; it usually uses the form of survey research or structured interviews. On the other hand, case studies aim to comprehend what can be real to the human living in the case being investigating (Yin 2013). There are two leading research methods: deductive and inductive. Both approaches promote gathering information and building theory. In the case of the deductive approach, the researcher starts with general theory and develops a hypothesis towards a particular study using his observations and confirmations underpinned by qualitative or quantitative data. Controversially, the deductive approach starts by obtaining information through observations and defines a pattern to generalise the outcome or extend an existing theory (Zikmund et al. 2013). It also uses statistics to analyse a large number of samples of observations to obtain findings that can be generalised to the population.

The approach of research should be consistent with the aim, objectives and questions of the study. Based on the research questions of the thesis (mostly 'what?' questions) and the theories used, a deductive and scientific approach to the study appear to be appropriate. This thesis aims to verify known theories (e.g. resource-based view, value co-creation) and test if these theories are valid in the new phenomenon of IoT deployment in healthcare. It is, therefore, testing theories conducted through developing testable hypotheses. Supporting or rejecting the hypotheses are based on the results of data collection and analysis. However, according to Popper (1959), objective observation does not exist, so theories are never proven to be true, they are only proven to be false.

A comprehensive literature review has been undertaken as part of the scientific approach to develop the research design and the conceptual framework. It also supported by the development of the research hypotheses. According to Robson (2002), a deductive approach requires five sequential stages, that include (1) creating testable hypotheses from the theory, (2) expressing the hypothesis in operational terms to demonstrate how concepts and variables are to be measured, (3) testing the operational hypothesis by collecting and analysis of data, (4) using the data analysis to confirm or reject the hypothesis, and (5) developing or modifying the theory (if applicable). These sequential stages are shown in figure (Figure 5.1).

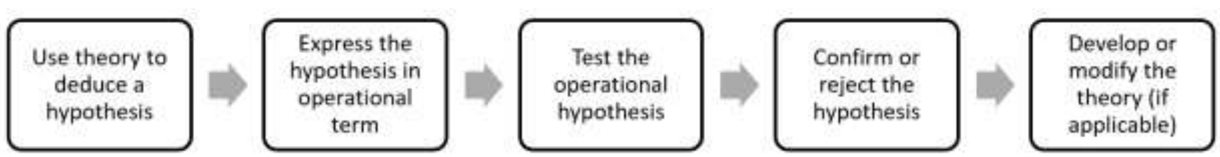

Figure 5.1 The deductive approach. Adapted from Robson (2002).

The research approach outlines the guidelines of how the research will be conducted. The research approach should use a highly structured methodology that enables replication in order to generalise the findings (Saunders et al. 2016). The deductive approach is appropriate for this thesis to examine causal relationships between different concepts. The concepts and variables of the research are demonstrated in operational terms in order to be measured quantitively (see chapter 4). A deductive approach dictates a high level of objectivity (Saunders et al. 2016), so in this study, the researcher should be independent of data collection process, therefore it employed a survey through a self-completed questionnaire which reduces the subjectivity and personal biases.

5.5 Research Design

The research design is a plan that describes the way the research problem is linked with the relevant empirical research (Bhattacherjee 2012). The research design defines the steps of the research, the required data, the method of using, collecting and analysing data, and how the research will appropriately combine all of these to answer the research question (Creswell 2014; Greener 2008). The study employs a quantitative approach to understand how the IoT-VCC relationship is related to service innovation performance and the impact of the internal organisational environment. This method seeks to grasp the possible relationship between several variables.

In general, researchers collect data by surveying people or through experiments or observations. The empirical data method was used to record and analyse the responses from the survey to find the hidden relationships among the variables. This study used the self-administrated survey for data collection approach. Usually, researchers use a self-administrated survey to get quick feedback (Cooper and Schindler 2006). Typically, researchers conduct a survey using several methods such as face-to-face, email and intercept-based methods to get quick feedback from individuals through questionnaires.

In order to make the right decision when selecting the research design and strategies, it is critical to understand the different research approaches (Easterby-Smith et al. 2012). The research study process usually goes through decision-making alternatives, based on the objective of the study, the unit of analysis, the setting of the study, the time allowed, and the level of researcher's interference (Cavana et al. 2001). According to Froza (2002), the researcher should define the unit of analysis, identify and examine the associated operational definitions and outline the hypothesis. Flynn (1990) defines a unit of analysis as a growth level of data during the analysis process, and it can be a system, company, a project, division, group or individual. In this study, the unit of analysis is the organisation.

In the case of theory verification, it is not necessarily a must to have large samples; hypothesis can be rejected by a single case (Flynn et al. 1990). The researcher needs to verify the reliability of all of the data collected and examine the validity of the results (Kvale and Brinkmann 2009; Stake 1995). Getting permission is essential before personal access data; the level of confidentiality is agreed with participants prior to the investigation (Stake 1995). Incomplete questionnaires are treated as social conversation (Forza 2002).

The researcher needs to ensure the high quality of all of the research processes, address constraints along the way, maintain sustainability, embrace the vital information, and ensure the feasibility of his work (Forza 2000). It is essential for research to have a well-organised, self-explanatory survey; the design should consider a clear introduction and precise instructions, this would help respondents to quickly answer the questions of the survey (Forza 2000). Other elements of study design may include the techniques used to collect data and the methods used to measure variables (Cavana et al. 2001). Protecting personal information is essential; the confidentiality of information needs to be assured (Fraenkel and Wallen 1993). The phase of collecting data starts by executing the survey and approaching the organisations and individuals and continually assess the quality of the measurements (Fraenkel and Wallen 1993.). One of the best practices while executing surveys is to approach the management of organisations first before asking individuals to participate in the survey, to ensure personnel is protected and understand the level of confidentiality of information (Fraenkel and Wallen 1993). Also, communicating the feedback of the study with research participants is preferred in order to share the present motivation and future contribution (Froza 2002). The researcher has to initially get permissions from participants and assure them that information will be used for the research purposes, and their answers will be kept confidential. Ethical considerations will be discussed in section 5.9.

According to Lammers et al. (2016), the halo effects are the human rationality biases associated with the first impression when meeting new people; they influence the individual's decisions and the way that respond to others people's behaviour. Understanding the impacts of halo effects is essential for the researcher to raise awareness of social interactions and any other possibility of falling into biases or wrong impressions against others. Consequently, the researcher needs to control the halo effects and avoid its consequences as much as it is practicable, by minimising human interaction.

After the surveys are collected, the findings of the questionnaires need to be analysed. The analysis can be achieved by using statistical software like Statistical Package for the Social Sciences (SPSS), which is a powerful tool with high capabilities. Generally, researchers use SPSS to conduct data analysis from basic things such as identifying the mean to more sophisticated analysis like structural equation modelling (SEM), this also includes testing frequency distributions, standard deviation, variance, range, central tendencies, inter-correlation matrix and finding the correlation and dispersion. Figure (5.2) presents the steps of the plan of this study that has been executed to achieve the aim and objectives of the research.

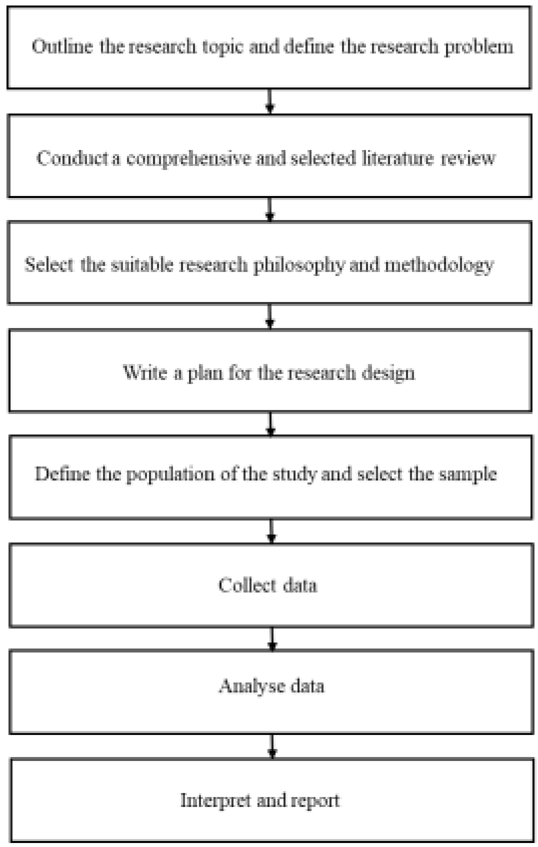

Figure 5.2 Plan of the research

5.6 Questionnaire Design and Development

Surveys are well-known as an effective method of research in social science; they are capable of studying a large number of concepts (Muijs 2004). Several methods of data collection would be covered by questionnaire, namely structured interviews, online surveys and telephone interviews (Saunders, Lewis and Thornhil 2016). A successful survey design and plan execution enhance the reliability, validity and response rate. The well-designed survey examines three forms of data variables during a collection phase; these include attributes, opinions, and behaviours (Dillman 2007). Designing a survey by critically selecting the questions is a fundamental practice in this phase (Saunders, Lewis and Thornhil 2016). Open-ended and close-ended questions can be used. Open-ended questions are used when the researcher is not confident about the answer or if detailed information is required (Dillman 2007; Saunders, Lewis and Thornhil 2016). One of the advantages of open-ended questions is that they enable participants to provide more information details. On the other hand, close-ended questions have a pre-defined and limited answer (Fink 2003). In this research, closed-ended questions have been used.

Saunders Saunders, Lewis and Thornhil (2016) classified closed-ended questions into six types: category, quantity, list, ranking, matrix and rating. In the *category* type, the participant can choose one answer from a provided set of answers; in *quantity*, an answer is a number. The *list* offers several answers where the respondent can choose any of them. *Ranking* presents a chance for the participant to sort items into an order. *Matrix* type presents two or more answers simultaneously. *Rating* form offers a rating instrument to record the response of participants.

In this research, rating type is selected with closed-ended questions, because the objective of the study is to collect information about participant's opinions about value co-creation practices and internet of things capabilities and the successful adoption of innovation. Usually, rating-type questions work with a Likert-type scale, which offers different levels of agreement for participants to choose from and a rating scale that ranges from one to seven (Corbetta 2003). This study uses continuous scale to measure the items (e.g. strongly agree to strongly disagree). A seven-point Likert-type scale is used and the level of agreement varies from one to seven. Finstad (2010) found that seven-point Likert items provide more accurate measures than five-point items, and are a better fit with electronically-distributed questionnaires.

Literature shows no standard for the number of points on rating scales. However, scholars propose that some scale lengths are preferable to increase reliability and validity (e.g Finstad 2010). The questionnaire is the preferred instrument when the research aims to include a large number of participants, which is equivalent to the researcher's intention in this work. According to Forza (2002), there are several ways to communicate a survey: handed-in personally, send through email or a telephone call. The researcher can improve the response rate by communicating earlier with participants through telephone calls (Forza 2002).

This study adopted the Drop-Off-Pick-Up (DOPU) method throughout the distribution process of the questionnaires. This technique was employed to improve the response rate of the questionnaire

(Bulmer and Warwick 1993). The interpersonal characteristic of the DOPU method contributes to the high response rates attained in research studies that adopt the DOPU method (Ibeh et al. 2004). The DOPU technique can achieve response rates better than online surveys because it utilises the face-to-face contact with participants and several follow-ups (Sauermann and Roach 2013).

Descriptive data can be ordinal or dichotomous. Ordinal data refers to ordering counts, such as impact level, or level of the agreement (e.g. high, usual, or low). Dichotomous data (also called binary) can only take two values (e.g. male and female). Numerical data can be divided into counts or continuous data; counts can be any number, such as the number of employees in the operations department, or the number of classrooms in a business faculty. According to Brown and Saunders (2007), numerical data is more precise than categorical data where data values are given to specific positions; also, more numerical tests can be examined as well. Continuous data can be any number between the minimum and maximum values of variables, like body temperature, speed of the vehicle, or gas pressure. Continuous data is divided into interval and ratio data. In interval data, the internal distance between readings can be translated without affecting their positions in the continuum, for example, the distance between (2 cm) and (4 cm) is the same distance between (11 cm) and (13 cm).

Ratio data, on the other hand, is interval data that refers to calculating the relative ratio difference between two values of a particular variable (Saunders, Lewis and Thornhil 2016). In ratio data, the number zero indicates the absence of variable, for example, weight is a ratio variable, but the temperature is not a ratio variable because zero degree centigrade does not mean that there is no temperature. Discrete data can only take absolute values or integer numbers. Preparing statistical data analysis to require the researcher to recognise and understand the different types of data as this is critical to the quality of the research study. The design of the data collection of this study divides the survey into two sections: specific and general. The first part of the questionnaire is the specific information; the purpose of this part is to measure the mutual impact of IoT capabilities and value co-creation practices on the service innovation performance. The researcher uses the general section to record information related to the participant characteristics such as organisation and work environment information that include the type of organisation (categorical data), work experience in years (continuous data), work title and job position (categorical data), and demographic information which include age (continuous data), gender and level of education (both are categorical data).

5.7 Scales development and operationalisation of variables

The variable operationalisation requests the appropriate development of measurements instrument. Therefore, the study pays attention to the type of instrument used, whether using an existing scale, adapting an existing scale, or developing a new scale to suit the aim of the research. Whenever feasible, the scales used in this study were adapted from published and validated measures.

The main idea behind the conceptual framework of this study is the organisational capabilities of IoT technologies. IoT capabilities are a high-order organisational concept (Verdouw et al. 2016; de Vass, Shee and Miah 2018). IoT capabilities refer to the capacity of the organisations to set up, install and deploy IoT resources in combination with other internal and external resources (Borgia, 2014; Chen et al., 2014). Unlike previous empirical studies, this research identifies four different capabilities of IoT monitoring, control, optimisation and collaboration (Wolf, Stumpf-Wollersheim and Schott 2019). Because of the lack of scale instrument of IoT capabilities in literature, this study develops a new measurement scale for each of the four IoT capabilities. Developing a new scale for measuring organisational activities (capabilities) is a challenge. However, following best practices for scale development, this study performed all analyses, including literature review, descriptive analysis, factor analysis and test of dimensionality. As a result, the study conceptualises IoT capabilities as a special type of organisational resource (Makadok, 2001).

5.7.1 IoT capabilities Scale development

IoT Monitoring capability can observe, sense, detect and identify individuals, items, behaviours, and environments through IoT technologies deployment. Specifying the domain for a scale was the first step in IoT monitoring items development. The scale items were identified based on extensive literature review and smart technology experts. Sixteen items were identified include *tracking individual items and behaviour, observation of the environmental condition observing the performance of individuals, equipment and service, providing real-time information, analytics and vitals observations, identifying the performance issues, detection of potential security vulnerabilities predicting of patients flow, observation and tracking of medical assets, and observation of waste reduction, recording the patients' complaints and detection of patterns.*

Table 5.1 IoT monitoring scale items

Number	Items	Reference
1	Tracking individual items	Van Den Hoven 2013; Dweekat, Hwang and Park (2017)
2	Track behaviour of individuals	Atzori, Lera and Morabito 2010, Lynch and Kenneth 2006, Zanella and Vangelista 2014, Lee and Lee 2015.
3	Observe the environmental condition	Atzori, Lera and Morabito 2010, Lynch and Kenneth 2006, Zanella and Vangelista 2014, Lee and Lee 2015.
4	Observe the performance of individuals	Lee and Lee 2015. Forkan et al. (2019).
5	Observe the performance of equipment	Lee and Lee 2015.
6	Observe the performance of service	Lee and Lee 2015.
7	Provide real-time information	Raji et al. 2016, Zois 2016, Hassanalieragh 2015, Hamrioui and Lorenz 2017.
8	Provide vitals observations	Raji, Jeyasheeli and Jenitha 2016, Varshney and Sneha 2006
9	Quickly identify performance issues	Forkan et al. (2019). MIT 2018
10	Provide real-time analytics	Sahu et al. 2020
11	Detect potential security vulnerabilities	Kim, S., Woo, S., Lee, H., & Oh, H. (2017). Alaba et al. (2017).
12	Predict patients flow	Domingos 2020
13	Observe and track medical assets	Lee Carman Ka Man, Cheng Mei Na and Ng Chun Kit2015
14	Observe waste reduction	Soh et al. 2019, Hobbs 2108; Dweekat, Hwang and Park (2017)
15	Log patients' complaints	Rallapalli, H., & Bethelli, P. (2017).
16	Detect patterns and anomalies in collected data	Shiwkh et al.2019; Lee and Lee 2015.

Management control refers to the process of directing organisations through settings in which they operate to accomplish short-term and long-term goals (Otley and Soin, 2014). IoT Control capability is the capacity to govern organisational aspects, roles, and responsibilities such as operations, processes, activities, and resources. The scale of IoT control was developed based on the same steps of monitoring capability. Nineteen items were recognised, including *control of performance KPIs*, *control of service activities*, *evaluation of the quality of healthcare service*, *corrective action support*, *issues identification*, *troubleshooting improvement*, *business insights* *improvement, support of efficiency and productivity gain, control progression, staff activities assessment, appraising work in progress improving results, correction of deviations and predicting future performance.* Table 5.2 shows the items with the relating sources.

Table 5.2 IoT control scale items.

Number	**Items**	**Reference**
1	Control performance KPIs	Vasu Pasupuleti 2017
2	Control the extent to which organisations attain performance goals	Brous, P., Janssen, M., & Herder, P. (2020)
3	Enable management to control healthcare service activities	Ahmadi et al. 2018; Milne, Andonova and Hajjat 2015
4	Evaluation of the quality of healthcare service	Dauwed and Meri 2019
5	Support swift corrective action	Buyya and Dastjerdi(2016), MIT 2018
6	Identify problems	Lee and Lee 2015
7	Enhance the troubleshooting process	Hassan 2018, MIT 2018
8	Enhance the business performance	Khan et al. 2017
9	Enhance business insights	Andrew Hobbs 2018
10	Support the efficiency/productivity gain	Buyya and Dastjerdi(2016
11	Control expectations	Hassan 2018
12	Control progress	Torre Diez et al. 2019; Li, Darema and Chang (2018)
13	Evaluate staff activities	Virginia, Sullivan and Wamba (2019)
14	Appraising work in progress	Ajami and Rajabzadeh, A. (2013); Shiklo (2018)
15	Improving results	Luis Rodriguez 2020
16	Regulating performance	Sridharan 2019
17	Correcting deviations from standards	Borgia 2014

18	Measuring performance against the standards	Laubacher 2006; Dweekat, Hwang and Park (2017)
19	Predict future performance	Akter and Holder (2019), Ardolino (2017)

Optimisation is defined as "a process of selecting a better or the best solution out of existing options" (Gosh, Surjadjaja and Antony, 2004). IoT optimisation capability enables an organisation to rationalise the internal processes to reduce cost and time, leading to higher efficiency. The study used the same previous steps to develop a measurement scale for IoT optimisation. Fourteen items were generated, including *Providing real-time information, large volume-variety of data to minimise the cost, real-time information to reduce waiting time, detection of an automaton-based situational event, prediction improvement, customer retention improvement, service reliability improvement support of re-engineering and change management, acceleration of innovation and delivery models improvement.* Table 5.3 shows the items with the relating sources.

Table 5.3 IoT optimization scale items.

Number	Items	Reference
1	Provide enough information to use resources efficiently	Yuan Jie Fan et al. 2014, Man et al. 2015, Janiesch et al. 2017.
2	Provide real-time information for efficient operations	Ben-Daya et al. 2017, Ferreira, Mogtinho and Domingos 2010, Dimitrov 2016, Lu et al. 2018
3	Provide real-time information to improve practices	Haddud et al. 2017, Ben-Daya et al. 2017
4	Provide a large volume-variety of data to improve processes	Khan et al. 2017, Mattern and Floerkmeier 2010, Lu et al. 2018, Zanella and Vangelista 2014
5	Provide a large volume-variety of data to minimise the cost	Radu 2018
6	Provide real-time information to reduce waiting time	Ahmadi et al. 2018; RAND

7	Immediately detect an automaton-based situational event (e.g. gas alert)	Cheng et al. 2016
8	Enhance the prediction of demand and inventory	Ka Man, Mei Na and Kit 2015
9	Increase customer retention	Yerpude and Singhal 2018
10	Increase service reliability	Ron Bartels 2019
11	Support process re-engineering	Liu, Li and Jiang 2014
12	Support change management	Raza 2019
13	Accelerate innovation	Muzumdar 2015
14	Potential of new health care delivery models	David Pare 2019

Collaboration refers to: "an evolving process whereby two or more social entities actively and reciprocally engage in joint activities aimed at achieving at least one shared goal" (Bedwell et al., 2012 p. 9). IoT Collaboration capability is the ability of an organisation to combine the internal and external processes towards achieving their goals via IoT technology implementation. Twelve items for the IoT collaboration measurement scale were identified based on extensive literature review and smart technology expert's feedback. These items include *information-sharing support, facilitation of interaction, facilitation of relationships, real-time communication, real-time collaboration, facilitate participation, cooperation, patient satisfaction improvement, improve performance, real-time visibility, service improvement.* Table 5.4 shows the items with the relating references.

Table 5.4 IoT collaboration scale items.

Number	Items	Reference
1	Strengthen information sharing within the organisation	Lee and Lee 2015, Gubbi et al. 2013
2	Facilitate interaction among parties within/out of the organisation	Jara, Parra and Skarmeta 2013, Atzori, Lera and Morabito 2010

3	Facilitate relationships among parties within/out of the organisation	Dijkman et al. 2015, Alam et al. 2016, Islam et al. 2015, Rohkale, Prasad, and Prasad 2011, Chen et al. 2014
4	Provide real-time communication	Atzori, Lera and Morabito 2010; Yang, Yang and Plotnick 2013
5	Provide real-time collaboration	Atzori, Lera and Morabito 2010
6	Facilitate the participation of patient and staff	Scutto, Ferraris and Bresciani 2016
7	Facilitate cooperation of parties with and out of the organisation	Chen et al. 2014, Gubbi et al. 2013, Nc and Wakenshaw 2015, Atzori, Lera and Morabito 2010
8	Improve patient satisfaction	Ahmadi et al. 2018; Wamba, Anand and Carter (2013)
9	Provide information on network performance	Li et al. 2017
10	Provide real-time visibility of activities Provide	Li, Darema and Chang (2018)
11	Provide real-time visibility of service status	Li, Darema and Chang (2018)
12	Improve service insights and patient experience	Zdravković, Noran and Trajanović (2014); Dauwed and Meri (2019); Manate et al. 2014; Kulkarni and Sathe (2014)

Two comprehensive dimensions capture value co-creation practices: (1) co-production and (2) value in use. The study used a scale developed by Ranjan and Read (2014). This scale is one of the most comprehensive scales of value co-creation (Frow et al., 2015). Co-production is measured by twelve items under three dimensions, knowledge, equity and interaction. Value-in-used is assessed by eleven items under three dimensions: experience, personalisation and relationship, as shown in figure 3.2.

Service innovation performance is the dependent variable measured based on the work of Voss (1992). In this study, service innovation conceptualised through process performance and result performance and captured through an eleven-item scale including the following concepts *the* *average cost of developing a new service comparing with competitors, the number of new services developed by competitors annually, the costs of new services competitors, the time to develop a new service model comparing with competitors, the time from development of new service models to entry comparing with competitors, cost efficiency achievement comparing with competitors, the extent to which organisation exceeding the growth target, seeking competitive advantages via innovative methods, the level of service quality compared with competitors, the level of providing reliability and the level of maintaining customer satisfaction compared with competitors.* See chapter 7 for IoT capability scale validation.

5.8 Sampling Strategy

A sample is a subset of the research population that the researcher chooses to participate in his study. The population is any complete set of people or things that share some common features (Bartlett, Kotrlik and Higgins 2001). Utilising probability sampling methods is the best technique to achieve a representative sample; in this way, the researcher ensures that all population members have an equal chance to be represented in a study with a determinable probability of selection (Pilot et al., 2010). Sampling shows that population representatives are selected to allow findings to be applied to the whole population (Polkinghorne 2005). Therefore, participant selection is critical; it provides a significant input structure and attributes of practices under investigation (Polkinghorne 2005). This study adopted Yamane's (1968) formula to compute the minimum desirable sample size required for the study analysis.

In the data collection stage, this study follows the seven stages defined by Zikmund et al. (2013); see figure 5.3; these steps work as guidelines for how a researcher should undertake his study. The first stage is to *define the target population*; this is a key step where a researcher can start. The target population for this study is hospitals, clinics, medical centres and homecare service firms applying IoT in their operations.

The second stage is *selecting the sample frame*. Creating a sample frame (or working population) is essential as it is a list of population elements where a research sample can be drawn (Zikmund et al., 2013). The third stage is selecting the appropriate sampling method, deciding if the probability or non-probability sampling techniques are required, and deciding the data collection units.

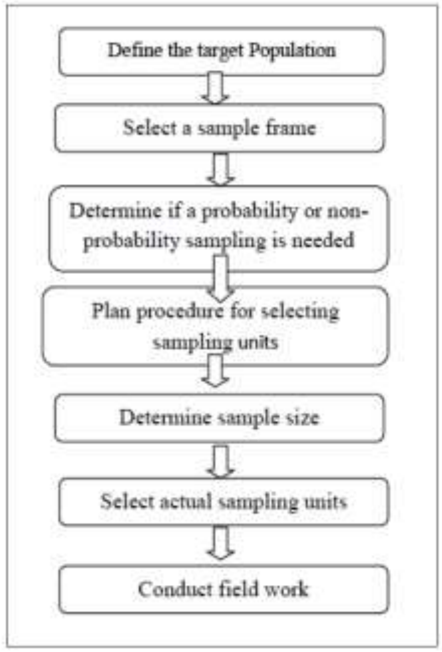

Figure 5.3 Sampling process stages (Zikmund et al. 2013)

The researcher needs to ensure all target population members have the same chance to be selected, that would be achieved by using probability random sampling technique (Bryman and Bell 2007). Then, dealing with non-probability samples, the researcher decides the probability that a member of the target population is included in the survey. In the purposive sampling technique, the researcher uses his judgement to select the representative sample. However, although purposive sampling can be used if the researcher does not want to generalise the results, this kind of sampling is limited in result generalisation (Robson 2011). Since this study aims to generalise the results, the probability random sampling technique has been applied. The next stage is the *plan the procedure for sampling unit selection*. Initially, a pilot study was conducted to enhance the quality of the questionnaire. The fifth stage is to *define the sample size;* the researcher must decide the appropriate sample size. This requires the researcher to apply statistical theory; selecting sample size can be affected by theoretical and practical conditions of the research (Robinson 2014).

Bartlett, Kotrlik and Higgins (2001) suggested sample size values for both categorical and continuous data with different alpha levels of 0.1, 0.05, and 0.01. The margin of error for continuous data in the suggested values is 0.03, so if this value is suitable for the research study, the researcher may use the proposed sample size values.

Table 5.5 Determination of the minimum sample size for a defined population (Bartlett, Kotrlik and Higgins 2001, p.48)

	Sample size					
	Continuous data (margin of error = .03)			Categorical data (margin of error = .05)		
Population size	alpha = .10 t = 1.65	alpha = .05 t = 1.96	alpha = .01 t = 2.58	p = .50 t = 1.65	p = .50 t = 1.96	p = .50 t = 2.58
100	46	55	68	74	80	87
200	59	75	102	116	132	154
300	65	85	123	143	169	207
400	69	92	137	162	196	250
500	72	96	147	176	218	286
600	73	100	155	187	235	316
700	75	102	161	196	249	341
800	76	104	166	203	260	363
900	76	105	170	209	270	382
1,000	77	106	173	213	278	399
1,500	79	110	183	230	306	461
2,000	83	112	189	239	323	498
4,000	83	119	198	254	351	570
6,000	83	119	209	259	362	598
8,000	83	119	209	262	367	613
10,000	83	119	209	264	370	623

5.9 Validity and Reliability Analysis

Evaluating the thoroughness of empirical research can be achieved through these four types of measures; these are internal validity, construct validity, external validity, and reliability (Gibbert et al. 2008). According to Guba and Lincoln (1998), qualitative researchers use different terms when assessing their studies, namely, credibility, confirmability, transferability and dependability.

Validity explains why claims are valid and how the researcher validates and justifies why he believes in things he claims (Norris 1997). The researcher should measure what he claims to measure (Muijs 2004). Cooper and Schindler (2008) suggest that internal validity is critical as it enables the questionnaire to measure what is the purpose of measuring and it shows the reality of what is being measured. Content validity can be defined as*: "a qualitative type of validity where the domain of the concept is made clear, and the analyst judges whether the measures fully* *represent the domain"* (Bollen 2014, p.185). It focuses on how dimensions and elements of the idea have been outlined (Sekaran and Bougie 2011).

Construct validity is used to check if the indicator variables (set of questions) are suitable to assess the latent variable (Urbach and Ahlemann 2010; Saunders, Lewis and Thornhil 2016). According to Bagozzi and Yi (2012, p.18), construct validity evaluates the *"degree of agreement of indicators hypothesised to measure a construct and the distinction between those indicators and indicators of a different construct(s)"*. Usually, construct validity is used to evaluate if a construct measures what it is supposed to measure (Greener 2008). According to Kerlinger (1986), reliability refers to the accuracy, trustworthiness, consistency and certainty that proof measurement analysis is driving to the same findings and conclusions on repetitive trials

In this study, internal validity has been considered through several strategies that are in line with what has been proposed by (Gibbert et al. 2008). First, the conceptual framework stems from literature, which demonstrates the internal relationship between the critical variables of the study: IoT, value co-creation and service innovation. Second, an in-depth and inclusive literature review has been conducted to evaluate the content and face validity. Likewise, the researcher has consulted with experts in the field of IoT technology and healthcare management to review the appropriateness and suitability of the research questions; this would enhance the content validity. Both content and face validity are used to confirm that indicators attain the meaning of the construct as set by the literature.

Analytical techniques describe the data tools and methods used to interpret and describe the collected data and acquired information (Flick 2006). Many descriptive statistics can be utilised to come up with results, namely frequencies (number of times that particular phenomenon occurs), a measure of central tendencies (mean, median, and mode), and the measure of shape (skewness and kurtosis) (Forza 2002). Testing the hypothesis is essential as it compares the results of collected data to the right approach of theory to minimise the opportunity of getting random variation results (Robson 2002). Typically, there are two fundamental approaches to test the significance (p-value) and the hypothesis; these are parametric and non-parametric techniques. Parametric is more commonly used for numerical data. For the non-normally distributed data, the non-parametric technique is used (Blimbrg, Cooper, and Schindler 2009).

5.10 Ethical Considerations

Ethical issues and consideration have become a major concern in any research project. Ethical considerations are critical to protect both the researched and the researcher (Myers and Venable 2013). Research ethics are concerned with the adoption of the appropriate behavior in relation to the rights of those being part of the research project or affected by it (Saunders et al. 2016). Research ethics are the morals and values in each step of a research project (McNabb 2013). Research ethical considerations involve an understanding of any associated risk of harm, obtaining consent from respondents, respecting the dignity of research respondents, protecting the privacy of the researched subject, ensuring anonymity of participants and organisations and ensuring the confidentiality of the data (Easterby-Smith Thorpe and Jackson 2012; McNabb 2013)

This research has been designed to be morally justifiable for all involved individuals that may be affected by it. The social norms dictate to a large extent the justifiable moral behavior. The social norms, regulation and legislation in both Jordan and UAE were considered. The questions asked in the questionnaire and those which were asked through interviews in the pilot study were developed without researcher bias or compulsion from any other individual or entity. Questions were designed to achieve the research objectives and answer the questions in an effective and simple manner. The purpose of the research was declared to the participants to gain their agreement of participation. Participants were not asked to disclose their organisations. Research related data was accessed from only one personal computer which is password-protected. The researcher ensured the confidentiality, privacy and anonymity of information during data collection and storage processes. The researcher analysed, interpreted and managed data carefully with honesty and integrity. Findings of the research presented transparently and honestly, with no deception or bias.

Chapter 6 Data Analysis:

6.1 Introduction:

This chapter presented the quantitative findings and collected data analysis using the thesis developed instruments. The statistical analysis involves multiple methods, including descriptive statistics, demographics, standard method variance, normality, reliability and hypothesis testing. Several software tools are available to perform data analysis, such as R, SPSS, MPlus and Stata. Among these tools, Statistical Package for Social Sciences (SPPS) is perhaps the most widely used software package by researchers to conduct statistical analysis (Field 2009). One of the advantages of SPSS is its compatibility with Microsoft Excel software which most researchers are familiar with. Also, SPSS is capable to effectively perform complicated analysis tests (Ann 2011) and many other analyses.

This thesis aims to examine the statistical relationship presented in the conceptual framework, as shown in chapter 4. The design of this quantitative study aims to ensure reliability and validity and to generalise the results from the population selected sample (Saunders, Lewis and Thornhill 2016). The sample responses were statistically studied and analysed to examine the interdependence relationships and causes between capabilities of IoT, value co-creation practices and service innovation performance.

6.2 Population and sampling techniques

Defining an appropriate sample size before data collection processes and estimating population characteristics is fundamental. Prior studies indicated that sample size is influenced by multiple factors, including resource availability, accuracy, the confidence level of findings and categories of analysis (Saunders et al. 2016; Sekaran and Bougie, 2011). Accordingly, the population of interest of the thesis involves caregivers (e.g. nurses, doctors, therapists) working in private, public and not-for-profit medical organisations in Jordan. The target population was identified by the statistics published by the Ministry of Health in Jordan. According to statistics of the ministry of health in Jordan, there are 1204 medical organisations in total. These organisations are spread around the country: 69 private, 31 governmental, 15 military, two educational (university) hospitals; 102 comprehensive health, 380 primary health, and 194 secondary health centres; 411

dentistry clinics and 464 motherhood and childhood clinics (MOH 2020). This thesis targets the medical organisations that provide regular healthcare for patients and use IoT technologies in their operations; hence; the primary, secondary, and motherhood and childhood clinics were **excluded** from random sampling as they did not meet the assumption of using IoT applications. This step turned the sample into **219** medical centres, including hospitals (private, governmental, not-for-profit, military and educational) and comprehensive administrative centres.

This study adopted the formula of Yamane (1968) to compute the minimum desirable sample size required for the analysis of the study.

Yamane's sample size determination formula states:

$$n = \frac{N}{1 + N(e^2)}$$

Where

N is the total population

n is the sample size for the study

e is the level of precision

Therefore, at 95% confidence level, the sample size for the medical organisations in Jordan was determined as:

$$n = \frac{219}{1+219\,(0.05^2)} = 141.518578 \approx 142$$

So, based on Yamane's formula, the minimum sample required of medical organisations is 142 organisations.

6.3 Descriptive Statistics:

The participants' feedback is crucial to the research objectives since using IoT technology requires respondents to be fully aware of the change in their relationship with the patients. The composition of organisations that participated is shown in Figure (6.1). In order to encourage organisations to participate in the study, an invitation letter was handed to each administrative department during a site visit. The research topic, objective, confidentiality and anonymity were explained to the management and participants in each organisation. Then a hard copy of the questionnaire was handed to each selected participant. At the time of completion of the research project, the researcher decided to summarise the research results (Easterby-Smith et al., 2012) to each participant as an incentive to encourage their employees to participate and raise response rates.

This study adopted the Drop-Off-Pick-Up (DOPU) technique during the distribution process of the questionnaires to enhance the response rate. According to Bulmer and Warwick (1993), the DOPU technique improves the questionnaire response rate in developing countries. Also, DOPU can positively increase the response rates compared with online surveys because it utilises face-to-face contact with participants and several follow-ups (Sauermann and Roach, 2013). Therefore, this technique was employed for this study. A total of 215 questionnaires were sent to medical organisations. After several telephone calls and site re-visits, the received sample was 211; out of this number, three responses were excluded from further analysis due to incomplete entries. Thus, several 208 usable responses were obtained. All collected data from the survey were coded and entered into IBM SPSS. Data were examined to detect any missing items and identify outliers that could influence the analysis. Statistical techniques such as descriptive statistics and inferential statistical analysis were taken into consideration. Descriptive statistics are commonly used in scientific research to summarise, depict and present quantitative data (Collis and Hussey 2013), while inferential statistics are used to make predication and inferences to conclude the population through analysing the sample data (Easterby-Smith, Thorpe and Jackson., 2012; Collis and Hussey, 2013).

It is imperative to check for missing and outlier responses to ensure that collected information is appropriate for analysis; this has been achieved by entering data into IBM SPSS. Missing data is a common problem for survey research, particularly in the case of a large number of responses (Sainani 2015). Furthermore, missing data can create a significant issue of bias for parameter estimates and reduce statistical power, which challenges the data analysis process mostly when applying structural equation modelling (Roth 1994). The techniques used in this thesis to prepare data and identify missing data include sieving unengaged responses, clearing the missing data and treating the outliers.

An example of the unengaged responses is the five (or more) repetitive answers across the items. These cases (n=3) were removed from the analysis. Precluding them from the further review may not affect the generalisability of research findings, as they are not many and insignificant compared with the ratio of variables (Hair et al., 2019).

6.3.1 Checking for missing data

The next step was checking for missing data. IBM SPSS software was used to identify the missing data. After entering all responses data in the software packages, data entry was confirmed case by case. The analysis revealed that several (3) organisations provided incomplete data. Hence, they were excluded from the final data analysis. If a substantial percentage of data in a survey tool is missing, the deletion technique is recommended (Tsikriktsis, 2005). However, the rate of lost data is less than 5%. According to Brown (2015), deletion of missed information is considered appropriate if missing data is less than 5% of samples. Therefore, this thesis finds no impact on data analysis by employing the complete deletion process.

6.3.2 Checking for outliers

The next step of data preparation was testing for outliers (Hair et al., 2019). Outliers can lead to significantly different results by dragging the mean away from the median (Blaikie, 2003). Outliers are two types: univariate outliers and multivariate outliers. A univariate outlier is a score that represents a unique value which affects individual variables, whereas multivariate outlier is a combination of extreme values on two or more variables (Tabachnick, Fidell and Ullman, 2001). In this study, univariate outlier test was implemented. The purpose of this selection is because univariate deals with variables that can be tested individually to identify the responses that fall outside the maximum and minimum threshold points (Hair et al.,2019).

In this case, outliers are identified by evaluating the standardised residuals at a critical point equal to ± 3.29, and an alpha level of $p = 0.001$. The process was performed by using SPSS, a number of (7) cases were identified as extreme outlier points and removed from further analysis. The identified cases were insignificant compared with sample size (Hair et al., 2019), so precluding them from the study may not affect the generalisability of results.

6.4 Common Bias Method CMB):

Data were inspected against a common bias method. Initially, there are two reasons for examining common bias method, first to check if one factor is the source of observed variance for the majority of data, second to verify that the variation is produced by theoretically supported factors (Venkatesh and Goyal, 2010). Evidence of common method bias in data can bias parameter estimates (Conway and Lance 2010; MacKenzie and Podsakoff, 2012). When testing for common bias method, the collected data were examined using Harman's Single-Factor. The test was performed by entering all variables into unrotated principal component factor analysis using SPSS software and checking the results (Lindell and Whitney, 2001). If one factor found to be account for greater than (50%) of the variance, then there is a possibility of a high threat of standard bias method (MacKenzie and Podsakoff). In this thesis, results show that there is no single factor accountable for more than (50%) of variance. Table (6.1) demonstrates the results of the test. The output of the principal component analysis revealed that (32) key factors account for (79%) of the total variance. Therefore, the result of the test provides evidence that the standard method is not considered as an issue in this thesis.

Table 6.1. Results of common bias method analysis

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	21.495	22.626	22.626	21.495	22.626	22.626
2	8.219	8.651	31.277	8.219	8.651	31.277
3	3.460	3.643	34.920	3.460	3.643	34.920
4	2.869	3.020	37.940	2.869	3.020	37.940
5	2.753	2.898	40.838	2.753	2.898	40.838
6	2.380	2.506	43.343	2.380	2.506	43.343
7	2.249	2.368	45.711	2.249	2.368	45.711
8	2.178	2.293	48.004	2.178	2.293	48.004
9	2.100	2.210	50.214	2.100	2.210	50.214
10	1.860	1.958	52.171	1.860	1.958	52.171
11	1.681	1.770	53.941	1.681	1.770	53.941
12	1.634	1.720	55.660	1.634	1.720	55.660
13	1.580	1.663	57.324	1.580	1.663	57.324
14	1.513	1.593	58.917	1.513	1.593	58.917
15	1.465	1.542	60.459	1.465	1.542	60.459
16	1.395	1.468	61.927	1.395	1.468	61.927

17	1.353	1.424	63.351	1.353	1.424	63.351
18	1.303	1.371	64.722	1.303	1.371	64.722
19	1.251	1.317	66.039	1.251	1.317	66.039
20	1.194	1.257	67.296	1.194	1.257	67.296
21	1.156	1.217	68.513	1.156	1.217	68.513
22	1.118	1.177	69.690	1.118	1.177	69.690
23	1.110	1.168	70.859	1.110	1.168	70.859
24	1.075	1.132	71.990	1.075	1.132	71.990
25	1.044	1.099	73.090	1.044	1.099	73.090
26	.966	1.017	74.107	.966	1.017	74.107
27	.944	.994	75.100	.944	.994	75.100
28	.937	.986	76.086	.937	.986	76.086
29	.879	.926	77.012	.879	.926	77.012
30	.826	.869	77.881	.826	.869	77.881
31	.817	.860	78.742	.817	.860	78.742
32	.763	.803	79.545	.763	.803	79.545

Source: IBM SPSS output

6.5 Reliability Analysis:

Reliability measurements are essential to any research project. Reliability refers to the level to which measurements items yield consistent findings (Saunders Lewis and Thornhill 2016). Reliability measurements are used to assess the consistency of measurements in results when research repeated in a different context (Easterby-Smith et al., 2012; Saunders Lewis and Thornhill 2016). Cronbach's alpha was used to evaluate and assess the reliability measure in this thesis. Cronbach's alpha is a test widely used by researcher to examine the internal consistency. The analysis provides results ranging from (0.0 -1.0), whereas (0.0) means no internal consistency, and (1.0) indicates perfect internal consistency. Nunnally and Bernstein (1994) recommend that alpha value equal to or greater than (0.7) is acceptable.

Overall, the analysis shows that reliability results are acceptable; all of Cronbach's alpha tests support the constructs measurements. Values are found ranging between 0.871 and 0.935. These results revealed a high level of internal consistency for the scales of all constructs. As the table (6.3) shows, the study used "Alpha if deleted" option to check if internal consistency can be improved by deleting unsupported items. No further improvement was reported, as all of Cronbach's alpha test results are more significant than 0.70. The conclusion is research measures passed the reliability test. The results of Cronbach's alpha analysis were presented in table (6.3).

6.5.1 Reliability analysis for IoT capabilities

Reliability analysis of IoT capabilities shows that all values are acceptable (Nunnally and Bernstein, 1994). Monitoring capability items report alpha coefficient of 0.867, which indicates well acceptable reliability and internal consistency of the scale. The reliability analysis of control capability also shows fair values. The variable scored an alpha coefficient of 0.891. The optimisation capability will score variable alpha coefficient of 0.863, shows an acceptable amount and internal consistency among its items. Finally, the analysis of collaboration capability indicates an acceptable Cronbach's alpha value by achieving the score of alpha coefficient = 0.836. The study presented in Table 6.2 shows no improvements could be obtained by removing any of the items.

Table 6.2 Results of reliability analysis for IoT capabilities

CONSTRUCT	CODE	ITEM	ALPHA IF DELETED	CRONBACH's ALPHA
Monitoring	MON1	Tracking individual items	.860	**0.867**
	MON2	Track behaviour of individuals	.863	
	MON3	Observe the environmental condition	.861	
	MON4	Observe the performance of individuals	.858	
	MON5	Observe the performance of equipment	.856	
	MON6	Observe the performance of service	.860	
	MON7	Provide real-time information	.857	
	MON8	Provide vitals observations	.861	
	MON9	Quickly identify performance issues	.863	
	MON10	Provide real-time analytics	.860	
	MON11	Detect potential security vulnerabilities	.855	
	MON12	Predict patients flow	.861	
	MON13	Observe and track medical assets	.858	
	MON14	Observe waste reduction	.859	
	MON15	Log patients' complaints	.861	

	MON16	Detect patterns and anomalies in collected data	.857	
Control	CON1	Control performance KPIs	.888	**0.891**
	CON2	Control the extent to which organisation attain performance goals	.887	
	CON3	Enable management to control healthcare service activities	.887	
	CON4	Evaluation of the quality of healthcare service	.885	
	CON5	Support swift corrective action	.887	
	CON6	Identify problems	.889	
	CON7	Enhance the troubleshooting process	.885	
	CON8	Enhance the business performance	.882	
	CON9	Enhance business insights	.886	
	CON10	Support the efficiency/productivity gain	.884	
	CON11	Control expectations	.887	
	CON12	Control progress	.884	
	CON13	Evaluate staff activities	.887	
	CON14	Appraising work in progress	.886	
	CON15	Improving results	.886	
	CON16	Regulating performance	.884	
	CON17	Correcting deviations from standards	.885	
	CON18	Measuring performance against the standards	.887	
	CON19	Predict future performance	.887	
Optimisation	OPT1	Provide enough information to use resources efficiently	.852	**0.863**
	OPT2	Provide real-time information for efficient operations	.852	
	OPT3	Provide real-time information to improve practices	.851	
	OPT4	Provide large volume-variety of data to improve processes	.854	
	OPT5	Provide large volume-variety of data to minimize the cost	.851	
	OPT6	Provide real-time information to reduce waiting time	.854	
	OPT7	Immediately detect an automaton-based situational event (e.g. gas alert)	.853	

	OPT8	Enhance the prediction of demand and inventory	.852	
	OPT9	Increase customer retention	.855	
	OPT10	Increase service reliability	.849	
	OPT11	Support process re-engineering	.852	
	OPT12	Support change management	.856	
	OPT13	Accelerate innovation	.855	
	OPT14	Potential of new health care delivery models	.864	
Collaboration	COL1	Strengthen information sharing within the organisation	.828	**0.836**
	COL2	Facilitate interaction among parties within/out of the organisation	.829	
	COL3	Facilitate relationships among parties within/out of the organisation	.821	
	COL4	Provide real-time communication	.815	
	COL5	Provide real-time collaboration	.842	
	COL6	Facilitate the participation of patient and staff	.817	
	COL7	Facilitate cooperation of parties with and out of the organisation	.822	
	COL8	Improve patient satisfaction	.818	
	COL9	Provide information on network performance	.824	
	COL10	Provide real-time visibility of activities Provide	.817	
	COL11	Provide real-time visibility of service status	.826	
	COL12	Improve service insights and patient experience	.824	

Source: the output of IBM SPSS

Overall, the analysis of reliability indicates that IoT constructs achieve acceptable values. This results of the coefficient of reliability and consistency show that there is an excellent internal consistency among the scale items, and they are closely related to each other as a group. The objective of reliability analysis is to ensure that each variable has an acceptable alpha coefficient, and items have shared covariance and set to measure the same underlying concept.

6.5.2 Reliability analysis for value co-creation practices

IBM SPSS was used to perform the calculations of reliability analysis. The results of VCC practices show that all alpha coefficients values are acceptable, as table 6.3 presents. The value of the alpha coefficient for co-production variable = 0.914. This value indicates a well acceptable internal consistency among items of the co-production scale. The reliability analysis of value-in-use shows acceptable values. The alpha coefficient value of VIU is 0.897, which shows an acceptable internal consistency among VIU scale items, and they are closely related to each other as a one set. Table 6.3 presents the results of reliability analysis for VCC practices as produced by SPSS.

Table (6.3) Results of reliability analysis for Value co-creation practices

CONSTRUCT	CODE	ITEM	ALPHA IF DELETED	CRONBACH's ALPHA
Co-Production	CPK1	My organisation is open to the patient's ideas and suggestions about existing services or towards developing a new service	.913	**0.914**
	CPK2	My organisation provides sufficient illustrations and information to the patient	.906	
	CPK3	In my organisation patient would willingly spare time and effort to share his ideas and suggestion to help it improve its services and processes further	.907	
	CPK4	My organisation provides suitable environment and opportunity to the patient to offer suggestions and ideas	.905	
	CPE1	My organisation provides easy access to information about the patient's preferences	.907	
	CPE2	The processes of service development are aligned with patient requirements (e.g. the way we wish them to be)	.908	
	CPE3	My organisation consider patient roles to be as crucial in the process of service creation	.908	
	CPE4	My organisation share an equal role with patients in determining the outcome of the treatment process.	.907	

	CPI1	During the process of service development, patients could conveniently express their specific requirements	.907	
	CPI2	My organisation convey to its patients the relevant information related to the treatment process	.906	
	CPI3	My organisation allows sufficient patients interaction in its healthcare processes (healthcare service development, assisting other patients)	.905	
	CPI4	To get the maximum benefit from the treatment process, my organisation plays a proactive role during interaction with patients	.904	
Value-In-Use	VUE1	My organisation creates a memorable experience for patients	.895	**0.897**
	VUE2	Depending upon the nature of individual participation, patient experiences in the process might be different from other patients	.889	
	VUE3	A patient can improve the process by experimenting and trying new things	.889	
	VUP1	The benefit, value, or fun from the process (or, the service) depend on the user and the usage condition	.891	
	VUP2	My organisation tries to serve the individual needs of each of its patients	.883	
	VUP3	Different patients, depending on their taste, choice, or knowledge, involve themselves differently in the process (or, with the service)	.887	
	VUP4	My organisation provides an overall pleasant experience, beyond the "functional" benefit	.880	
	VUR1	In my organisation, the extended facilitation is necessary for patients to enjoy the process (or, the service) fully	.882	
	VUR2	Our employees feel an attachment or relationship with the patients	.889	
	VUR3	There is usually a group, community, or a network of patients and customers who are a fan of my organisation	.890	
	VUR4	My organisation is renowned because its patients usually spread the positive word about it in their social networks	.894	

Source: the output of IBM SPSS

6.5.3 Reliability analysis for service innovation performance

The analysis of service innovation construct reliability shows an acceptable result having the alpha coefficient score 0.934, which indicates acceptable reliability and internal consistency among items of the scale. Table 6.4 presents the analysis results performed by SPSS and indicates the value of the alpha coefficient if item deleted for each item.

Table 6.4 Results of reliability analysis for service innovation

CONSTRUCT	CODE	ITEM	ALPHA IF DELETED	CRONBACH's ALPHA
Service Innovation Performance	SIN1	In my organisation, the average cost of developing a new service is less than those of other competitors	.908	0.911
	SIN2	In my organisation, the number of new services developed annually is more than those of competitors	.901	
	SIN3	In my organisation, the costs of new services are less than those of competitors	.905	
	SIN4	In my organisation, the time to develop a new service model is less than those of Competitors	.902	
	SIN5	In my organisation, the time from development of new service models to entry is less than that of competitors	.901	
	SIN6	My organisation achieved better cost efficiency than competitors	.901	
	SIN7	My organisation is exceeding the growth target (e.g. obtained more new patients than planned)	.903	
	SIN8	My organisation seeks to obtain competitive advantages (e.g. new offerings, innovative services)	.907	
	SIN9	In my organisation, the service quality we provide is better than those of competitors	.904	
	SIN10	In my organisation, we provide higher reliability service than those of competitors (e.g. patients never seek for different treatment by other competitors)	.905	
	SIN11	In my organisation, the service provided has higher customer satisfaction than competitors	.902	

In conclusion, the analysis of reliability indicates that all the constructs achieve acceptable values. These results of alpha coefficient values show that a well-established internal consistency among scale items exists in each construct, and they are closely related to each other as one set. The objective of reliability analysis is to ensure that each variable has an acceptable alpha coefficient and designed to measure the same underlying concept. Although internal consistency is achieved in this thesis, this is not an evidence for scale unidimensionality. The next chapter will discuss the argument of performing exploratory factor analysis (EFA) to examine the dimensionality of scales.

6.6 Descriptive Analysis:

The data collection period lasted for 10 weeks, including the follow-ups. The demographic categories were selected based on the research objectives, questions and literature review. The categories include the sector of organisations, size of organisations, job level of respondents, number of years of experiences and educational level for respondents. Table (6.5) demonstrates the frequency and percentage of each demographic category and their distribution details.

Table 6.5 Demographic Summary of surveyed organisations

Description	Frequency	%
Sectors of Organisations		
Public	118	57%
Private	77	37%
Military	8	4%
University	1	1%
Not-for-Profit	4	2%
Total	208	100%
Size of Organisations		
Less than 50	25	12%
50-999	144	69%
1000-4999	37	18%
5000 or more	2	1%
Total	208	100%
Job level for participants		
Employee	119	75%
Middle management	78	38%
Top management	11	5%
Total	208	100%
Years of experience for participants		
2 or less	35	17%
3 - 5	42	20%

6 - 10	71	34%
11 - 19	48	23%
20 or above	12	6%
Total	208	100%
Educational level for participants		
High school graduate or less	10	5%
College Degree	34	16%
Bachelor Degree	124	60%
Master Degree	32	15%
Doctorate or above	8	4%
Total	208	100%

The following section explains the details of demographic profile.

6.6.1 Type of organisations:

There are several types of hospitals and medical centres in Jordan, as mentioned earlier. This thesis intends to represent all types of healthcare organisations. According to the ministry of health in Jordan; the medical organisations divided into; (1) *Public hospitals* and *medical centres* which is administrated by government, (2) *Priave hospitals* which is managed by the private sector, (3) *military hospitals* that are administrated by Jordanian Armed Forces and two other *educational hospitals* administrated by two universities: University of Jordan and Jordan university of science and technology. As figure (6.7) presents, all medical organisations types were represented in the sample of this research. The majority of participating organisations come from public sector 57%, and this accounts for 118 respondents out of the 208 samples. In contrast, the private sector came at second rank which accounts for 77 responses out of 208 and equals to 37% of the total sample. The remaining came from military, 8 responses represents 4% of the sample, and 4 answers from not-for-profit represent 2%, and one response came from educational hospitals as there is only two university hospitals in the country (MOH 2020).

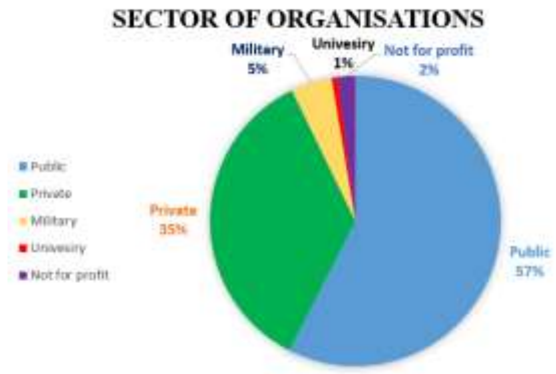

Figure (6.1) Participated organisations by sector

6.6.2 Size of Organisations:

The size of an organisation is counted based on the number of employees, as figure (6.2) shows. Around (69%) of the sample represents medium medical organisations which have employees between 50 – 999, this equals to 144 organisations out of 208 available samples, whereas 37 respondents or (18%) belong to large size organisations that have employees of 1000 but less than 5000. The small healthcare organisations represent (12%) of the sample = 25 responses. The statistics shows that equivalent of a large organisation is represented by 2 hospitals, which is equivalent to (1%).

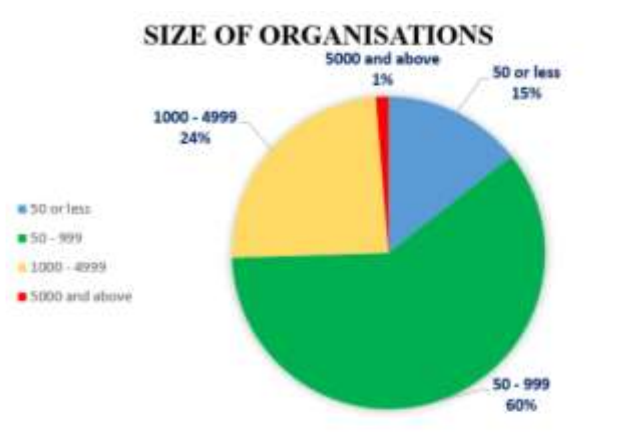

Figure (6.2) Size of organisation

6.6.3 Years of experience:

Figure 6.3 shows the years of experience for the participants. Around (63%) of respondents have more than 6 years of experience. Experience category 6 - 10 years is the most scored category, with 34% or 56 respondents. The second category was respondents with experience between 11-19 years, scored 23% with 48 respondents. The group of 3-5 years of experience came third and scored 20% with 42 participants. The high experienced category is of those who have 20 or more years of experience, scored 6% with 12 participants. Finally, the group of 2 years or less experience represnts 17% with 35 participants. The sample shows a range of skills, with a majority of well-experienced participants who are aware of co-creating value practices with patients.

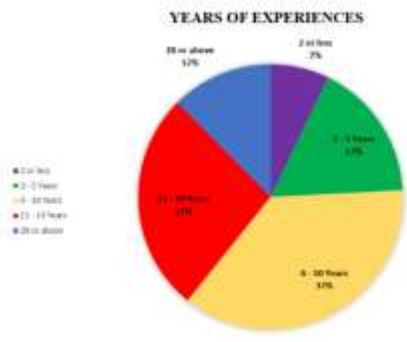

Figure (6.3) Years of experiences for participants

6.6.4 Job level:

The population target in this study is the caregivers who directly interact with a patient; the intention is to obtain their feedback to visualise the way of co-creating value with the patient. Figure (6.4) shows the percentages of job level of participants. This category was defined by three levels, namely, top management, middle management and employee. Senior management scored the lowest in the sample compared with middle management and employees; it was represented by 8 participants (4%), all respondents in the sample are caregivers. However, they work in a higher position; most of them are doctors who usually engage with the administration and medical issues. The middle management employees include the supervisors, head of divisions/ sectors who also interact directly with patients; they represented 78 out of 208 of the sample. Employees (e.g. doctors, nurses and therapists) category represents the majority, with 119 participants that represent (75%) of the sample.

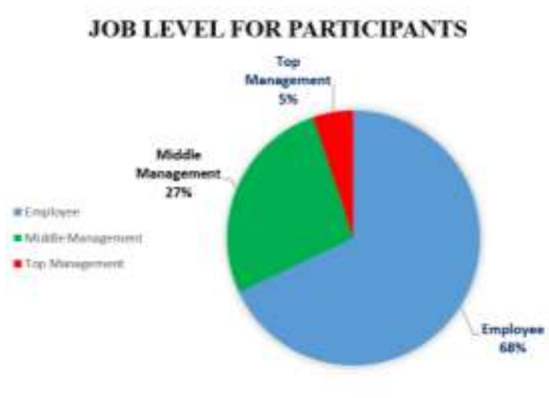

Figure (6.4) Job level for the participant

6.6.5 Educational Level:

Survey also collected information about the educational level of participants. It divided into five categories *Doctorate or above*, *Master*, *Bachelor*, *Colleg*e and *high school or less*. The bachelor degree holders represent the majority of sample 124 (60%), which constitute around two-thirds of the sample. College degree holders are equal to 34 (16%). Master degree holders 32 represent 15% of the participants. The remaining perticipants are "high school or less" category with 10 or (7%) and the PhD holders equal to 8 and represent 4% of the sample. Remarkably, it is evident that the majority of participants were highly educated academically in which almost 79% of participants hold a university degree. Therefore, all categories of the educational level were represented in the sample in a variety and similarity method to the healthcare sector. Figure 6.5 shows the distribution of educational level.

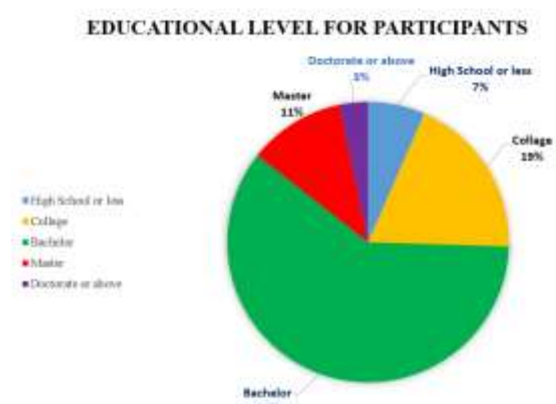

Figure (6.5) distribution of educational level.

6.7 Descriptive Analysis of variables

The previous section showed the demographic profile analysis and the distribution variety of the selected categories, and it also presented the similarity between the groups and the healthcare sector. The following discussion explains the descriptive analysis of the thesis variables.

6.7.1 Descriptive analysis of IoT capabilities:

This section calls attention to the significance of the measurement's indicators of the research survey. The discussion of each particular level's attributes provides an idea of how outcomes can be measured on each affected part, rather than examining the performance on a higher level. On that account, high-scored indicators were identified in each performance level and presented based on their significance in the analysis

6.7.1.1 Monitoring

The first capability of IoT is Monitoring. Table 6.6 presents the descriptive statistics of the monitoring capability, which indicates measurement of 16 items for this variable. Statistics show that Mon 8 has the highest mean score (mean = 6.01) and standard deviation SD = 0.960. MON8 states *"IoT technology is capable of providing vitals observations"*. MON9 represents the item of identifying performance issue, scored very close to MON8 with a mean of 5.93 and a standard deviation of 0.877. In contrast, statistics indicate that MON2 has the lowest mean score with 5.60 and a standard deviation of 1.049. MON2 states that *"IoT technology is capable of tracking the behaviour of individuals"*.

All in all, it is shown that the difference between the highest and lowest scored mean is very small, so this finding indicates the high level of harmony among respondents towards items of scale measurements. The overall values of monitoring capability show that participants believe in IoT technology that can have its impact to human life and the relationship with the patient.

Table 6.6 IoT monitoring capability descriptive analysis

Item number	Item code	Measure	Mean	SD
Q1	MON1	Tracking individual items	5.75	1.025
Q2	MON2	Track behaviour of individuals	5.60	1.049
Q3	MON3	Observe the environmental condition	5.82	.934
Q4	MON4	Observe the performance of individuals	5.64	1.002
Q5	MON5	Observe the performance of equipment	5.87	.863

Q6	MON6	Observe the performance of service	5.87	.923
Q7	MON7	Provide real-time information	5.91	.954
Q8	MON8	Provide vitals observations	6.01	.960
Q9	MON9	Quickly identify performance issues	5.93	.877
Q10	MON10	Provide real-time analytics	5.75	.961
Q11	MON11	Detect potential security vulnerabilities	5.82	.999
Q12	MON12	Predict patients flow	5.80	.940
Q13	MON13	Observe and track medical assets	5.89	.850
Q14	MON14	Observe waste reduction	5.83	.987
Q15	MON15	Log patients' complaints	5.86	.932
Q16	MON16	Detect patterns and anomalies in collected data	5.95	.835

6.7.1.2 Control

Control is the second capability of IoT. As explained in Chapter 3, control capability is measured by a new scale of 19 items, also shown in table 6.6. CON4 scored the highest mean with 6.02 and standard deviation SD = 0.882. The issue is about the capability of IoT to evaluate the quality of healthcare service. It can be concluded that this score indicates the caregivers believe in IoT technology as one of the evaluation tools for the quality of medical service (Dauwed and Meri 2019). CON3 item scored in the second rank by a mean score of 6.00 and a standard deviation of 0.816. CON3 states that *"IoT control capability enables management to control healthcare service activities"* which is also an indication of the trust in IoT technology to support the management to administrate and optimise the healthcare service provided (Ahmadi et al. 2018; Milne, Andonova and Hajjat 2015). The results of statistics indicate that CON1 has the lowest mean score with 5.75 and a standard deviation of 0.974. Control capability items have an almost small difference between highest and lowest scored similarly to monitor capability.

Table 6.7, IoT control capability descriptive analysis

Item number	Item code	Measure	Mean	SD
Q1	CON1	Control performance KPIs	5.75	.974
Q2	CON2	Control the extent to which organisation attain performance goals	5.89	.913
Q3	CON3	Enable management to control healthcare service activities	6.00	.816
Q4	CON4	Evaluation of the quality of healthcare service	6.02	.882
Q5	CON5	Support swift corrective action	5.91	.956
Q6	CON6	Identify problems	5.88	.859
Q7	CON7	Enhance the troubleshooting process	5.97	.890
Q8	CON8	Enhance the business performance	5.94	.820
Q9	CON9	Enhance business insights	5.81	.979
Q10	CON10	Support the efficiency/productivity gain	5.88	.879
Q11	CON11	Control expectations	5.91	.910
Q12	CON12	Control progress	5.99	.955
Q13	CON13	Evaluate staff activities	5.92	1.025
Q14	CON14	Appraising work in progress	5.88	.855
Q15	CON15	Improving results	5.97	.830
Q16	CON16	Regulating performance	5.95	1.025

Q17	CON17	Correcting deviations from standards	5.90	.885
Q18	CON18	Measuring performance against the standards	5.95	.900
Q19	CON19	Predict future performance	5.98	.958

6.7.1.3 Optimisation

Optimisation capability was measured by a new scale of 14 items measurement. The result of descriptive analysis is shown in table 6.7. The highest scored items are both OPT3 (Mean=5.94) with a standard deviation of 0.943. OPT3 is about IoT capability to provide real-time information to improve practices. Statistics show that OPT2 and OPT1 scored very close to the highest score with a mean of 5.93 and a standard deviation of 1.002 and 0.925 respectively. This result represents a common understanding among sample respondents about the power of this technology in affording real-time data to supporting daily operations. The lowest score is OPT10 by a mean of 5.81 and a standard deviation of 0.972. OPT 10 is about service reliability improvement.

Table 6.8 IoT optimisation capability descriptive analysis

Item number	Item code	Measure	Mean	SD
Q1	OPT1	Provide enough information to use resources efficiently	5.93	1.002
Q2	OPT2	Provide real-time information for efficient operations	5.93	.925
Q3	OPT3	Provide real-time information to improve practices	5.94	.943
Q4	OPT4	Provide large volume-variety of data to improve processes	5.90	.882
Q5	OPT5	Provide large volume-variety of data to minimize the cost	5.83	.935
Q6	OPT6	Provide real-time information to reduce waiting time	5.86	1.052
Q7	OPT7	Immediately detect an automaton-based situational event (e.g. gas alert)	5.95	.944
Q8	OPT8	Enhance the prediction of demand and inventory	5.91	1.024
Q9	OPT9	Increase customer retention	5.88	1.028
Q10	OPT10	Increase service reliability	5.81	.972
Q11	OPT11	Support process re-engineering	5.89	.942
Q12	OPT12	Support change management	5.87	.952
Q13	OPT13	Accelerate innovation	5.90	.935
Q14	OPT14	Potential of new health care delivery models	5.85	1.066

6.7.1.4 Collaboration:

Collaboration capability presents the outcome of the previous IoT capabilities (Wolf, Stumpf-Wollersheim, and Schott 2019). It came as the last stage in the IoT capabilities sequence. Comparable to other skills; a new scale measures collaboration. The scale measurements consist of 12 items, as explained in chapter 3 and shown in table 6.8. COL12 scored the highest by mean of 6.06 and a standard deviation of 0.891. COL12 is about the IoT capability to improve service insights and patient experience. At the same time, COL9 and COL11 came very close to COL12 by scoring 5.99 abd 5.98 respectively and a standard deviation of 0.848 for COL9 and 0.862 for COL11. COL9 is about the capability of IoT to provide information on network performance, and COL11 is about IoT capability to provide real-time visibility of service status. Unexpectedly, COL5 scored the lowest among items with a mean of 5.61 and the highest standard deviation of 1.11. The score of COL5 is a sign of high variability among participants about their understanding of supporting real-time collaboration.

Table 6.9 IoT collaboration capability descriptive analysis

Item number	Item code	Measure	Mean	SD
Q1	COL1	Strengthen information sharing within the organisation	5.86	.889
Q2	COL2	Facilitate interaction among parties within/out of the organisation	5.81	.912
Q3	COL3	Facilitate relationships among parties within/out of the organisation	5.96	.810
Q4	COL4	Provide real-time communication	5.86	.916
Q5	COL5	Provide real-time collaboration	5.58	1.164
Q6	COL6	Facilitate the participation of patient and staff	5.91	.826
Q7	COL7	Facilitate cooperation of parties with and out of the organisation	5.83	.932
Q8	COL8	Improve patient satisfaction	5.96	.853
Q9	COL9	Provide information on network performance	5.98	.848
Q10	COL10	Provide real-time visibility of activities Provide	5.90	.868
Q11	COL11	Provide real-time visibility of service status	5.99	.862
Q12	COL12	Improve service insights and patient experience	6.06	.891

All the mean values of IoT capability items scored over point 5 of the measurements scale; this would suggest the existence of the features measured by manifest variables. The values distributed around the mean show that the data sample is appropriate for further analysis.

6.7.2 Value co-creation descriptive analysis

This section explains the VCC dimensions of descriptive analysis. All items were entered in SPSS, the essential descriptive statistics mean and standard deviation SD were calculated, the values were compared and interpreted.

6.7.2.1 Co-Production:

The first construct of VCC is co-production. Table 6.10 shows the descriptive statistics of co-production related practices. The scale measurement of co-production consists of 12 items adapted from Ranjan and Read (2014), as explained in chapter 3. Results show that item CPE3 scored highest mean among all other objects with mean = 5.71 and SD = 0.925. CPE3 states *"My organisation consider patient roles to be as important in the process of service creation"*. This result would suggest that medical organisations believe strongly in the importance of the patient role in the value co-creation process. Likewise, item CPK2 scored very carefully in mean to CPE2 by mean = 5.70, this item states *“My organisation consider patient roles to be as crucial in the process of service creation"*. This result would indicates high appreciation to the role of patients in value co-creation process. Conversely, item CPK4 scored the lowest mean = 5.52. This item states *"My organisation provides a suitable environment and opportunity to the patient to offer suggestions and ideas" that* is an indication that medical organisation are reserved to open doors for patient opinions and propositions during the treatment process.

Table 6.10 VCC co-production related practices descriptive analysis

Item number	Item code	Measure	Mean	SD
Q1	CPK1	My organisation is open to the patient's ideas and suggestions about existing services or towards developing a new service	5.58	1.177
Q2	CPK2	My organisation provides sufficient illustrations and information to the patient	5.68	.991
Q3	CPK3	In my organisation patient would willingly spare time and effort to share his ideas and suggestion to help it improve its services and processes further	5.55	1.187
Q4	CPK4	My organisation provides suitable environment and opportunity to the patient to offer suggestions and ideas	5.52	1.183
Q5	CPE1	My organisation provides easy access to information about the patient's preferences	5.56	1.170
Q6	CPE2	The processes of service development are aligned with patient requirements (e.g. the way we wish them to be)	5.68	1.025
Q7	CPE3	My organisation consider patient roles to be as crucial in the process of service creation	5.71	.925
Q8	CPE4	My organisation share an equal role with patients in determining the outcome of the treatment process.	5.53	1.211
Q9	CPI1	During the process of service development, patients could conveniently express their specific requirements	5.64	1.175
Q10	CPI2	My organisation convey to its patients the relevant information related to the treatment process	5.67	1.142
Q11	CPI3	My organisation allows sufficient patients interaction in its healthcare processes (healthcare service development, assisting other patients)	5.63	1.204
Q12	CPI4	To get the maximum benefit from the treatment process, my organisation plays a proactive role during interaction with patients	5.59	1.055

6.7.2.2 Value-in-use:

The second dimension of VCC practices is value-in-use. 11 items represent the scale measurements of this variable adapted from Ranjan and Read (2014). Results show that item VUP2 scored the highest mean among all other things with a mean of 5.74 and SD = 1.051. Item VUP2 is about organisational attempts to serve patients’ needs for each individual, which shows that medical organisation believe in customization need of healthcare service, as each patient has a different case. Items VUE1 and VUE2 both scored high and are very close to the most top item with mean = 5.72 and 5.69 respectively. VUE1 is about creating memorable experiences and interactions with patients, whereas VUE2 focuses on a variety of experiences based on the patient case. This result would suggest the importance of high care taken by medical organisations towards building relationships with patients based on planned and memorable experiences to co-create value.

On the other hand, the lowest score of mean was reported by item VUR2, which focuses on relationship feeling with patients. The standard deviations of the value-in-use variable are ranging between 0.858 and 1.267; they show higher reported variation values than IoT capabilities. The descriptive statistics of value-in-use related to practices are presented in Table 6.11.

Table 6.11 VCC value-in-use related practices descriptive analysis

Item number	Item code	Measure	Mean	SD
Q1	VUE1	My organisation creates a memorable experience for patients	5.69	1.022
Q2	VUE2	Depending upon the nature of individual participation, patient experiences in the process might be different from other patients	5.72	.858
Q3	VUE3	A patient can improve the process by experimenting and trying new things	5.53	1.120
Q4	VUP1	The benefit, value, or fun from the process (or, the service) depend on the user and the usage condition	5.65	1.015
Q5	VUP2	My organisation tries to serve the individual needs of each of its patients	5.74	1.051
Q6	VUP3	Different patients, depending on their taste, choice, or knowledge, involve themselves differently in the process (or, with the service)	5.55	1.141
Q7	VUP4	My organisation provides an overall pleasant experience, beyond the "functional" benefit	5.67	1.134
Q8	VUR1	In my organisation, the extended facilitation is necessary for patients to enjoy the process (or, the service) fully	5.52	1.107
Q9	VUR2	Our employees feel an attachment or relationship with the patients	5.37	1.267
Q10	VUR3	There is usually a group, community, or a network of patients and customers who are a fan of my organisation	5.58	1.177
Q11	VUR4	My organisation is renowned because its patients usually spread the positive word about it in their social networks	5.61	1.223

6.7.3 Service Innovation:

Service innovation represents the dependent variable in this thesis; it was measured by 10 items scale, as they presented in table 6.12. Results show that item SIN10 scored highest mean = 5.61 and also lowest variations SD = 1.048. This item emphasises the importance of service reliability when interacting with patients. Therefore, this can be an indication that healthcare organisation believe that they provide a reliable service, so their patient does not search for different treatment from the various health care provider. On the other hand, item SIN4 reported the lowest score by mean = 5.29, but SD = 1.375 (highest variations around the mean when compared to other items). Item SIN4 states *"In my organisation, the time to develop a new service model is less than those of Competitors"*. This result would suggest that medical organisations do not consider competition as a critical factor when developing a new service model which might be the case for governmental, educational and military hospitals.

Table 6.12 service innovation descriptive analysis

Item number	Item code	Measure	Mean	SD
Q1	SIN1	In my organisation, the average cost of developing a new service is less than those of other competitors	5.52	1.228
Q2	SIN2	In my organisation, the number of new services developed annually is more than those of competitors	5.48	1.243
Q3	SIN3	In my organisation, the costs of new services are less than those of competitors	5.42	1.360
Q4	SIN4	In my organisation, the time to develop a new service model is less than those of Competitors	5.29	1.375
Q5	SIN5	In my organisation, the time from development of new service models to entry is less than that of competitors	5.38	1.346
Q6	SIN6	My organisation achieved better cost efficiency than competitors	5.51	1.204
Q7	SIN7	My organisation is exceeding the growth target (e.g. obtained more new patients than planned)	5.41	1.126
Q8	SIN8	My organisation seeks to obtain competitive advantages (e.g. new offerings, innovative services)	5.46	1.120
Q9	SIN9	In my organisation, the service quality we provide is better than those of competitors	5.59	1.130
Q10	SIN10	In my organisation, we provide higher reliability service than those of competitors (e.g. patients never seek for different treatment by other competitors)	5.61	1.048

Chapter 7: Factor Analysis:

7.1 Exploratory Factor Analysis (EFA):

EFA is an appropriate analytical technique for initial item selection (Clark and Watson 1995). Researchers use exploratory factor analysis to identify structures within a collection of measures (Stewart, 1981). Generally, EFA is used to find the underlying structure when having a developed scale (Pallant, 2016). It loads all latent variables (factors) on all observed variables (Coote, 2010). Exploratory factor analysis is used to verify the existence of relationship among a set of variables (Hair et al. 2019). It identifies unidimensionality as the main factor within analysis of measurements (Segars, 1997). It is also used when the attributes of elements are not existing or predefined, and factors are entirely exploratory. EFA assist the researcher in figuring out the number of latent variables which can be obtained from the measurement items (DeVellis, 2016).

This thesis uses EFA to evaluate the validity of the research construct and to investigate the initial factor structure and evaluate the items of the measurement scale. EFA is considered to be the first step before applying the SEM analysis technique. In EFA, there is no limit to the number of factors, as this stage is entirely exploratory (Kline, 2011). EFA step comes before confirmatory factor analysis (CFA) which is a descriptive technique for a restricted analysis that includes tuning of values for multiple parameters; *a priori*ty to prove the relationship hypotheses (Harrington, 2009). In later sections will explain CFA in details.

EFA can remove data duplicity and redundancy from a set of correlated variables and produce factors that are relatively independent of each other (Osborne and Costello, 2009). Another advantage of EFA is determining the underlying factor structure to facilitate the assessment of unidimensionality, reliability, discriminant validity and convergent validity (Costello and Osborne, 2005). Factors that extracted by EFA can also be rotated to conclude a more meaningful interpretation of analysis (Marsh et al., 2014).

Like any other statistical technique, EFA has some limitations; these include the inability to detect some degree of correlation error for measurement items (Blunch, 2016) and incompetence to offer an evident test of unidimensionality (Marsh et al. 2014). This thesis used a mix of new and tested measures. EFA was conducted to new and established scales to obtain items that capture the projected construct based on sample responses. Although, the study uses a set range for value-in-use and co-production of constructs measurement. There is a possibility that some items may not capture what they should measure; due to some issues related to the research context, nature of participants and the tendency of a questionnaire to produce errors. There are multiple options available for the researcher to conduct EFA analysis; these include the extraction method, structure of factors and rotation of elements. These choices enable the researcher to ensure a significative and optimum factor solution is produced (Curran et al. 1996).

7.1.1 Selection of Rotation Method

One of the critical steps in performing EFA is selecting the rotation method, where the researcher decides how many factors need to be loaded in a given variable. In the rotation method, the "high items loading" will be considered, whereas "low item loadings will be removed" (Williams, Onsman, and Brown, 2010). Rotation method has two types orthogonal (*varimax or quart max*) and oblique (*promax*) rotation methods (Hair et al. 2019). Oblique rotation technique enables association between obtained factors, whereas the orthogonal rotation technique produces uncorrelated extracted factors (Field 2018; Williams, Onsman and Brown 2010).

Nevertheless, of the rotation method used; the goal is to ensure expected and theoretically consistent results (Hair et al. 2014). In social science studies where human activities are existing, it is expected to find correlated relationships between item measurements (Williams, Onsman and Brown 2010). As the key concept in this is to investigate the human interaction with advanced technology (value co-creation practices and IoT capabilities); the promax of oblique rotation method is selected. It is chosen because it is expected to find some form of correlation between research variables, including IoT capabilities, value co-creation practices and service innovation performance.

7.1.2 Statistical tests prior EFA

Multiple statistical tests have been performed before conducting EFA method; these include the **Kaiser-Meyer-Olkin (KMO)** test for adequacy of sample, **Bartlett's test of sphericity**. These tests were used to verify if there is an acceptable correlation between item measurements and their theoretical clusters. The Kaiser-Meyer-Olkin test is commonly used in quantitative researches. It is used to confirm if data is appropriate for EFA (Kaiser, 1970). KMO index values range from 0.0 to 1.0. Better costs are closed to one, but 0.50 is recommended to be adequate for conducting factor analysis (Field 2018; Williams et al., 2010). KMO Values less than 0.50 indicate that sample is not sufficient, and the researcher needs to either collect more data or rethink about which variable should be considered in the analysis (Field 2018). All of the KMO results in this thesis are greater than 0.87 as shown in next sections. These results mean that sample is adequate for further analysis, no remedial action needed, and assure proper selection of variables that is adequate to conduct factor analysis.

On the other hand, Bartlett's test of sphericity examines the existence of correlations among research variables and considers the redundancy between them. The test is also, verify if there is a significant divergent between correlation matrix of variables and identity matrix (Tobias and Carlson 1969). The identity matrix is a matrix that indicates all diagonal elements are equal to 1, and other details are similar to 0.0. The following sections show that the results of Bartlett's test are significant under p-value < 0.05. Therefore, the thesis will proceed to the next step of factor analysis.

7.2 Results of Exploratory Factor Analysis (EFA):

This section explains the statistical method of EFA performed on the constructs of the research to uncover the underlying constructs of the variables and to identify the underlying relationships between measured variables. In this thesis, EFA is presented on the four central constructs; IoT capabilities, value co-creation practices and service innovation performance.

7.2.1 IoT Capabilities:

In this section, the factor analysis of the measurements of IoT capabilities is presented. The study was generated by IBM SPSS. All items were included in the test, as Cronbach's alpha analysis removed none of them. Table 7.1 shows the results of KMO and Bartlett's test. KMO measure of sampling adequacy was equal to 0.87. Bartlett's test of sphericity shows that chi-squared value is fair to (5669.575) with 1830 degree of freedom (df) and p-value < 0.05 (Hair et al., 2019). This indicates that the collected data has an appropriate level of correlation between variables. It is an indication that the sample data was collected from a population that has equal variances making it suitable for EFA.

Table 7.1 KMO and Bartlett's Test for IoT capabilities

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.854
Bartlett's Test of Sphericity	Approx. Chi-Square	6402.943
	df	1830
	Sig.	0.000

The extraction method used for factor analysis of IoT capabilities is maximum likelihood analysis with promax rotation to produce linearly independent factors. Table 7.2 shows the EFA result. Most of the items were successfully loaded (loading > 0.45) (Cua, McKone, & Schroeder, 2001). The unrelated and low loading items (less than 0.4) were removed. This resulted in 26 retained items.

Table 7.2 items loading for IoT capabilities construct

Code	Item Description	Factor			
		1	2	3	4
OPT2	Provide real-time information for efficient operations	.887			
OPT3	Provide real-time information to improve practices	.856			
OPT1	Provide enough information to use resources efficiently	.845			
OPT11	Support process re-engineering	.761			
OPT6	Provide real-time information to reduce waiting time	.721			
OPT10	Increase service reliability	.689			
OPT9	Increase customer retention	.681			
OPT8	Enhance the prediction of demand and inventory	.674			
OPT7	Immediately detect an automaton-based situational event (e.g. gas alert)	.661			
OPT4	Provide large volume-variety of data to improve processes	.655			
COL4	Provide real-time communication		.778		
COL6	Facilitate the participation of patient and staff		.738		
COL3	Facilitate relationships among parties within/out of the organisation		.722		
COL7	Facilitate cooperation of parties with and out of the organisation		.682		
COL2	Facilitate interaction among parties within/out of the organisation		.674		
COL1	Strengthen information sharing within the organisation		.652		
CON13	Evaluate staff activities			.735	
CON15	Improving results			.722	
CON16	Regulating performance			.716	
CON17	Correcting deviations from standards			.711	
CON19	Predict future performance			.674	
MON2	Track behaviour of individuals				.870
MON1	Tracking individual items				.776
MON4	Observe the performance of individuals				.771
MON3	Observe the environmental condition				.762
MON5	Observe the performance of equipment				.754
% of Variance		**34.806**	**7.224**	**6.451**	**5.674**
Cumulative %		**34.806**	**42.030**	**48.481**	**54.155**

Source: IBM SPSS output

As per EFA analysis, the extraction method was set to produce four factors. According to the research design; these items belong to the IoT capability construct, which consists of four variables derived from literature, as explained in chapter 2. As table 7.2 presents, most of the items were loaded initially in their expected factors. Items loaded with < 0.45 values were removed. There are ten items packed in the first factor to shape the first latent cluster which is named as optimisation capability. Six issues were loaded in the second potential cluster; all of them are related to collaboration capability variable. In the third latent variable, there were five items packed; all of them are related to the control capability variable. Five items were loaded in the fourth potential factor, all of them associated with monitoring capability variable. EFA results indicate that the optimisation factor formed the most significant influence of the IoT capabilities, which explains 34.8% of the total variance. Collaboration capability has the second most significant influence, explaining 7.22% of the difference in skills. Both capabilities of Monitoring and Control, which represent the base of other capabilities, have the lowest impact explaining 6.54% and 5.681% respectively.

7.2.1.1 Optimisation capability:

Table 7.2 presents the EFA results of optimisation factor; 10 item measurements were loaded in this cluster which accounted of total variance of (36.5%), these items are: (1) *IoT is capable to provide real-time information for efficient operations* (Ben-Daya et al. 2017; Ferreira, Mogtinho and Domingos 2010;Dimitrov 2016; Lu et al. 2018); (2) *IoT is capable to provide real-time information to improve practices* (Haddud et al. 2017; Ben-Daya et al. 2017); (3) *IoT is intelligent to provide enough info to use resources efficiently* (Yuan Jie Fan et al. 2014; Man et al. 2015, Janiesch et al. 2017); (4) *IoT is capable to support process re-engineering* (Liu, Li and Jiang 2014); (5) *IoT is intelligent to provide real-time information to reduce waiting time* (Ahmadi et al. 2018); (6) *IoT is capable to increase service reliability* (Bartels 2019); (7) *IoT is intelligent to increase customer retention* (Yerpude and Singhal 2018); (8) *IoT is capable to* enhance the prediction of demand and inventory (Ka Man, Mei Na and Kit 2015) (9) *IoT is capable to immediately detect an automaton-based situational event* (e.g. gas alert) (Cheng et al. 2016); (10) *IoT is intelligent to provide large volume-variety of data to improve processes* (Khan et al. 2017;Mattern and Floerkmeier 2010; Lu et al. 2018;Zanella and Vangelista 2014).

According to the EFA results in table 7.2; it can be concluded that first four items focus on information, they were loaded higher than others. This show the importance of information flow among actors within the healthcare ecosystem. Processing information is the heart of IoT technology, and data is the foundation for decision making and optimisation process. Optimisation is the process where decision-maker selects the best solution among multiple alternatives (Gosh, Surjadjajaand Antony. 2004). Analysis of data and information is critical for having the right decision to optimise operations, practices, process and resources. This result is in line with the argument of (Ardolinoet al. 2011) who have emphasised the importance of information for optimisation process within IoT technology deployment. The results underline the criticality of large data volume, which supports the argument of (Khan et al. 2017) who highlighted the power of IoT data mining analysis for generating business value for the organisation.

7.2.1.2 Collaboration capability:

There were seven items loaded in collaboration cluster as presented in table 7.2; these are (1) *IoT is capable to provide real-time communication* (Atzori, Lera and Morabito 2010; Yang, Yang and Plotnick 2013); (2) *IoT is capable to facilitate the participation of patient and staff* (Scutto, Ferraris and Bresciani 2016); (3) *IoT is intelligent to facilitate relationships among parties within/out of the organisation* (Dijkman et al. 2015; Alam et al. 2016; Islam et al. 2015; Rohkale, Prasad, and Prasad 2011; Chen et al. 2014), (4) *IoT is capable to facilitate cooperation of parties with and out of the organisation* (Chen et al. 2014; Gubbi et al. 2013; Nc and Wakenshaw 2015; Atzori, Lera and Morabito 2010); (5) *IoT is capable to facilitate interaction among parties within/out of the organisation* (Jara, Parra and Skarmeta 2013; Atzori, Lera and Morabito 2010), (6) *IoT is capable to strengthen information sharing within the organisation* (Lee and Lee 2015; Gubbi et al. 2013).

The results indicate that COL4 is the most significant item loaded. The issue focuses on the capability of IoT to provide real-time communication. Items of establishing the participation, cooperation, relationship and interaction are packed in this factor. This issue explains the strong influence of information flow among actors which support the arguments of (Atzori, Lera and Morabito 2010; Yang, Yang and Plotnick 2013; Lee and Lee 2015; Gubbi et al. 2013), who concluded that the flow of real-time information among actors and within/out of organisations is very influential in facilitating the relationship and interaction of all involved parties.

7.2.1.3 Control capability:

Exploratory factor analysis results revealed that five items loaded in the third factor; all of them belong to the control capability variable as table 7.2 shows. These items are: (1) *IoT is capable of evaluating staff activities* (Virginia, Sullivan and Wamba 2019); (2) *IoT is exceptional to improving results* (Rodriguez 2020); (3) *IoT is capable of regulating performance* (Sridharan 2019); (4) *IoT is intelligent to correcting deviations from standards* (Borgia 2014); (5) *IoT is capable of predicting future performance* (Akter and Holder 2019; Ardolino et al. 2017). Items CON13 and CON15 were loaded in high grade. Item CON13 emphasises the ability of IoT technology to evaluate the employee's activities, whereas CON15 focuses on the strength of IoT technology to enhance the results achieved by operations within organisations.

7.2.1.4 Monitoring capability:

Table 7.2 shows that 5 item measurements were loaded in monitoring cluster; these items are: (1) *IoT is capable of tracking the behaviour of individuals* (Lee and Lee 2015. Forkan et al. 2019); (2) *IoT is capable of monitoring individual items* (Van Den Hoven 2013; Dweekat, Hwang and Park2017); (3) *IoT is capable of observing the performance of individuals* (Lee and Lee 2015. Forkan et al. 2019); (4) *IoT is capable of finding the environmental condition (*Atzori, Lera and Morabito 2010, Lynch and Kenneth 2006, Zanella and Vangelista 2014, Lee and Lee 2015); (5) *IoT is capable of observing the performance of equipment* (Lee and Lee 2015).

The monitoring capability is the foundation of all other IoT capabilities (Wolf, Stumpf-Wollersheim, and Schott 2019). Observation of individual behaviour, performance, items and environmental conditions are essential in IoT technology. Interestingly, all of these primary activities were loaded highly in monitoring capability factor which supports the arguments of (Parry et al., 2016; Bressanelli et al., 2018; Suppatvetch Godsell and Day, 2019; Schott 2019; Lee and Lee 2015) who emphasised the powerful IoT technology in tracking and observing humans and things.

7.2.2 Value co-creation practices:

This section presents the results of EFA for value co-creation related practices. The extraction method used was of the maximum likelihood, and the rotation method is promax rotation. The scale of value co-creation practices was adopted from Ranjan and Read (2014). VCC has two dimensions: *value-in-use and co-production*. Value-in-use was measured by three factors: experience, personal and relations, while co-production factor was measured by three factors: knowledge, equity and interaction. EFA was conducted on all VCC items as all items retained after the analysis of previous tests.

7.2.2.1 Value-in-use

Results of KMO and Bartlett's test for value-in-use are shown in table 7.3. KMO value equals to (0.911); this result indicates that the sample is adequate for analysis. Bartlett's test of sphericity shows that chi-squared value is fair to (998.701) with df = 55, under p-value < 0.05 (Hair et al., 2019); thus this indicates no correlation among primary variable as shown in table (7.4).

Table 7.3 KMO and Bartlett's tests results

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.893
Bartlett's Test of Sphericity	Approx. Chi-Square	1074.354
	df	55
	Sig.	.000

Results of the table (7.4) show that three variables were extracted; experience, personal and relations. Eight items were loaded in the three factors, and three issues were deleted; one for knowledge, one relation and one for personal. Based on these results, no construct would be removed at this stage.

Table 7.4 items loading for Value-In-Use construct

Code	Item Description	Factor		
		1	2	3
VUE1	My organisation creates a memorable experience for patients	.885		
VUE2	Depending upon the nature of individual participation, patient experiences in the process might be different from other patients	.749		
VUP1	The benefit, value, or fun from the process (or, the service) depend on the user and the usage condition		.868	
VUP2	My organisation tries to serve the individual needs of each of its patients		.768	
VUP3	Different patients, depending on their taste, choice, or knowledge, involve themselves differently in the process (or, with the service)		.711	
VUR2	Our employees feel an attachment or relationship with the patients			.794
VUR1	In my organisation, the extended facilitation is necessary for patients to enjoy the process (or, the service) fully			.744
VUR3	There is usually a group, a community, or a network of patients and customers who are a fan of my organisation			.736

The experience factor represents the most significant impact of value-in-use, which explains 50.2% of total variance whereas the other two factors, personal and relation explain 5.9% and 4.9% respectively.

7.2.2.2 Co-production

Results of KMO and Bartlett's test for co-production are presented in table 7.5. KMO value equals to (0.927), this means that sample is adequate for analysis. Bartlett's test of sphericity shows that chi-squared value is fair to 994.482 with df = 55, under p-value < 0.05 (Hair et al., 2019).

Table 7.5 KMO and Bartlett's tests results

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.922
Bartlett's Test of Sphericity	Approx. Chi-Square	1283.512
	df	55
	Sig.	.000

The results of EFA show that three variables (interaction, equity and knowledge) were extracted by using maximum likelihood method and extraction method of orthogonal using promax rotation. 8 items were loaded in the three elements and four items were deleted; two for investment and two for knowledge. This result is presented in Table 7.6. According to this analysis, no construct would be deleted at this stage.

Table 7.6 items loading for co-creation construct

Code	**Item Description**	**Factor**		
		1	2	3
CPI1	During the process of service development, patients could conveniently express their specific requirements	.914		
CPI3	My organisation allows sufficient patients interaction in its healthcare processes (healthcare service development, assisting other patients)	.817		

CPI2	My organisation convey to its patients the relevant information related to the treatment process	.742		
CPI4	In order to get the maximum benefit from the treatment process, my organisation plays a proactive role during interaction with patients	.719		
CPE1	My organisation provides easy access to information about the patient's preferences		.886	
CPE2	The processes of service development are aligned with patient requirements (e.g. the way we wish them to be)		.874	
CPK1	My organisation is open to the patient's ideas and suggestions about existing services or towards developing a new service			.867
CPK2	My organisation provides sufficient illustrations and information to the patient			.795

7.2.3 Service Innovation

KMO and Bartlett's tests were performed for service innovation construct. The results KMO show that sample is adequate to proceed with additional analysis, whereas KMO value equals to (0.926). Bartlett's test of sphericity shows that chi-square value is equal to 1068.838 with df = 55, under p-value < 0.05. This result indicates that the collected data has an appropriate level of correlation between at least number of variables and it also indicates that the sample data was collected from a population that has equal variances or variance homogeneity which makes it suitable to proceed to EFA.

Table (7.7) KMO and Bartlett's tests results

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.914
Bartlett's Test of Sphericity	Approx. Chi-Square	1206.671
	df	55
	Sig.	.000

Eleven items measured service innovation construct. EFA was performed on service innovation performance using SPSS. Maximum likelihood method and extraction method of orthogonal using promax rotation were employed in the analysis. All indicators have retained (loading greater than 0.45) (Cua, McKone, and Schroeder, 2001). The investigation resulted in two latent clusters, as presented in table 7.8. The first latent cluster consisting of 6 indicators focus on how organisations execute their processes; so it was named as *process* factor. The indicators of second cluster focus on the outcome of innovation performance, hence called as *result* factor

Table (7.8) items loading for service Innovation construct

Code	Item Description	Factor	
		1	2
SIN9	In my organisation, the service quality we provide is better than those of competitors	.865	
SIN11	In my organisation, the service provided has higher customer satisfaction than competitors	.842	
SIN10	In my organisation, we provide higher reliability service than those of competitors (e.g. patients never seek for different treatment by other competitors)	.788	
SIN8	My organisation seeks to obtain competitive advantages (e.g. new offerings, innovative services)	.735	
SIN7	My organisation is exceeding the growth target (e.g. obtained more new patients than planned)	.724	
SIN2	In my organisation, the number of new services developed annually is more than those of competitors	.721	
SIN4	In my organisation, the time to develop a new service model is less than those of Competitors		.835
SIN5	In my organisation, the time from development of new service models to entry is less than that of competitors		.813
SIN3	In my organisation, the costs of new services are less than those of competitors		.746
SIN1	In my organisation, the average cost of developing a new service is less than those of other competitors		.742
SIN6	My organisation achieved better cost efficiency than competitors		.682

7.2.4 IoT capability Scale Validation

The scale development process derives from prior research studies that generated valid measures (Churchill, 1979). The initial steps focus on item generation. Latent variables cannot be directly observed or measured, and the direct measurement of the items works as an indirect measure for its underlying construct (Byrne, 2013).

Domain specification: the latent constructs were explicitly identified and defined from the extensive literature. Then multi-item measures were developed to assess the construct of concern efficiently. The result of this process was 61 measurement items. Tables 5.1 through 5.4 shows the lists of these items.

Items review: the measurement items were reviewed by experts to obtain feedback and assess the initial items' quality and clarity. Researchers recommend an expert review of the initial item pool (e.g. Churchill, 1979; Flynn et al., 2010). The expert review helps the researcher to confirm content validity (De Vellis, 2016) and improve face validity (Hardesty and Bearden 2004). The questionnaire was reviewed by five academic experts specialising in technology and information management and five smart technology and healthcare experts to critique questions' clarity, contents, and appropriateness. Reviewers' feedback on clarity and wording of items, length and appropriateness of items, sequence and format of items were recorded and considered.

Unidimensionality assessment: Unidimensionality test is critical; without unidimensionality, a measure of the construct goes beyond the stated definition, and the construct is considered meaningless (Segars, 1997). Unidimensionality is defined as a single latent construct that underlies a group of items (Hair et al., 2019). This set is deemed unidimensional if the correlations among items are accounted for by one common factor (Hair et al., 2019). To test the unidimensionality, EFA was used, followed by CFA to confirm the hypothesised factor structure (Segar 1997). EFA was conducted using SPSS, with each construct being tested individually. Results of the analysis showed that all constructs were unidimensional. See table 7.9.

After an expert review of items, seven items were dropped. See Appendix B. The remaining 54 items were simultaneously entered into EFA. The result of EFA shows that multiple items did not properly load in the construct of interest. Table 7.2 shows the loaded items. The items that did not properly load (26 items) were removed. EFA results show that the optimisation factor formed the most significant influence of the IoT capabilities, which explains 36.5% of the total variance. Collaboration capability has the second most significant influence, explaining 6.5% of the difference in skills. The EFA analysis is available in more detail for each variable in section 7.2.

After dropping the problematic items, the remaining 28 items were analysed by using CFA. Each construct was connected with its related item set. The initial CFA results showed that some items were potentially problematic (loaded with a value less than 0.70) (Haire et al., 2019). Therefore, all problematic items were dropped, and the remaining items were used for the second analysis of CFA. Appendix B indicates which items were removed. The analysis result showed that the model fit the data well, which supports the conclusion that constructs are unidimensional. The fit indices used for CFA assessment are available in table 7.11.

Reliability Assessment: Reliability refers to the degree to which the collection of data and the interpretation process will result in consistent findings (Saunders, Lewis and Thornhil 2016). The purpose is to ensure that the research method generates stable and consistent results and to guarantee that if the study is conducted again later by another researcher, following the same procedures, it should come up with the same findings and conclusions (Gibbert et al. 2008; Yin

2013). It also defines the extent to which multiple indicators with each other to examine a given construct (Hair et al. 2019). The most popular analysis to assess internal consistency is Cronbach's alpha (Haire et al. 2019). Reliability analysis of the four IoT capabilities shows that all values are acceptable (Nunnally and Bernstein, 1994). Therefore, table 7.9 indicates that all four constructs exhibit an acceptable level of internal consistency which means the newly created scale is reliable.

Monitoring capability items report an alpha coefficient of 0.867, indicating acceptable reliability and internal consistency of the scale. The reliability analysis of control capability also shows fair values. The variable scored an alpha coefficient of 0.891. The optimisation capability will score a variable alpha coefficient of 0.863, shows an acceptable amount and internal consistency among its items. Finally, the analysis of collaboration capability indicates a fair Cronbach's alpha value by achieving the score of alpha coefficient = 0.836. The study presented in Table 6.2 shows that no improvements could be obtained by removing any items. Overall, the analysis of reliability indicates that IoT constructs achieve acceptable values. These results of the coefficient of reliability and consistency show that there is an excellent internal consistency among the scale items, and they are closely related to each other as a group. The objective of reliability analysis is to ensure that each variable has an acceptable alpha coefficient, and items have shared covariance and are set to measure the same underlying concept.

Convergent validity assessment: Convergent validity is a test to measure the "high shared variance among multiple measures of each construct, relative to the amount of variance due to the measurement error" (Batra and Ahtola, 1991, p.160). It is measured by testing the score of average variances explained (AVE). Also, the CFA approach is used to assess convergent validity when individual items load significantly on a single construct, and the measurement model exhibits acceptable fit metrics (Segars, 1997; Hatcher, 1994). Convergent validity was assessed by utilisation of AVE (see table 7.9). AVE value should be greater than 0.50 to establish convergent validity (Awang 2010) by checking if the variance shared between items and the construct is greater than the variance explained by individual errors linked with each item. As it is shown in table 7.9, scales meet the recommended value of AVE. The results assure that convergent validity is demonstrated.

Discriminant validity assessment: Discriminant validity is the degree to which a construct is distinct from other similar concepts (Hair et al., 2019). Discriminant validity is established when the AVE score is higher than its shared variance of any factor (Farrell, 2010). It was evaluated by examining the Correlation between composite constructs and ensuring they are lower than their composite reliability values (Kline 2011). Discriminant validity was assessed by comparing the AVE values of each construct with the shared variance between constructs. Table 7.9 supports discriminant validity as the AVE value of each construct is greater than the squared Correlation between pairs. In conclusion, results show that the sample effectively presented the necessary validation for the IoT capability scales, as the assessment and validation analysis indicate the scales are valid representations of the IoT constructs.

Table 7.9 IoT capabilities Reliability, AVE and Correlation

	CR	**Cronbach α**	**AVE**	1	2	3	4
1. Monitoring	0.822	0.867	0.684	**0.816**			
2. Control	0.751	0.891	0.608	.358*	**0.764**		
3. Optimisation	0.879	0.863	0.636	.472*	.587**	**0.772**	
4. Collaboration	0.791	0.836	0.619	.303**	.504*	.550*	**0.827**
CR = Composite Reliability. AVE = Average Variance Explained, Values (Bold) in the diagonal line = square root of AVE							
** Correlation is significant at the 0.01 level.							
* Correlation is significant at the 0.05 level.							

7.3 Structural Equation Modelling (SEM):

Structural Equation Modelling (SEM) is a powerful technique for multivariate data analysis widely known among researchers. This method was developed to address the issues experienced in the previous methodology of Ordinary Least Square (OLS) regression (Awang 2010). SEM enables researchers to examine complicated relationships between coefficients (Hair et al., 2019). It can respond to multiple statistical requirements; such as performing CFA analysis, executing multiple regression model analysis, working with path analysis which has various dependents, executing regressions with multi-collinearity problems, calculating the estimates for correlations and covariances, and modelling the inter-relationship among variables, assessing the fitness of measurements and structural models, analysing the influence of mediation and moderating variables within a model, working with both first-order and second-order constructs (Awang

2010). It is a set of statistical techniques that examine relationships between independent variables (one or more) and dependent variables (one or more). SEM can work with both continuous and discrete data. It is a standard model for hypothesis testing and analysing multiple statistical techniques including factor analysis, multiple regression, analysis of variances and covariance, multilevel modelling and path analysis. The relationships between factors within SEM methods may impact each other directly or through another factor, which can be manifest or latent. The advantage of having latent variables is that they facilitate a reduction in dimensionality to assist interpretation of data structure and improve the reliability of measures (Henseler, Hubona and Ray 2016).

SEM uses several forms of models to conceptualize the relationships among observed variables for the purpose of testing quantitatively a theoretical model set by the researcher (Schumacker and Lomax 2004). SEM technique aims to explain the extent to which hypotheses of the research model is supported by collected data. SEM is appropriate to this study because it can evaluate multiple dependence relationships and mediation influence between variables with calculations of estimates of error variance parameters, which makes it applicable to this study to test the conceptual model and the relationship within. It also can work with inferential data analysis and hypotheses testing as the relationships among constructs of the research model derived from existing theory (Hair et al., 2019).

SEM can be presented by matrix algebra. However, it can be simply understood when demonstrated by the graphical display as a path diagram, and this illustration is essential for researchers. Figure 7.1 is a basic example of a hypothesised structural model. The model represents a latent variable relationship through a mediator variable. The path diagram of SEM illustrates a certain SEM model that is equivalent to its mathematical equations. It represents a schematic drawing of the hypothesised models to provide a visual illustration of the variable's relations derived from theory. SEM is schematically demonstrated by geometric symbols including *ovals, or ellipses* which indicate the unobserved or unmeasured latent variables, the *rectangles which* indicate the manifesto observed variables, *circles* represent the residual error in prediction of the latent variable, *single-headed arrows* represent the influence of one variable to another and *two-headed arrows* represent the covariances between two variables.

It is essential to distinguish between *exogenous* and *endogenous* variables, presented in figure 7.1. Endogenous is the independent and latent variables that cause fluctuations in the values of other variables in the model. Variations in exogenous values are considered to have resulted from external factors and not explained by the model (Byrne 2010). On the other hand, endogenous variables are the dependent variables that are impacted directly or indirectly by the exogenous. Changes in the values of endogenous constructs are considered to be explained by the model because it is affected by latent construct within the model specification (Byrne 2010). The error related to the observed variables indicates to *measurement error*. The measurement error refers to the degree to which the manifest variable is not accurately measuring the latent construct. The *residual* refers to the amount of variation between the actual and estimated value of any relationship with a model. In SEM, residual is the difference between the observed and expected covariances.

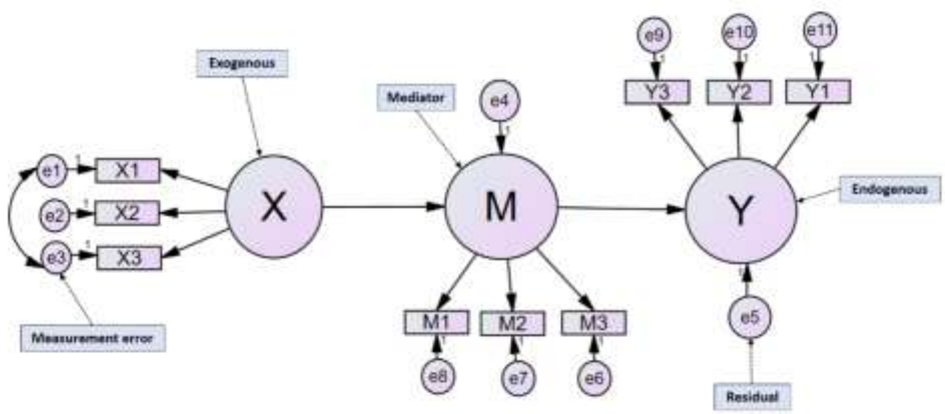

Figure 7.1. Basic structural equation model as demonstrated by AMOS

7.3.1 Using Analysis of Moment Structure (AMOS) software

There are multiple software packages for SEM in the market, which are user-friendly, easy to use by most of the researchers and able to produce equivalent results. These includes LISREL, EQS and AMOS. This thesis used IBM Analysis of Moment Structure version 24.0 (AMOS) for conducting SEM analysis. AMOS is one of the most popular software, packages for SEM. It is useful software, which does not require a programming background to conduct analysis, researchers with basic knowledge of computer skills and statistical techniques can simply evaluate their research models. AMOS uses a graphical interface to test hypothesis and estimate parameters. It uses a theoretical model to generate a path diagram that involves variables and hypothesised relationships with calculations of model specifications. The other advantage of AMOS is its compatibility with IBM SPPS (IBM owns both). The researcher can access AMOS directly from SPSS, so they work as one is the extension for the other, which makes exchanging data between them is a natural process.

7.3.2 The sample size used in SEM

There are everlasting debates in the literature about the size of the data used to perform SEM. However, there is no definite answer to this, since research projects are different in context, model complexity, number of constructs and their items. Hair et al. (2019) suggest a requirement for minimum sample size using by SEM. The conditions are set according to model complexity and the characteristics of the measurement model. The minimum sample size of 100 respondents is required when the model includes five or fewer constructs, each measured by at least three items. The conceptual model of this study has four constructs all has more than three items, and the number of respondent's (n = 208), therefore the sample size is appropriate for SEM analysis.

7.4 Confirmatory Factor Analysis CFA:

CFA is a multivariate statistical technique that aims to determine the level of which data represents the hypothesised construct. It examines a *priori* hypothesis and highly driven by theory (Byrne 2010). This technique is applicable to use when the researcher outlines the theoretically underlying latent structure of an instrument (Hoyel and Panter, 1993). CFA requires identified hypotheses in advance and the factors with their loaded items. The factor structure resulted from EFA will be used to determine the CFA measurement model in each data set. It is an appropriate method to test the hypothesis and confirm whether identified factors reflect the associated items by entering the same items obtained through EFA. In this thesis, CFA was used to test the factorial structure of research constructs; IoT capabilities, value co-creation practices and service innovation performance. And so, the models were set to specify which items would be loaded under each factor. It also was used to test the causal relationship between IoT capabilities and service innovation performance directly and through the mediation effect of both VCC practices.

Path analysis was used to study the level of relationships of the model. Before performing the SEM, several preliminary tests were conducted to assess the hypothesised constructs against convergent discriminant validity, reliability and the fitness of the model. The study started by specifying a theoretical model based on theory. Each construct in the research model is considered as latent. And these latent constructs were measured by a set of items in a survey. The researcher developed elements of the new construct (IoT capabilities), items of other latent construct were adopted from established scales in literature and amended to suit the objective of the research. CFA was used to analyse the measurement model for every construct to confirm that items efficiently represent their underlying construct. The number of factors that indicate the underlying structure of variables had already been identified through EFA earlier in this chapter.

The factor loading was assessed for each item. The factor loading refers to the level of correlation between the original variable and the factor, and the squared factor loading represents the variance percentage in the variable (Hair et al. 2019). CFA was initially run for every measurement model individually, then pooled CFA was performed. The items that demonstrate low factor loading were deleted from the measurement model as it leads to reduced fitness indexes for the construct. To determine the significant level and to evaluate the factor loadings, the guidelines for specifying statistical significance of factor loading was proposed by Hair et al. (2019). Since this thesis has a sample size of (n = 208), then factor loading > 0.45 is considered significant. Therefore, each packing of 0.45 and higher was retained, and items resulting in factor loading less than 0.45 cut-off value was excluded from further analysis. The elimination is expected to improve the fitness indexes. In case of having a low fitness indexes model even after removal of small loading factors; Modification Indices (MI) will be inspected. MI is generated by AMOS to show the correlations between items. High scores of MI indicate that things are surplus, then one item needs to be removed to enhance the model fit.

7.4.1 Scale evaluation

A measurement scale of multi-items needs to be evaluated for accuracy and applicability (Malhotra Nunan and Birks, 2017). This process includes an assessment of the reliability and validity of the scale measurement. The below section presents explanation procedures of these assessments.

7.4.1.1 Reliability Analysis

Reliability refers to the extent to which items consistently measure the purposed construct if repeated measurements are made (Saunders, 2016). Safety is evaluated by the amount of proportion of systematic variation in a scale (Malhotra, Nunan and Birks, 2017). There are different approaches to assess reliability. *Internal consistency reliability* is one of a standard method to determine the reliability of a multi-item scale, where each item contributes to the measurement of the entire scale. Cronbach's alpha coefficient is a common significant statistic used to measure reliability. The internal safety is achieved if the alpha coefficient is more significant than 0.7 (Awang 2010). In this thesis, the internal reliability assessment was conducted by using SPSS. All constructs were proven to possess internal consistency reliability since all of them scored an alpha coefficient of greater than 0.7. The results of Cronbach's alpha scores were presented in chapter 6.

The *Composite Reliability* (CR) is another measure of internal consistency of a multi-items scale. The minimum required value for achieving composite reliability for a construct is CR equal to or greater than 0.6 (Awang 2010) to demonstrate an acceptable level of reliability. AMOS does not support CR calculations, so in this thesis, the researcher has calculated the values of CR manually for all latent constructs using the following formula:

$$CR = (\Sigma Ҟ)^2 / [(\Sigma Ҟ)^2 + (\Sigma 1 - Ҟ^2)]$$

Where Ҟ is the factor loading of each item.

Results of CR calculations show that all values are scored above 0.7. Therefore, internal consistency is achieved by CR measurement. Results are presented in table 7.2.

7.4.1.2 Convergent validity

Convergent validity is a test to measure the "high shared variance among multiple measures of each construct, relative to the amount of variance due to the measurement error" (Batra and Ahtola, 1991, p.160). It is measured by testing the score of average variances explained (AVE). AVE refers to "*the average percentage of variation explained among the items of a construct*" (Hair et al. 2019 p. 659). AVE is comparable to the explained variance in exploratory factor analysis (EFA). AMOS does not support the calculation of AVE; therefore, researcher has calculated all of the scores manually using the following formula:

$$\mathbf{AVE = \Sigma\ Ķ^2 / n}$$

Where:
Ķ is the factor loading for each item
n is the number of item in the model

AVE value should be greater than 0.50 to establish convergent validity (Awang 2010). The ideal value is 0.70 or higher to demonstrate satisfactory convergent or internal consistency (Hair et al. .2019). As table (7.2) shows, the results reveal that all of the research item measures have acceptable AVE values. These results show that the construct measures of the research achieved acceptable convergent validity.

7.4.1.3 Discriminant Validity

Discriminant validity is the degree to which a construct is distinct from other similar concepts (Hair et al. 2019). Each factor should demonstrate discriminant validity from others. The high value of discriminant validity is a sign that a construct can measure some phenomena that other measures do not. Poor discriminant validity would lead to a lowering of confidence in results and reduction of ability to confirm the hypothesised relationship of research model (Farrell, 2010). Discriminant validity is established when the AVE score is higher than its shared variance of any factor (Farrell, 2010). In this research, discriminant validity test of the constructs was evaluated by examining the correlation among composite constructs and ensuring they are lower than their composite reliability values (Kline 2011). Discriminant validity was assessed by the comparison of AVE values (calculated manually) of each factor with the shared variance between factors. Table 7.2 shows that all of the correlation coefficients are below 0.78.

In contrast, the composite reliability scores are all above 0.78. The construct correlation of 0.85 and above represents evidence of poor discriminant validity (Harrington 2009). Since all of the correlation coefficients are lower than 0.85, then these results indicate that all research models possess discriminant validity.

7.4.14. Unidimensionality

Unidimensionality is achieved when researcher ensure that each measuring item has a significant factor loading for the relevant latent construct, and any issue with low factor loading according to the criteria explained in the previous section should be deleted. The requirements follow the guidelines of Hair et al. (2019) to retain items with factor loading greater than 0.45 and exclude items with loading less than this value.

7.5 The model-fitting process:

The model-fitting process is an assessment of using sample data to test a specified model, and demonstrate to which extent the hypothesised model is accounted for the data with the goodness-of-fit indices. A model fit test is a difference between theory (estimated covariance matrix) and reality (observed covariance matrix) (Hair et al. 2019). A goodness-of-fit is the practical level of agreement between a model prediction and observed data. It examines the relationship between the hypothesised model and the observed data. The good-fit model is obtained when the relationship between the hypothesised model and observed data is satisfactory, by achieving a specified threshold, which indicates support for the theoretical underpinnings (Preacher, 2006). Researchers report various fit indices to demonstrate how well a model fit. There are many guidelines to propose a model fit, but there are no specific scores available, and there are differences in the reporting model fit indices in the literature. The values related to acceptable models are those that achieve a balance between the number of variables, sample size and commonalities of factors (Hair et al. 2019).

The researcher can report various types of indexes to estimate the model fit. However, it is not realistic to say each index, because it can burden both the researcher and the reviewer (Hooper, Coughlan and Mullen 2008). It is recommended to report a wide variety of indices to demonstrate different characteristics of the model (Crowley and Fan, 1997). There is no such rule to specify which fit indices to report; this study has used the most consistently indicated indices in literature; chi-square, comparative fit index (CFI), root mean square error of approximation (RMSEA) and standardized root mean residual (SRMR) and p close (Hu and Bentler, 1999; Mc Donald and Ho, 2002; Kline, 2005). All of these indices involve a level of sensitivity to model specification, biases of fit indices and small sample size. A "rule of thumb" cut off criteria is offered to determine what establishes a good model fit (Hu and Bentler, 1999). Table 7.3 shows more details about the description of indices used in the study with criteria of cut-off values for a model fit.

Table 7.10 Reliability and correlation matrix

	Mean	SD	CR	AVE	1	2	3	4	5	6	7	8	9	10	11			
1. Monitoring	5.75	0.71	**0.726**	**0.684**	**0.827**													
2. Control	5.99	0.65	**0.761**	**0.711**	.425**	**0.843**												
3. Optimisation	5.95	0.62	**0.896**	**0.743**	.421**	.574**	**0.861**											
4. Collaboration	5.89	0.60	**0.721**	**0.849**	.354**	.505**	.447**	**0.945**										
5. Interaction	5.60	0.95	**0.806**	**0.628**	.324**	.322**	.295**	.354**	**0.792**									
6. Equity	5.59	0.99	**0.817**	**0.793**	.211**	.257*	.357**	.284**	.546**	**0.89**								
7. Knowledge	5.68	0.94	**0.762**	**0.743**	.287**	.214*	.218**	.272**	.526**	.512**	**0.862**							
8. Experience	5.69	0.86	**0.741**	**0.744**	.357**	.242**	.215**	.361**	.567**	.447**	.432**	**0.862**						
9. Personalisation	5.64	0.91	**0.726**	**0.782**	.361**	.319**	.357**	.238**	.534**	.456**	.468**	.661**	**0.884**					
10. Relations	5.50	0.98	**0.747**	**0.674**	.274**	.198**	.252**	.362**	.626**	.449**	.654**	.615**	.659**	**0.820**				
11. Service Inn.	5.35	1.08	**0.815**	**0.691**	.268**	.276	.216**	.277**	.445**	.365**	.443**	.567**	.365**	.572**	**0.831**			

CR = Composite Reliability. AVE = Average Variance Explained, SD = Standard Deviation, Values (Bold) in the diagonal line = square root of AVE

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

*. Correlation is significant at the 0.05 level (2-tailed).0

7.5.1 Chi-Squared χ2statistic

The chi-square is a statistical model fit index that compares the observed and theoretical estimated covariance metrics to evaluate the theoretical structure of the model (Hair et al. 2019). Chi-square represents the difference between the hypothesised model and the underlying data. In SEM researcher's goal is to accept the hypothesised model. Therefore, a low chi-square value and high p-value are desirable (Kim, 2005). Chi-square is accounted for all probable relationships between variables and indicators; consequently, it is reported to be the most difficult to attain (Cheng, 2001).

Table 7.11 goodness of fit indices

Category	**Name of index**	**Description**	**level of acceptance**	**Literature**
Absolute fit measures	**Chi Squareχ2**	Chi-Square is a common measure for overall fit; it represents the difference between the hypothesised model and the underlying data values. It also examines the difference between observed, estimated variance and covariance matrices.	Significance P > 0.05	(Hu and Bentler 1999); (Hair et al. 2019); (Tabachnick and Fidell 2007., Kim 2005)
Absolute fit measures	**χ2/df** Normed chi-square test	The normed chi-square test is a ratio of chi-square to the degrees of freedom for a model.	1-3 excellent, 3-5 acceptable, >5 poor	Hu and Bentler 1999
Absolute fit measures	**RMSEA** Root Mean Square Error of Approximation	RMSEA is an absolute fit index that represents the difference between the observed covariance matrix and hypothesised covariance matrix	≤0.06. Good fit. <0.06 to ≤0.08 Acceptable fit. > 0.8 Poor fit	(Hu and Bentler 1999)
Incremental fit measures	**CFI** Comparative Fit Index	CFI is an incremental fit index; it evaluates the extent to which the tested model is superior to the alternative model in reproducing the observed covariance matrix (Cheng 2007 p 468). CFI generate values range between 0.0 and 1, with values close to 1 indicating better fit.	≥.95 Good fit ≥.90 to <.95 Acceptable fit < .90 poor fit	(Hu and Bentler, 1999)
Absolute fit measures	**SRMR** Standardized Root Mean Square)	SRMR is an absolute fit index; it measures the average of standardized residuals between the observed and the hypothesised covariance matrix (Cheng 2007 p 467). SRMR produces	<0.08, Good fit. <0.8 to ≤1.0, Acceptable	(Hu and Bentler, 1999; Hooper, Coughlan and Mullen 2008)

		values between 0.0 and 1, scores closed to 0 indicate excellent fit.	>1.0 fit poor fit	

In SEM, there are three appropriate model categories for researchers to report; ideal fit, incremental fit and parsimonious fit. The absolute fit index is used to assess a model with no comparison to a related model. Additional fit indexes compare the model with baseline models. Parsimonious fit, on the other hand, enhances the fitness of the model by increasing the number of parameters. Scholars recommend using at least one fitness index from each one of the three categories (Hair et al. .2019; Awang 2010).

7.6 Measurement Models: Assessment of Model Fit

This section presents first-order factor models for each of the latent construct include IoT capabilities, VCC practices, and service innovation performance, with the CFA factor values and the scores of model fit indexes.

7.6.1 IoT capabilities model:

Figure 7.2 shows the hypothesised structure of IoT capabilities constructs. AMOS software package 24 was used to analyse the hypothesised model with parameter estimated through maximum likelihood method. Table 7.3 shows the fit indices scores of the model

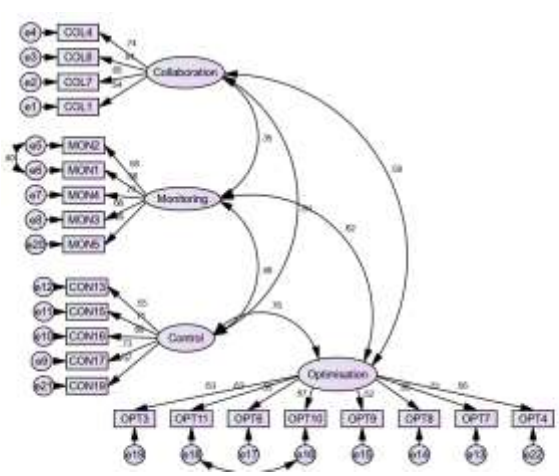

Figure 7.2 hypothesised four-factor structure of IoT capabilities

CFA conducted on the hypothesised model of IoT capabilities involves initially 21 items. Results, as produced by AMOS, revealed that model summary notes show that the model has 253 distinct sample moments (number of information that data offer). The model has 52 distinct parameters to be estimated, with 201 degrees of freedom, and a chi-square value of 287.404 with a probability level equal to 0.000. Model fit results show an **unacceptable model**. Results were as the following: CMIN = 320.789 p<0.001; CMIN/DF= 1.580; CFI= 0.90, RMSEA= 0.062, SRMR = 0.055. Therefore, modification applied to enhance the model fit results.

In the case of model fit enhancement; scholars recommend improving the model fit by freeing the corresponding path of modification indices (MI) of greater than 4.0 and making the connection between the pair of error terms (Hair et al. 2019). However, making a theoretically unsound modification to models (Hair et al. 2019; Byrne 2010) is not the purpose of this study. Inspecting modification incidents (MI) results as produced by AMOS, found modification index e5<-->e6in monitoring factor equal to 17.35, and modification index e16 <-->e18 in optimisation factor equal to 11.19, then, improvement applied by freeing the corresponding path to be estimated. The modified model fit has obtained an enhanced fit value according to the acceptable cut-off values shown in table 7.3. Output shows the following results CMIN = 287.404; p<0.001; CMIN/DF= 1.43; CFI= 0.927, RMSEA= 0.053, SRMR = 0.05. So, all model fits values successfully meet the requirements of cut-off values; therefore, it can be concluded that this **model fit is acceptable**.

Table 7.12 Initial and modified indices for IoT capabilities model fit

	CMIN*	CMIN/DF	CFI	SRMR	RMSEA	P CLOSE
Initial model	320.789	1.580	0.900	0.055	0.062	0.069
Modified Model	287.404	1.43	0.927	0.051	0.053	0.344
* with P value = 0.000						

7.6.1.1 IoT capabilities as a second-order construct:

The previous section showed that the first-order CFA yielded an acceptable IoT measurement model. The interest is also to examine IoT capabilities at a higher level. Thus, a second-order CFA was conducted. As Figure 7.2 below shows, the first-order factors of IoT capabilities (monitoring, control, optimisation and collaboration) are treated as items. A higher-order construct of IoT capabilities was estimated by using the consolidated scores of the four factors from their items.

The results of AMOS show that the model has 253 distinct sample moments, 50 distinct parameters to be estimated, with 203 degrees of freedom, and chi-square value of 291.574 with a probability level equal to 0.000. Model fit results: CMIN/DF= 1.436; CFI= 0.925, RMSEA= 0.054, SRMR= 0.052. Although most of the indices show a good fit score; modification indices were examined, it found that the e12 <--> e26 indices relationship has MI of value = 8.12. A path was added for freeing the covariance between these two error variances. Better fit statistics obtained and the modified model has been slightly improved: the number of distinct sample moments = 253, the number of distinct parameters to be estimated = 51, chi-square 281.738, degree of freedom DF = 202, probability level p = 0.000. CMIN/DF = 1.395; CFI= 0.933, RMSEA= 0.051, SRMR= 0.050. The modified model has an acceptable fit of data; it presented in figure 7.2.

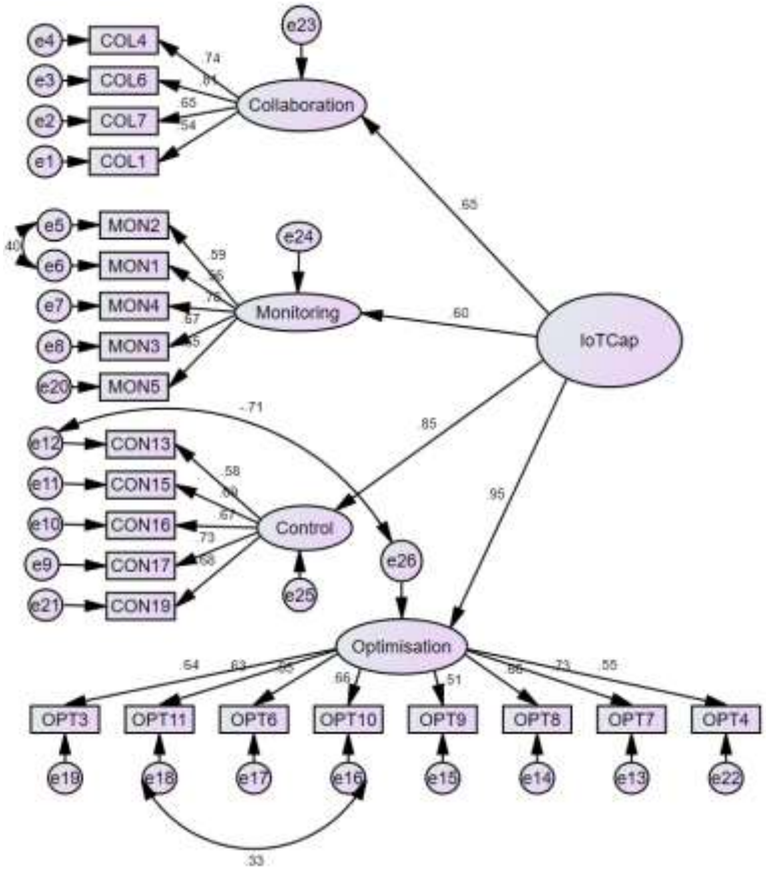

Figure 7.3 Second-order measurements model of IoT capabilities.

Table (7.13) Initial and modified indices for IoT capabilities 2nd order model fit

	CMIN*	CMIN/DF	CFI	SRMR	RMSEA	P CLOSE
Initial model	291.574	1.43	0.925	0.052	0.054	0.066
Modified Model	281.738	1.395	0.933	0.050	0.051	0.444
* with P value = 0.000						

7.6.2 Value co-creation:

This section explains the assessment of the goodness of fit for the VCC practices model. The analysis involves the two dimensions of VCC, co-production and value-in-use models. The model was assessed by different indices to ensure various features included in the assessment and to define the model of the fit efficiently. The construct retained 16 items in total after EFA, 8 for value-in-use and 8 for co-production as presented in figures 7.3 and 7.4 below.

7.6.2.1 Value-in-use model

CFA was applied to value in use scale. AMOS performed the calculations and produced the following results: model summary notes show that the model has 36 distinct sample moments (number of information that data offer) and 19 separate parameters to be estimated, leaving a degree of freedom DF = 17, and chi-square value of 41.845 with a probability level equal to 0.001, and the following model fit indices CMIN/DF= 2.462; CFI= 0.957, RMSEA= 0.098, SRMR= 0.055.

These results showed an **inadmissible fit** since RMSEA value is greater than the desired value of 0.06; it did not satisfy the cut-criteria adopted by this study (specified in table 7.1). Therefore, modification to the model applied, MI inspected found that the modification index between e3 and the endogenous factor (relationship) is equal to 11.3, which is greater than 4 (Hair et al. 2019), accordingly, improvement applied by freeing the corresponding path, as presented in figure 7.5. The new model resulted in the following indices values CMIN/DF= 1.509; CFI= 0.986, RMSEA= 0.058, SRMR= 0.043. So, all model fits values successfully meet the requirements; consequently, it can be concluded the model is acceptable.

Table (7.14) Initial and modified fit indices for value-in-use model

	CMIN*	CMIN/DF	CFI	SRMR	RMSEA	P CLOSE
Initial model	41.845	2.462	0.957	0.055	0.098	0.020
Modified Model	25.653	1.509	0.986	0.043	0.058	0.354
* with P value = 0.001						

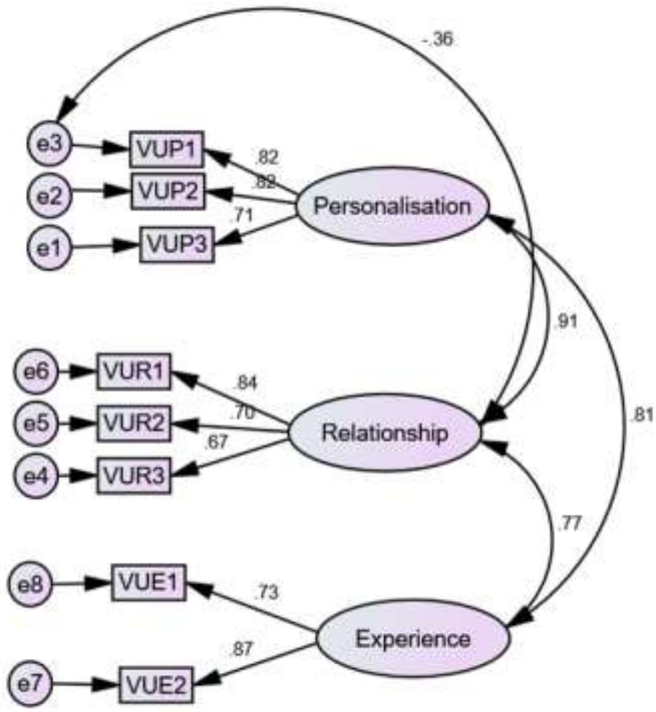

Figure 7.4 hypothesised three-factor structure of value in use

7.6.2.1.1 Value-in-use as a second-order construct:

The first order CFA produced an acceptable value-in-use measurement model, as explained in the previous section; the interest is also to examine value-in-use construct at a higher level. Therefore, a second-order CFA was conducted. The first-order dimensions of value-in-use (personalisation, relationship and experience) are treated as items. A higher-order construct of value-in-use was estimated by using the consolidated scores of the three factors from their items.

The results of AMOS show that the model has 36 distinct sample moments, 19 distinct parameters to be estimated, with 17 degrees of freedom, and chi-square value of 41.854 with a probability level equal to 0.001. Model fit results: CMIN/DF= 2.462; CFI= 0.957, RMSEA= 0.098, SRMR= 0.055. These results showed an inadmissible fit. Therefore, modification indices MI were examined, it found that the e10 <--> e3 indices relationship has MI of value = 17.3. A path was added for freeing the covariance between these two error variances. A better fit statistic obtained and the modified model has been highly improved showing these results: the number of distinct sample moments = 36, the number of distinct parameters to be estimated = 20, chi-square 24.138, degree of freedom DF = 16, probability level p = 0.087. CMIN/DF = 1.509; CFI= 0.933, RMSEA=

0.058, SRMR= 0.043. The modified model has an acceptable fit of data; it is presented in figure 7.5.

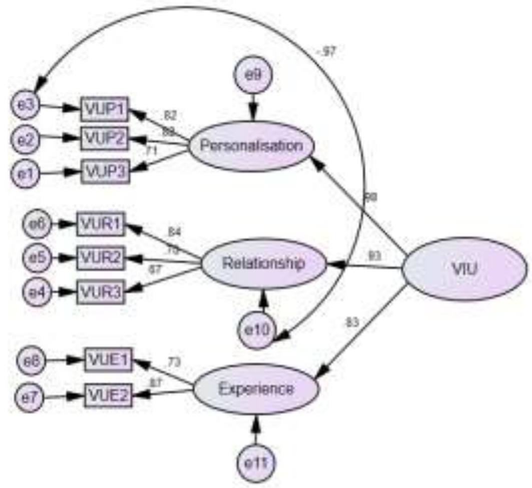

Figure 7.5 Second-order measurements model of Value-In-Use

Table (7.15) Initial and modified fit indices for value-in-use second-order model

	CMIN	CMIN/DF	CFI	SRMR	RMSEA	P CLOSE
Initial model	41.854*	2.462	0.957	0.055	0.098	0.020
Modified Model	24.138**	1.509	0.933	0.043	0.058	0.354
* with P value = 0.001 ** with P value = 0.087						

7.6.2.2 Co-production model:

The hypothesised model of co-creation retained eight items after EFA. AMOS was used to conduct CFA; results show initial findings of the scale are satisfactory. Model summary notes show that the model has 36 distinct sample moments (number of information that data offer) and 19 distinct parameters to be estimated, leaving degree of freedom DF = 17, and chi-square value of 25.915 with a probability level equal to 0.076, and the following model fit results CMIN/DF= 1.524; CFI= 0.986, RMSEA= 0.059, SRMR= 0.041. This model has initially achieved a good fit model requirement.

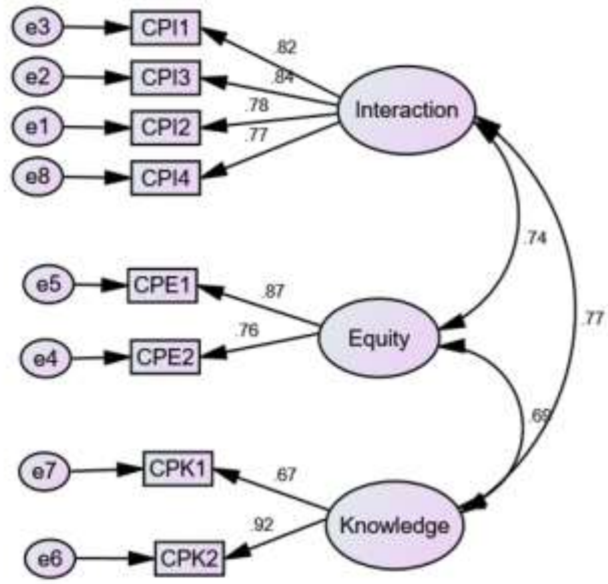

Figure 7.6 Hypothesised three-factor structure of co-production

Table (7.16) Initial and modified fit indices for the co-production model

	CMIN*	CMIN/DF	CFI	SRMR	RMSEA	P CLOSE
Initial model	25.915	1.524	0.986	0.041	0.059	0.340
Modified Model	The model achieved acceptable fit indices without modification					
* with P value =0.076						

7.6.2.2.1 Co-production as a second-order model:

In the previous section, AMOS produced a good-fit first-order model of co-production. Now, co-production construct will be examined at a higher level. Accordingly, the second-order analysis of CFA was conducted. In this analysis, the co-production first-order factors (interaction, equity and knowledge) were considered as items. A higher-order construct of value co-creation was estimated by using the consolidated scores of the three factors from their items.

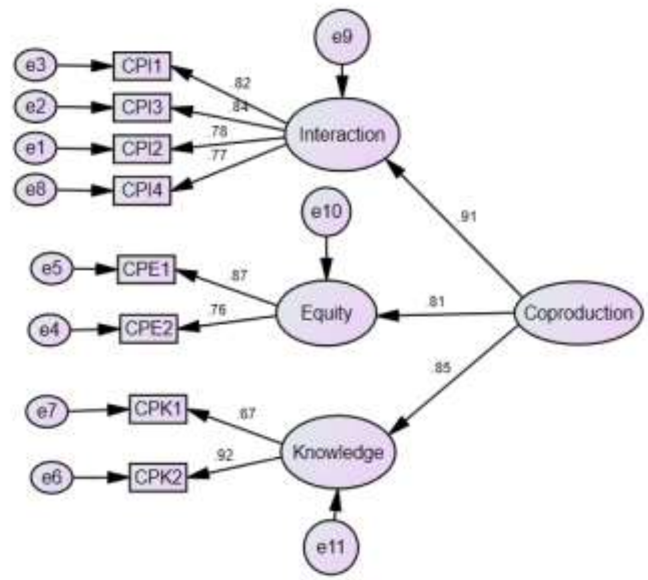

Figure 7.7 Second-order co-production measurements model

Test results show that the model has 36 distinct sample moments, 19 distinct parameters to be estimated, with17 degree of freedom, and chi-square value of 25.915 with a probability level equal to 0.076. Model fit results: CMIN/DF= 1.524; CFI= 0.986, RMSEA= 0.059, SRMR= 0.041. Therefore, the model has an excellent fit. All fit indices are well within acceptable values. The graphical demonstration of the model is presented in figure 7.7.

Table (7.17) Initial and modified fit indices for value-in-use second-order model

	CMIN*	CMIN/DF	CFI	SRMR	RMSEA	P CLOSE
Initial model	25.915	1.524	0.986	0.041	0.059	0.340
Modified Model	The model achieved acceptable fit indices without modification					
* with P value =0.076						

7.6.3 Service Innovation Model

The results of EFA conducted on service innovation construct as presented in chapter 6 revealed that the construct has two factors; *process* factor (with three items) and *result* factor (with six items). The hypothesised relationships were examined by AMOS to examine the initial parameter estimates. SEM results for the original model revealed that the model obtained an excellent fit. Results shows that the model has 45 distinct sample moments (number of information that data offer), and 19 distinct parameters to be estimated, leaving degree of freedom DF = 26, and chi-square value of 37.713 with a probability level equal to 0.064, CMIN/DF = 1.45; CFI= 0.986, RMSEA= 0.054, SRMR= 0.061. All model fit indices are well within acceptable values. Therefore, the measurements model for service innovation achieves a good fit. The model is presented in figure 7.8, and the fit indices are presented in the table

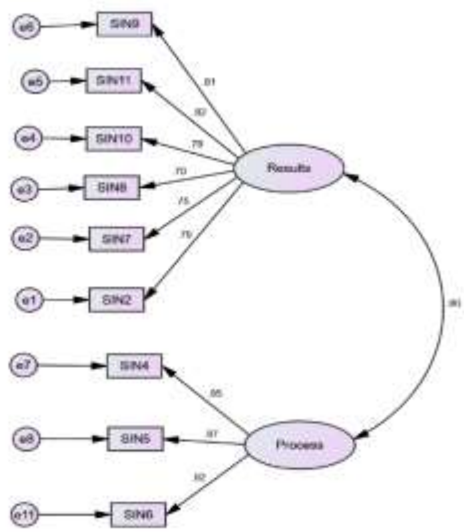

Figure 7.8 Hypothesised two-factor structure of service innovation

Table (7.18) Model fit indices for service innovation construct

	CMIN	CMIN/DF	CFI	SRMR	RMSEA	P CLOSE
Initial model	37.713*	1.45	0.986	0.061	0.054	0.392
* with P value = 0.064						

Chapter 8 Path analysis and testing of hypothesis:

8.1 Structural Path Model Analysis

The previous chapter explained the measurement models of the research constructs. Measurement model analysis is a reliable method to ensure the validity of latent construct measurements. After confirmation of latent construct measurements, the relationship between latent constructs will be examined through a structural model. A structural model is a theorised connection of the measurement model of the independent construct with the measurement model of the dependent construct (Awang 2010). The proposed model developed in chapter 5 aims to identify and test the relationship connection among IoT capabilities, value co-creation practices, adaptation competencies and service innovation performance in the context of healthcare in Jordan. It describes the underlying relations among unobserved variables and defines the way by which specific particular latent variables directly or indirectly cause changes in the values of creation of other latent variables in the model (Byrne 2010).

The analysis of measurement models in chapter 7 shows correlational relationships between constructs. However, the structural model attempts to establish a causal relationship between constructs. Figure 8.1 presents a diagram of a fundamental structural equation model and CFA measurement model. The conceptual framework of this study proposes that there is a relationship (link) between IoT capabilities and service innovation performance. AMOS can measure the causal effect of independent latent constructs on the dependent latent construct. A causal effect between the two latent constructs is depicted by a single-headed arrow, as presented in Figure 7.1. The arrow is heading from latent exogenous construct directed to the latent endogenous construct. The significance and direction of the hypothesised path are calculated and presented in this chapter. The theoretical relationships of constructs in the structural model were built based on an extensive theoretical background, as discussed in chapter 3. The validity of the established research instrument was discussed in chapter 6, and consequently, a valid measurement model was presented. This measurement model is the foundation for the assessment of the structural model. The results obtained by CFA results conducted in chapter 7 show that all measurements have satisfactory construct reliability to be used for further analysis.

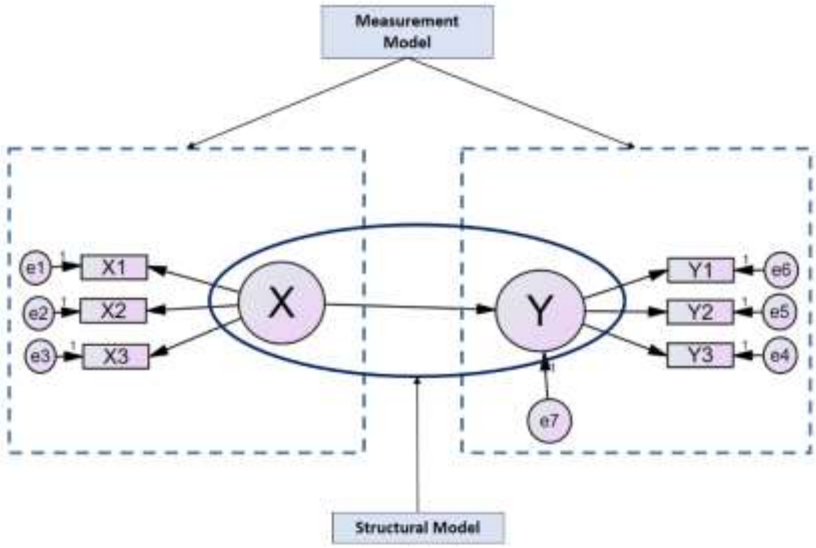

Figure 8.1 Basic structural equation model

8.1.1 IoT capabilities – Service innovation direct relationship

As explained in chapter 5, there is a hypothesised relationship between IoT capabilities and service innovation performance. The IoT latent construct consists of four factors (monitoring, control, optimisation and collaboration) whereas the latent construct service innovation consists of two factors process and results. The intention here is to test the direct relationship between these two latent constructs. The hypothesised relationship was analysed by AMOS to obtain initial parameter estimates. Figure 7.12 presents the structural model and shows the causal relationship between exogenous construct (IoT capabilities) and the endogenous constructs (service innovation performance).

The results of the original conceptual model of the IoT capabilities and service innovation structural model show that initial model gained an **inadmissible fit** model where the model has 496 distinct sample moments and 70 distinct parameters to be estimated, leaving a degree of freedom DF = 426, and chi-square value of 704.985 with a probability level equal to 0.000, CMIN/DF = 1.655; CFI= 0.869, RMSEA= 0.066, SRMR= 0.155. Therefore, modification indices were examined to verify if values are greater than four and add a path between each pair with these values. This would improve the overall model fit. The covariance between e168 <--> e169 = 71.67, and the covariance between e168 <--> e178 = 16.96. The analysis was repeated after treated these covariances as free parameters. The model fit was highly improved and obtained the following results: the number of distinct sample moments = 496, and 72 distinct parameters to be estimated, chi-square = 591.155 with DF = 424 and a probability level equal to 0.000. Whereas CMIN/DF = 1.394; CFI= 0.921, RMSEA= 0.051, SRMR= 0.071. These results show an **acceptable fit** model. The results of initial and modified models are presented in Table 7.6

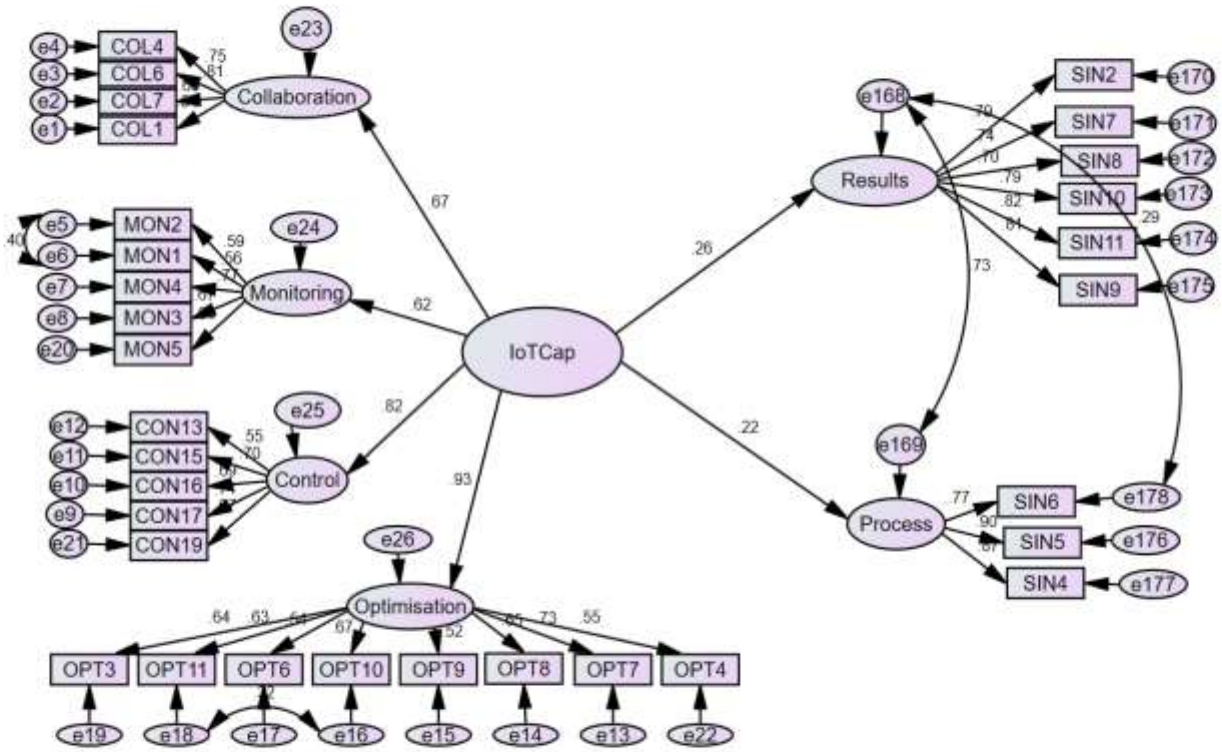

Figure 8.2 The structure model of IoT capabilities – service innovation direct relationship

Table 8.1 Model fit indices for IoT and service innovation direct relationship

	CMIN	CMIN/DF	CFI	SRMR	RMSEA	P CLOSE
Initial model	704.985*	1.655	0.869	0.155	0.066	0.002
Modified Model	591.155*	1.394	0.921	0.071.	0.051	0.43
* with P-value = 0.000						

8.1.2 IoT capabilities and VCC practices direct relationship

This section demonstrates the structural model of the relationship between IoT capabilities construct and value co-creation. A similar analysis was conducted to examine the structural model of each capability and its effect on VCC dimensions, value-in-use practices and co-production practices. The findings of the analysis and the values of fit indices were summarised in table 8.2. The initial model of IoT - VCC relationship gained **inadmissible** fit, where model has 741 distinct sample moments and 91 distinct parameters to be estimated, leaving degree of freedom DF = 650, and chi-square value of 1022.311 with a probability level equal to 0.000, CMIN/DF = 1.573; CFI= 0.864, RMSEA= 0.061, SRMR= 0.104. Modification indices were examined, it found that the pairs of error variances; e23 <--> e24, e55 <--> e61, e23 <--> e46, e46 <--> e61, e50 <--> e59 all have values greater than 4. A path was added to each pair for freeing the covariance between each two error variances. A better fit statistic obtained and the modified model has been greatly improved showing these results: the number of distinct sample moments = 741, the number of distinct parameters to be estimated = 96, chi-square 844.653, df = 645, probability level p = 0.000. CMIN/DF = 1.390; CFI= 0.908, RMSEA= 0.051, SRMR= 0.066. The results of the fit indices show that the modified model has an **acceptable** fit of data.

The hypothesised relationships between IoT capabilities and VCC practices were analysed by SEM, the rules of estimates and standard error S.E. were applied to identify the significance of the path coefficient between latent constructs. The findings of the results were evaluated based on the level of significance (p-value), path coefficient (β) and critical ratio (C.R), which were produced by AMOS. The results show that all of the hypothesis was supported. Table 8.3 summarised the results of IoT capabilities and VCC practices hypothesised relationship.

Table 8.2 Model fit indices for IoT and VCC direct relationship

	CMIN	CMIN/DF	CFI	SRMR	RMSEA	P CLOSE
Initial model	1022.311	1.573	0.864	0.104	0.061	0.003
Modified Model	844.653	1.390	0.908	0.066	0.051	0.480
* with P-value = 0.000						

8.2 Test of direct hypotheses:

This section explains the analysis of direct hypothesis proposed in chapter 4. The standardised estimates were calculated to present the key figures relevant to the fitness of the model. These figures include the fit indices, the beta coefficient that measures the influence of exogenous construct on the endogenous construct, the values of R^2 to reflect the explained variance of endogenous constructs in the structural model, the factor loading for every item and the correlation between exogenous constructs. The fitness indices are essential because they demonstrate how fit is the hypothesised model with the sample data under study. If the fit indices do not report the required level for each model, then multiple problems with the model are suspected. Low factor loadings, the high correlation between constructs (or multi-collinearity) are some examples of these problems.

A set of hypotheses were articulated in chapter 4 to answer the research questions. In this section, the hypothesised relationships will be tested through SEM. Multiple criteria were used in hypothesis testing: The Standard Error (S.E.) of estimates, it describes the error of regression weight, the Critical Ratio (C.R.) significance level (p-value), path coefficient (β). The critical ratio should be equal or greater than ±1.96 for 0.05 level and ±2.58 for 0.01 level (Kline, 2016).

8.2.1 Hypotheses relating to IoT capabilities and service innovation:

There are four hypotheses proposed to investigate the relationship between IoT capabilities and service innovation performance, all derived from the hypothesis 'IoT capabilities have a direct and positive impact on service innovation performance'. The proposed hypotheses are:

H1a: IoT monitoring capability has a direct and positive impact on service innovation performance.

The hypothesis aims to explore the relationship between IoT monitoring capability and service innovation performance in the healthcare context. The relationship is found to be statistically significant; $\beta = 0.16$, $t = 2.16$, and p-value < 0.05. Therefore, these results provide sufficient evidence to support the direct positive relationship between monitoring capability and service innovation performance, so the hypothesis is supported.

H1b: *IoT control capability is positively associated with service innovation performance.*

This hypothesis sought to examine the connection between IoT control capability and service innovation performance. As shown in table 8.4, the path coefficient of control capability and service innovation performance are non-significant in the hypothesised model; $\beta = -0.16$, $t = -0.968$, and p-value > 0.05. This result presents an insufficient direct relationship between IoT control capability and service innovation performance. Therefore, the hypothesis is not supported.

H1c: *IoT optimisation capability is positively associated with service innovation performance.*

This hypothesis attempt to explore the association between optimisation capability of IoT technology and healthcare service innovation performance. The result shows that the path coefficient of optimisation capability and innovation performance in the structural model are not significant. As table 8.4 presents, the determinant values are; $\beta = 0.08$, $t = 0.48$, and p-value > 0.05. This result did not provide enough support for the hypothesis. Therefore, the relationship between the optimisation capability and healthcare innovation performance were found to be statistically insignificant; consequently, the thesis is not supported.

H1d: *IoT collaboration capability is positively associated with service innovation performance.*

The hypothesis describes that the collaboration capability of IoT technology has a direct and positive relationship with healthcare innovation performance. It was evidenced to have significant coefficient for the proposed model; $\beta = 0.417$, $t = 2.72$, and p-value < 0.05. Therefore, this result concludes that there is a direct link between the collaboration capability of IoT technology possessed by an organisation and its ability to manage service innovation processes and performance.

Table 8.3 Summary of results of a direct path between IoT capabilities and VCC practices

Construct	Path	Construct	Estimate	S.E.	C.R.	P-value	Result
Monitoring capability	→	Service innovation	0.23	0.225	2.025	0.035	Supported
Control capability	→	Service innovation	-0.305	0.319	-0.955	0.339	Not supported
Optimisation capability	→	Service innovation	0.109	0.339	0.322	0.747	Not supported
Collaboration capability	→	Service innovation	0.871	0.368	2.37	0.018	Supported

8.2.2 Hypotheses relating to IoT capabilities and value co-creation:

This section explains the analysis and the results of hypotheses (H2a – H2h) testing. The hypotheses were set to explore the relationship between the four types of IoT capabilities monitoring, control, optimisation and collaboration, and the two constructs of value co-creation value-in-use and co-production. Therefore, the first objective of this thesis is to investigate the relationship between IoT capabilities and value co-creation practices in the context of the healthcare industry. Overall the four capabilities explained 26% (R = 0.26) of the variance in Value-In-Use practices and 28% (R = 0.28) invariance for co-production practices. The results of each of the IoT capabilities are presented below:

The eight hypotheses were derived from this hypothesis: IoT capabilities have a direct and positive impact on value co-creation practices, these hypotheses are:

H2a: IoT monitoring capability has a direct and positive impact on co-production practices.

The hypothesis demonstrates that IoT monitoring capability has a positive relationship with value co-production (knowledge, equity and interaction) practices, was evidenced by a significant coefficient ($\beta = 0.32$, $t = 2.38$, and p-value < 0.05). Overall, this results show that there is a positive direct relationship between monitoring capability of IoT technology possessed by organisations and practices that promote knowledge, equity and interaction in the healthcare provider domain and the joint sphere domain of co-creation.

H2b: IoT monitoring capability is positively associated with value-in-use practices.

The hypothesis attempt to explore the relationship between IoT technology monitoring capability and value-in-use practices (experience, personalisation and relationship). The relationship is found to be statistically significant; $\beta = 0.27$, $t = 2.62$, and p-value <0.05. Therefore, these results provide sufficient evidence to support the direct positive relationship between monitoring capability and value-in-use co-creation practices that motivate experience, personalisation and relationship within the organisation, so the hypothesis is supported.

H2c: *IoT control capability is positively associated with co-production practices.* This hypothesis sought to explain the relationship between IoT control capability and value co-production practices including knowledge, equity and interaction. As shown in table 8.3, the path coefficient of control capability and value co-creation practices relationship are non-significant in the hypothesised model; $\beta = -0.017$, $t = -0.087$, and p-value > 0.05. These results demonstrate an insufficient direct relationship between IoT technology control capability and co-production practices. Therefore, the hypothesis not supported.

H2d: *IoT control capability is positively associated with value-in-use practices.*

This hypothesis attempts to explore the relationship between IoT control capability and value-in-use practices including experience, relationship and personalisation. The results of the estimated path coefficient in the model are ($\beta = 0.028$, $t = 0.093$, and p-value > 0.05). The relationship between the two constructs found to be statistically insignificant. Hence, these results did not provide enough support for the hypothesis.

H2e: *IoT optimisation capability is positively associated with co-production practices.*

The hypothesis explains that optimisation capability of IoT technology has a direct and positive relationship with co-production practices. It was evidenced to have significant coefficient for the proposed model ($\beta = 0.21$, $t = 2.26$, and p-value < 0.05). So, these results show that there is a direct link between the control capability of IoT technology possessed by the organisation and its ability to facilitate and manage co-production practices such as knowledge, equity and interaction.

H2f: *IoT optimisation capability is positively associated with value-in-use practices.*

This hypothesis attempt to explore the connection between optimisation capability of IoT technology and healthcare organisational capability to facilitate practices that promote experience, personalisation and relationship, and engage with the patient through co-creation practices. The results show that the path coefficient of the hypothesised model is significant ($\beta = 0.1$, $t = 0.01$, and p-value > 0.05). This result did not provide enough support for the hypothesis. Therefore, the relationship between the optimisation capability and value-in-use found to be statistically insignificant, and the hypothesis is not supported.

H2g: *IoT collaboration capability is positively associated with co-production practices.*

The hypothesis demonstrates that IoT collaboration capability is positively associated with co-production related practices (knowledge, equity and interaction). The analysis results revealed a significant coefficient values ($\beta = 0.35$, $t = 2.59$, and p-value <0.05). Hence, there is enough evidence to support the assumption of having a positive and direct relationship between IoT technology collaboration capability possessed by organisations and practices that encourage knowledge, equity and interaction in the healthcare provider domain and the joint sphere domain of co-creation.

H2h: *IoT collaboration capability is positively associated with value-in-use practices.*

The hypothesis presents that IoT collaboration capability has a direct and positive connection with value-in-use related practices. It was evidenced to have significant coefficient for the proposed model ($\beta = 0.38$, $t = 2.62$, and p-value <0.05). These results demonstrate that there is a strong and direct link between the control capability of IoT technology possessed by the organisation and its ability to enable and manage value-in-use related practices such as knowledge, equity and interaction.

Table 8.4 Summary of results of a direct path between IoT capabilities and VCC practices

Construct	Path	Construct	Estimate	S.E.	C.R.	P-value	Result
Monitoring capability	→	Co-production	0.321	0.153	2.378	0.021	Supported
Monitoring capability	→	Value in Use	0.27	0.144	2.62	0.020	Supported
Control capability	→	Co-production	-0.017	0.231	-0.087	0.851	**Not supported**
Control capability	→	Value in Use	0.028	0.214	0.093	0.862	**Not supported**
Optimisation capability	→	Co-production	0.211	0.232	2.26	0.011	Supported
Optimisation capability	→	Value in Use	0.002	0.251	0.01	0.846	**Not supported**
Collaboration capability	→	Co-production	0.381	0.240	2.593	0.013	Supported
Collaboration capability	→	Value in Use	0.589	0.262	2.619	0.011	Supported
Value in Use	→	Co-production	0.62	0.115	10.31	0.000	Supported

8.2.3 Hypotheses relating to IoT capabilities and value co-creation:

H3: *Value-in-use related practices have a direct and positive impact on co-production related practices*

The hypothesis demonstrates how value-in-use practices the experience, personal and relations affect the co-production practices knowledge, equity and interaction of personal. This assumption was set to confirm impact of personal skills on the co-production practices. The analysis results revealed a significant coefficient values ($\beta = 0.62$, $t = 1031$, and p-value <0.05). Therefore, there is enough evidence to support the assumption of having a positive and direct relationship between value-in-use practices and co-production practices, that highlight the skills of health care giver in value co-creation with patients.

8.2.4 Hypotheses related to the relationship between VCC and service innovation

The engagement of a firm and customer in a collaborative relationship to co-create value for both sides is the desired goal. The co-production as one of the value co-creation dimensions is considered as one of the firm's competitive advantages (Prahalad and Ramaswamy, 2004a), and understanding of market needs would enable an organisation to easily co-create value with its customers. Two dimensions of value co-creation practices (co-production and value-in-use) were examined against their influence on the performance of service innovation. This section demonstrates the results of the hypothesis test proposed to investigate the relationship between both co-production and value-in-use, and the performance of healthcare innovation. In these settings, there were two hypotheses derived from the hypothesis 'H3: value co-creation practices have a direct and positive impact on service innovation performance'; the first one is:

H4a: *co-production related practices have a direct and positive impact on service innovation performance.*

The structural path model analysis for this hypothesis revealed a significant coefficient value (β = 0.25, t = 3.175, and p-value < 0.05). So, there is enough evidence to support that there is a positive direct relationship between co-production related practices and the performance of service innovation.

The second one is: H4b: *value-in-use related practices have a direct and positive impact on service innovation performance.*

This hypothesis assume that value-in-use related practices have a direct and positive connection with healthcare innovation performance. It was evidenced that there is a significant coefficient for the hypothesised model, where, β = 0.31, t = 3.415, and p-value < 0.05. This result shows that there is a strong and direct connection between the value-in-use related practices possessed by the organisation and its ability to promote healthcare innovation culture and to manage the innovation culture.

Table 8.5 Summary of direct hypothesis

Hypothesis statement	Estimates	P-value	Results
H1a: IoT monitoring capability has a direct and positive impact on service innovation performance.	0.15	0.021	Supported

H1b: IoT control capability is positively associated with service innovation performance.	-0.14	0.284	Not supported
H1c: IoT optimisation capability is positively associated with service innovation performance.	0.08	0.672	Not supported
H1d: IoT collaboration capability is positively associated with service innovation performance.	0.42	0.012	Supported
H2a: IoT monitoring capability has a direct and positive impact on co-production practices.	0.32	0.032	Supported
H2b: IoT monitoring capability is positively associated with value-in-use practices.	0.27	0.025	Supported
H2c: IoT control capability is positively associated with co-production practices.	-0.02	0.776	Not supported
H2d: IoT control capability is positively associated with value-in-use practices.	0.03	0.841	Not supported
H2e: IoT optimisation capability is positively associated with co-production practices.	0.21	0.013	Supported
H2f: IoT optimisation capability is positively associated with value-in-use practices.	0.10	0.868	Not supported
H2g: IoT collaboration capability is positively associated with co-production practices.	0.35	0.012	Supported
H2h: IoT collaboration capability is positively associated with value-in-use practices.	0.38	0.000	Supported
H3: Value in use practices have a direct and positive impact on value co-production practices.	0.62	0.000	Supported
H4a: Co-production related practices have a direct and positive impact on service innovation performance.	0.25	0.000	Supported
H4b: Value-in-use related practices have a direct and positive impact on service innovation performance.	0.31	0.019	Supported

8.3 Analysing the mediation effects

Mediation analysis is a statistical method used to evaluate hypothesised relationship of how causal antecedent variable X transmits its impact on a consequent variable Y (Hayes 2018). Figure 8.5 shows a simple mediation model. As it can be shown, the model consists of three variables X (exogenous), M (mediator) and Y (endogenous). Variables X and M are antecedents, and variables M and Y are consequent variables of the model. X casually influences both variables M and Y, and variable M causally influencing the outcome variable Y. In the model, there are two ways by which the exogenous variable X can influence endogenous Y. One way is through the arrow transferred from X to Y in a straight line and called *direct effect*. The second way is through the arrow transferred to M and then to Y which is called the *indirect effect.* In this thesis, SD logic approach and adaptation are conceptualised as a mediation process that links the relationship between IoT advanced technology and healthcare service innovation performance. The mediation process here is considered as a causal explanation, and the practices of co-creation of value and adaptation competencies are causally connected to IoT implementation with service innovation performance.

Having the mediator variable M between exogenous variable X and endogenous variables Y would lead to reducing the direct influence of X on Y because some of the impacts will be shifted through the mediator. There are two forms of mediation; *complete mediation* and *partial mediation* (Hair 2019). Partial mediation occurs if the indirect effect is reduced but still stay significant. On the other hand, complete (or full) mediation occurs when the direct effect is reduced and no longer stay significant. This study will examine the direct effects of, and the indirect effect of IoT deployment on the performance of service innovation through co-creation related practices and through the adaptation competencies. If the direct effect of IoT on service innovation performance is reduced and the indirect effect (through co-creation related practices) is significant, then VCC is said to play a mediating role in connecting IoT capabilities and innovation performance indirectly.

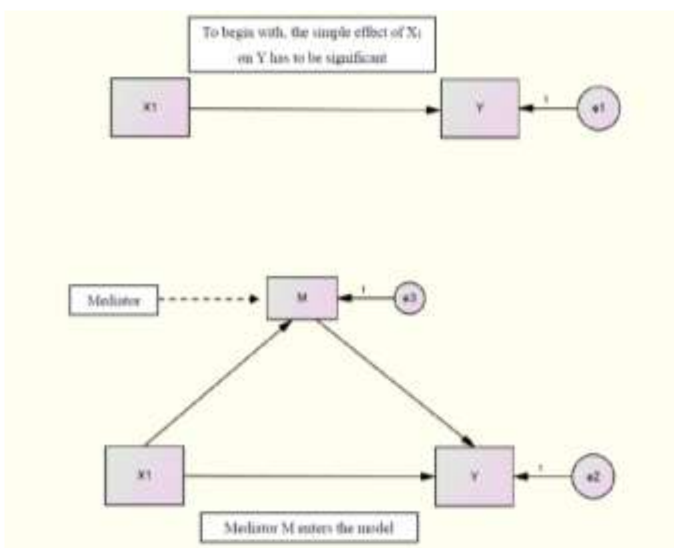

Figure 8.3 Mediation effect (Adapted from Awang 2010)

Mediating variable explains the correlation among independent (exogenous) variable and dependent (endogenous) variable, and defines the way by which a direct relationship occurs (Frazier, Tix and Barron 2004). The direct impact of IoT capabilities (independent variable) on the service innovation performance (dependent variable) is significant, as presented in table 8.2. However, when value co-creation practices (mediator variable) enter the model, the direct effect becomes highly reduced, since some of the impacts has shifted through the mediator. The effect of IoT capabilities was reduced and no longer significant; therefore, this mediation is a complete mediation (Awang 2010).

The mediation assessment in this thesis follows the guidance of Kock (2013) and Hair et al. (2019). The first step is to determine the relationship between exogenous and endogenous variables without including the mediating variable. See figure 8.8 if the relationship is significant, then the assessment will proceed to the next step. Inclusion of the mediating variable in the relationship comes next. If the indirect effect of exogenous on endogenous is significant and its direct effect remains significant as well, the conclusion is that partial mediation has taken place. On the other hand, if the indirect effect is significant and the direct effect turn out to be insignificant, then the result is that the model has full mediation. If the indirect effect found to be insignificant, then the conclusion is no mediation effect within the model. SEM is used for path analysis procedure. According to relationships among independent, dependent and mediator variable in figure 8.8, the regression equations for analysis are:

$$\mathbf{Y = i_1 + cX + \varepsilon_1}$$

$$\mathbf{M = i_2 + aX + \varepsilon_2}$$

$$\mathbf{Y = i_3 + c'X + bM + \varepsilon_3}$$

Where Y is the value of the independent variable, X is the independent variable, M is the mediating variable in the equation, c, c' and a are paths coefficients as figure 8.8 presents, i is the intercept of each equation, and $\boldsymbol{\varepsilon}i$ is the equations residual (Jose 2013).

8.3.1 Analysing the mediating effect of co-production

This section analyses the mediating relationship of co-production between IoT technology and service innovation performance. Chapter seven shows the results of the direct relationship of IoT capabilities on co-production, and the results of the direct effect of co-production on the performance of healthcare innovation. Literature has shown the positive impact of co-production and actors collaboration on the practices of innovation (e.g. Chen et al. 2011; Schilling and Phelps, 2007). IoT technologies bring humans and devices closer together and facilitate the practices of co-production and enhance inter and intra-organisational collaboration. Based on guidance explained in the previous section, the structural model was assessed by AMOS.

The analysis for mediation begins by demonstrating that the direct effect of IoT capabilities on service innovation is significant. Beta coefficients, S.E., t and p-values are presented in table 8.8. When value co-production practices variable enters the model, the value of the beta coefficient for IoT capabilities is expected to reduce, and this means the direct effect of IoT capabilities on service innovation would be decreased when the mediator comes in the model. Figure 8.10 shows the model when the co-production variable is entered as a mediator. This study aims to prove that value co-production variable mediates the relationship between IoT capabilities and service innovation performance. Table 8.11 presents the regression weight estimates for the model. Table 8.12 shows the multiple regression weights of IoT- service innovation relationship. The fit indices of both models are presented in tables 8.12 and 8.14, respectively.

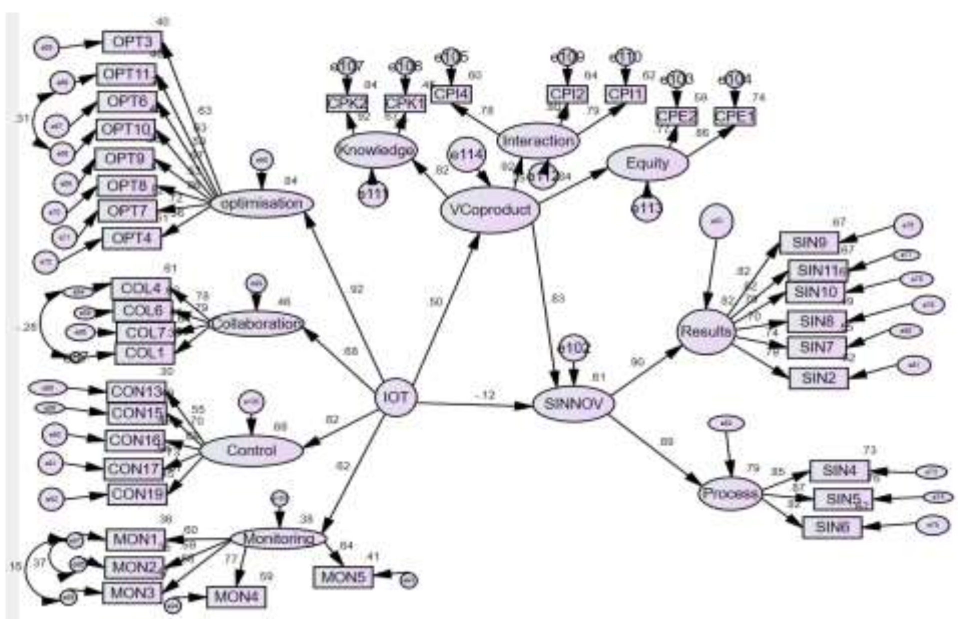

Figure 8.4 value co-creation as a mediator between IoT capabilities and service innovation

Table 8.6 Results of fit indices for the direct effect of IoT on service innovation model

	CMIN*	DF	CMIN/DF	CFI	SRMR	RMSEA	P CLOSE
Mediation Model	599.113	423	1.416	0.917	0.071	0.052	0.339
	* with P-value = 0.000						

Table 8.7 Multiple regression weights for IoT - service innovation relationship

Construct	Path	Construct	Estimate	S.E.	C.R.	P-value	Result
IoT capabilities	→	Service innovation	0.785	0.338	2.242	0.025	Significant

Table 8.8 Results of fit indices for the mediation model

	CMIN*	DF	CMIN/DF	CFI	SRMR	RMSEA	P CLOSE
Mediation Model	916.803	649	1.413	0.905	0.072	0.052	0.324
	* with P-value = 0.000						

Table 8.9 Multiple regression weights (co-production mediates IoT and innovation)

Construct	Path	Construct	Estimate	S.E.	C.R.	P-value	Result
IoT capabilities	→	Service innovation	-0.353	0.285	-1.238	0.216	Insignificant
IoT capabilities	→	Coproduction	0.993	0.254	3.914	***	Significant
Co-production	→	Service innovation	1.227	0.187	6.577	***	Significant

Values of beta coefficients can be seen in figure 8.4. The indirect effect of IoT on service innovation = 0.5 x 0.83 = 0.415, whilst direct effect = 0.12. Since the indirect effect is greater than the direct effect, mediation takes place. The mediation type here is full mediation because the direct effect of exogenous variable became insignificant after the mediator variable enters the model.

8.3.2 Analysing the mediating effect of value-in-use

This section describes the analysis of the mediating effect of value-in-use between IoT technology and service innovation performance. Results of the direct relationship of IoT capabilities on value-in-use and the direct effect of value-in-use on service innovation were presented in the last chapter. Co-creation literature has shown the positive influence of new health technology such as tele-health and m-health on value-in-use related practices (e.g. DeBlois and Millefoglie 2015; Dai, Yu and Dong 2020). The hypothesised model was assessed by SEM using AMOS. The first step in the analysis was to examine the significance of the direct effect of IoT capabilities on value-in-use. Results of direct model analysis estimates, S.E., t and p-values are presented in table 8.11. When the value-in-use variable comes in the model, the value of the estimates is expected to reduce, in other words, the direct effect of IoT capabilities on service innovation would be decreased when the mediator enters the model

Figure 8.11 presents the model when the value-in-use variable is entered as a mediator. The intention here is to prove that value-in-use mediates the link between IoT capabilities and innovation performance. The results of the analysis presented in tables below. Table 8.10 shows the fit indices of the model. The regression weight estimates for the model are presented in table 8.11.

Table 8.10 Results of fit indices for the mediation model

	CMIN*	DF	CMIN/DF	CFI	SRMR	RMSEA	P CLOSE
Mediation Model	969.954	685	1.416	0.903	0.072	0.052	0.303
	* with P-value = 0.000						

Table 8.11 Multiple regression weights (value-in-use mediates IoT and innovation)

Construct	Path	Construct	Estimate	S.E.	C.R.	P-value	Result

IoT capabilities	→	Service innovation	-0.291	0.217	-1.343	0.179	Insignificant
IoT capabilities	→	Value-in-use	1.023	0.267	3.827	***	Significant
Value-in-use	→	Service innovation	1.002	0.177	5.671	***	Significant

Values of beta coefficients can be obtained from figure 8.5. The indirect effect of IoT on service innovation = 0.49 x 0.82 = 0.40, whilst direct effect = 0.12. Since the indirect effect is greater than the direct effect, mediation occurs.

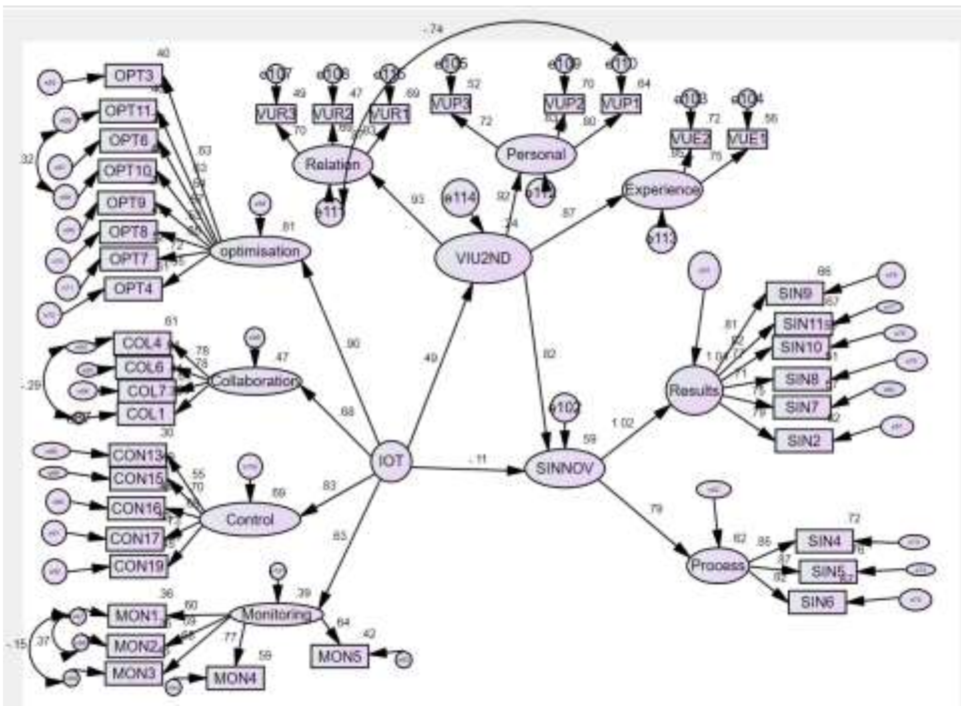

Figure 8.5: Value-in-use as a mediator between IoT and service innovation

The Final structural model

The result of the proposed conceptual model is shown in the estimated model fit indices. The fit indices values show that the model obtained good-fit results as in table 8.12. The constructs of the overall model fit for the conceptual model were assessed simultaneously based on SEM methods of assessing model fit as explained in chapter 7. Various model fit indices were used in the assessment process to ensure that the model is evaluated thoroughly using robust techniques to establish reliable research findings.

The initial model gained **inadmissible** fit. One of the good statistical practices is to improve the model is to check the modification indices as recommended earlier in this chapter. Gaskin (2012) indicates that modification indices needs to be checked as a remedy for discrepancies between the proposed and estimated models. After consultation with modification indices, model shows that it has 28 distinct sample moments and 26 distinct parameters to be estimated, leaving degree of freedom DF = 2, and chi-square value of 84.301 with a probability level equal to 0.000, CMIN/DF = 42.150; CFI= 0.908, RMSEA= 0.052, SRMR= 0.077. The results of the fit indices show that the modified model has an **acceptable** fit of data. The final model explains 61% (R square = 0.61) of the variance in service innovation performance. R squre (also known as the coefficient of determination) is defined as "the amount of explained variance of endogenous latent variables in the structural model" (Hair et al. 2019 p.97). Researchers suggested that the evaluation of R square of the endogenous latent variable is important step in evaluating the structural model (Hair et al. 2019; Hulland 1999). Literature shows that no consent on the acceoptable value of R square over disciplines (Chin 1998). Researchers indicated that R square values of 0.75, 0.50 and 0.25 can be seen as high, moderate and weak (Chin 1998). Table 8.14 summarises the coefficient values of R square.

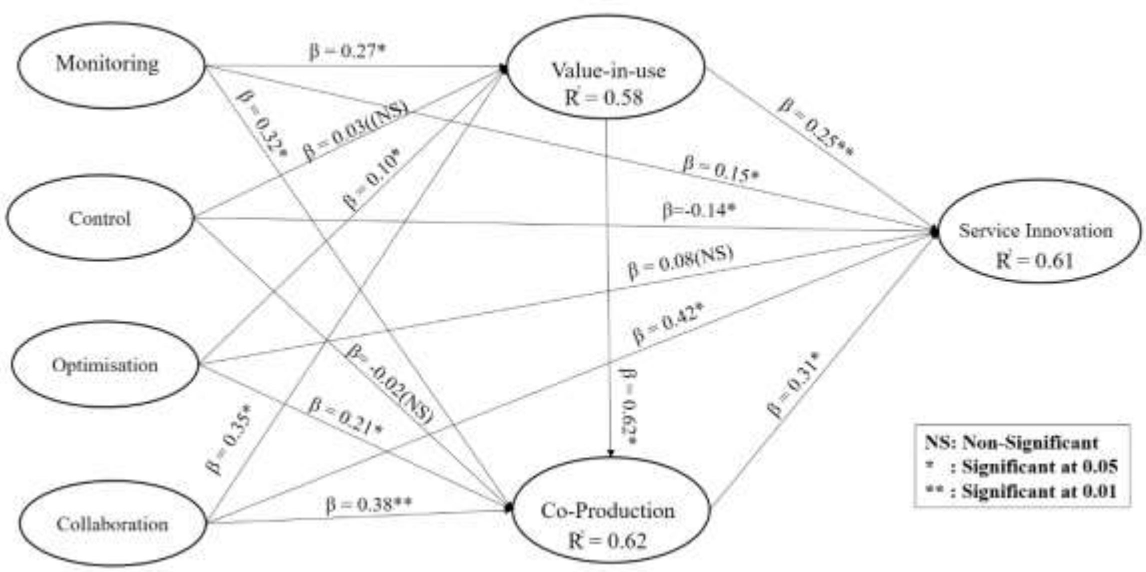

Figure 8.6. Final conceptual Model

Table (8.12) Model fit indices for the final hypothesised model

	CMIN*	CMIN/DF	CFI	SRMR	RMSEA	P CLOSE
Model values	84.301	42.150	0.908	0.077	0.052	0.262
* with P-value = 0.000						

Table 8.13 Multiple regression weights final structural model

Construct	Path	Construct	Estimate	S.E.	C.R.	P-value
Monitoring	→	VIU	0.270	0.094	3.339	***
Control	→	VIU	0.028	0.265	0.0843	0.882
Optimisation	→	VIU	0.002	0.283	0.114	0.874
Collaboration	→	VIU	0.352	0.118	2.981	0.002
Monitoring	→	Coproduction	0.321	0.103	2.193	0.028
Control	→	Coproduction	-0.17	0.331	-0.802	0.716
Optimisation	→	Coproduction	0.211	0.256	0.241	0.012
Collaboration	→	Coproduction	0.381	0.255	3.210	000
VIU	→	Coproduction	0.621	0.065	10.627	***
Coproduction	→	SIN	0.302	0.089	3.385	***
VIU	→	SIN	0.394	0.113	3.475	***
Monitoring	→	SIN	0.15	0.116	-1.309	0.019
Control	→	SIN	-0.14	0.357	-0.668	0.231
Optimisation	→	SIN	0.08	0.362	0.985	0.662
Collaboration	→	SIN	0.42	0.221	3.027	***

Table 8.14 Path coefficient p-values and R^2

Hypothesised relationship	Beta	P-value	(R^2)	Description
Monitoring -----> Coproduction	0.32	0.028	0.62	Positive, significant and moderate
Control -----> Coproduction	-0.02	0.716	0.62	Negative, Insignificant and moderate
Optimisation -----> Coproduction	0.021	0.012	0.62	Positive, significant and moderate
Collaboration ----> Coproduction	0.38	0.000	0.62	Positive, significant and moderate
Monitoring -----> VIU	0.27	***	0.58	Positive, significant and moderate
Control -----> VIU	0.03	0.882	0.58	Positive, significant and moderate
Optimisation -----> VIU	0.10	0.874	0.58	Positive, significant and moderate
Collaboration-----> VIU	0.35	0.002	0.58	Positive, significant and moderate
VIU-----> Coproduction	0.62	***	0.62	Positive, significant and moderate
VIU-----> SINN	0.31	***	0.61	Positive, significant and moderate
Coproduction-----> SINN	0.25	***	0.61	Positive, significant and moderate
Monitoring -----> SINN	-0.08	0.019	0.61	Negative, Insignificant and moderate
Control -----> SINN	-0.14	0.231	0.61	Negative, Insignificant and moderate
Optimisation -----> SINN	0.08	0.662	0.61	Positive, significant and moderate
Collaboration -----> SINN	0.42	***	0.61	Positive, significant and moderate

8.5 Test of mediating hypothesis:

This section explains the analysis of indirect hypothesis proposed in chapter 4. The hypothesised relationship has been tested through SEM. There are multiple criteria used for testing the hypothesis, including significance level (p-value) and path coefficient (β) as it can be seen in the above tables.

Table 8.15 Summary of mediation hypotheses

Hypothesis statement	Estimates	P-value	Mediation type	Results
H5a: Co-production practices mediate the relationship between IoT collaboration and service innovation performance.	0.38*0.31 = (0.118)	0.001	Full Mediation	Supported

IoT collaboration → Co-production → Service Innovation				
H5b: Value-in-use practices mediate the relationship between IoT collaboration and service innovation performance ***IoT collaboration → Value-in-use → Service Innovation***	0.35*0.25 = (0.087)	0.004	Full Mediation	Supported

Table 8.17 presents the results of IoT impact on service innovation through one-variable and multiple mediations. These results are presented as the following:

Hypothesis 5a: Co-production practices mediate the relationship between IoT collaboration capability and service innovation performance. This proposed hypothesis sought to examine the intervention of co-production related practices on the link between IoT and service innovation. The results show that the path coefficient for the model ($\beta = 0.118$, $p < 0.01$) is significant, so the result provides support for the hypothesis.

Hypothesis 5b: Value-in-use practices mediate the relationship between IoT collaboration capability and service innovation performance. The hypothesis aims to explore the mediating influence of value-in-use on the relationship between IoT capabilities and service innovation performance in the healthcare context. The mediating effect is found to be statistically significant ($\beta = 0.087$, $p < 0.05$). Therefore, it can be concluded that the hypothesis is supported.

8.6 Additional paths in the conceptual model

The modification indices of SEM output proposed additional paths within conceptual model to ensure better fit between the data and the model. These paths of mediation and indirect effects contribute to relationship between the elements of the conceptual model. The SEM output suggests these additional links to provide additional insights and extend the understanding of association between variables. This section briefly interprets these additional paths:

Value-in-use and co-production in a series mediate the relationship between IoT capabilities and service innovation performance. This relationship combines value-in-use and co-production to test the relationship between IoT capabilities and service innovation. As shown in table 8.14, the path coefficient shows a significant result ($\beta = 0.044$, $p < 0.05$). This result shows that the sequential path of the three variables mediate the IoT-service innovation relationship, so the hypothesis is supported.

Value-in-use in a series mediate the relationship between IoT capabilities and service innovation performance. The path investigates the impact of mediations of value-in-use sequentially on the relationship between IoT capabilities and service innovation performance in the healthcare context. The mediating effect is found to be statistically significant ($\beta = 0.018$, $p < 0.01$). Therefore, these results provide sufficient evidence of the connections of value-in-use that mediate the relationship between IoT and service innovation; therefore, the hypothesis is supported.

Value-in-use and co-production is a series which mediate the relationship between IoT capabilities and service innovation performance. This link examines the multiple mediation impact of value-in-use and co-production on the IoT and service innovation relationship. As shown in table 8.14, the path coefficient shows a significant result ($\beta = 0.034$, $p < 0.05$). So the result provides support for the hypothesis.

Chapter 9: Discussion

9.1 Introduction:

This chapter aims to discuss the contribution to theory and contribution to knowledge. It discusses and summarises the findings of the research with respect to the literature and the context of the research questions and hypothesised relationships This chapter also explains the research results and their consistency and contradictions with extant literature, and shows how aim and objectives of the study were achieved on the basis of the discussion, analysis and responding to the research questions. This study was driven by the desire to understand the possible influence of IoT-enabled value co-creation on innovation performance of healthcare service. Preceding studies have highlighted the importance of technology-enabled value co-creation and its possible impact of enhancing innovation performance. Yet, only very few studies have explicitly investigated the effect of IoT-enabled value co-creation on healthcare innovation performance.

This thesis has synthesized the technology-enabled value co-creation research with service innovation research. It hypothesises that IoT capabilities positively influence co-creation practices and service innovation performance. Three key constructs were selected for this study: IoT capability, VCC and service innovation. Issues related to the scales and measures were properly addressed. The measurement scales for IoT capabilities were refined, developed and tested in the context of the Jordanian healthcare sector. Dimension scales for VCC, adaptation and service innovation were adapted from literature. The theoretical framework was tested on a sample of 208 organisations representing all types of healthcare organisations in Jordan.

The sections below demonstrate the key findings arising from this research. The focus of the discussion will be on the theoretical contribution of the study and the method of answering the research questions. This thesis was motivated by the necessity to understand the way IoT technology capabilities offer new avenues for value co-creation by integrating actors' efforts in healthcare services. The prime focus of this thesis is to contribute to the existing knowledge of IoT and value co-creation and to address multiple gaps identified in the literature. The study presented evidence, as discussed in chapter 2, that there has been a paucity of empirical research investigating the influence of IoT-enabled value co-creation and adaptive capability on service innovation in the context of healthcare. Furthermore, far too little attention has been paid to the role of IoT technology capabilities in supporting service innovation performance, particularly in this context. In addition, it was evident that IoT technology and its operational and management potential has seldom been explored. Therefore, this thesis attempts to contribute to the knowledge of this area of research through a conceptual framework presented in chapter 4. The main goal of which is to answer these research questions:

1. What are the IoT capabilities that influence healthcare co-creation practices and consequently impact service innovation performance?
2. What is the relationship between IoT-enabled co-creation and the performance of service innovation?

9.2 What are the IoT capabilities that influence healthcare co-creation practices and consequently impact service innovation performance?

One of the key premises of this study is that IoT has four capabilities comprising of monitoring, control, optimization and collaboration. This study has confirmed that premise by showing that IoT is a second-order construct that consists of four variables (capabilities). The structural model presented in figure 7.3 shows that CFI = 0.933, RMSEA = 0.051, and SRMR = 0.050. This thesis provides an insightful analysis of IoT by examining all capabilities together with validated measures. Four scale measures for the four variables were developed and tested to evaluate the IoT capabilities within healthcare organisations. This result endorses the argument of Wolf, Stumpf-Wollersheim, and Schott (2019) who argue that the four capabilities of IoT (monitoring, control, optimization and collaboration) cumulatively work together and are able to provide three forms of value creation proposed by Mejtoft (2011): "*manufacturing, supporting and value co-creation*". This result is strongly consistent with Porter and Heppelmann (2014) who argue that monitoring, control, optimisation and automation capabilities should be considered as a one group each builds on the preceding one to capture the maximum value and influence the boundaries of the industry.

The IoT technology has greatly contributed to transforming healthcare service towards smart service where the data value chain is shared between the hospital and the patient. The nature of IoT technologies enables actors to collect, analyse and apply data to derive valuable insights that support their decision-making process and develop resultant actions. Results show that among other IoT capabilities, IoT collaboration has the most statistically significant and positive relationship with both co-production and value-in-use. Collaboration represents the outcome of all other capabilities. It demonstrates how the data value chain is shared between the provider (hospital) and the beneficiary (patient) with a high impact on value co-creation. The findings are consistent with Lenka, Parida, and Wincent (2017) proposing that digitalization capabilities are important in expanding the VCC joint sphere and improving the level of the interaction process. This result is in line with the argument of Schüritz et al. (2019) who indicate the role of smart services in expanding the joint sphere of value co-creation based on the nature of data value sharing among actors and how it enables them to co-create more value.

The results agree with arguments that consider IoT as an avenue for transforming the traditional healthcare service into smart service (Stenhaug, Johansen and Johansen 2016; Hofdijk et al. 2016; Sermakani 2014). All four capabilities were found to form prominent measures for the IoT construct with path coefficient values of 0.95 for optimisation, 0.85 for control, 0.65 for collaboration and 0.60 for monitoring, and $p > 0.001$ as presented in SEM model figure (7.3). This result shows that capabilities vary in their contribution to measuring IoT adoption in organisations.

Previous quantitative research has studied IoT capabilities as a one-dimensional construct (e.g. De Vass and Shee 2018; Shafique et al. 2018; Yu, Nguyen and Chen 2016). This thesis is the first empirical study that analyses the benefits of IoT capabilities as a multi-dimensional construct to examine the effect of these four capabilities on the leverage of the competitive advantage of an organisation.

This thesis demonstrates that IoT capabilities positively impact value co-creation related practices. The findings reveal that the IoT managerial capabilities of monitoring and collaboration have a direct and significant influence on two constructs of value co-creation practices: co-production and value-in-use. However, the impact levels of these capabilities on co-creation practices are not equal. This finding represents a strong agreement with the argument of Porter and Hepplemann (2014). The findings also reveal that the greater statistical influence on co-creation comes from the capability of collaboration. This finding supports the analysis of Mejttoft (2011) who conceptualised IoT as a value creation driver through three modes: *manufacturing*, *supporting and co-creative*. Co-creation represents the most influential level among the three modes, where IoT can intelligently connect parties with each other and act as a co-creation partner. However, examining the IoT capabilities separately with VCC reveals that not all capabilities positively impact VCC practices. The hypotheses of positive associations between the control capability and value co-creation constructs were not supported. Also, the hypothesis of a positive influence of the optimization capability with value-in-use related practices was not supported.

9.2.1 Monitoring capability is the foundation for IoT-enabled co-creation:

Monitoring is an essential capability of IoT for advanced technology in healthcare. Health monitoring includes but not limited to the following processes: real-time monitoring (Raji, Jeyasheeli and Jenitha 2016; Cosma et al. 2017; Babar et al. 2017; McWhorter et al. 2017), ambient assisted living (Raji, Jeyasheeli and Jenitha 2016; Zois 2016; Kim and Chung 2017; Wan et al. 2017), detection (Pappas et al. 2001; Zhao, Chaowei and Nakahira 2013; Ahuja et al. 2016; Jara et al. 2010; Torre Diez et al. 2019; Ukil et al. 2016), environmental sensing (Patel, Nanda and Sahoo 2016; Chen 2014;), identification (Antonio Jara et al. 2013; Chen 2014; Ahuja et al. 2016; Atzori 2010), location sensing and sharing (Chen 2014), monitoring of disease progress (Ivascu et al. 2015; Torre Diez et al. 2019), prediction (Alam et al. 2016; Hadjem, Salem and Naït-Abdesselam 2014), remote monitoring (Zhao, Chaowei and Nakahira, 2011), telemedicine (Raji, Jeyasheeli and Jenitha 2016), monitoring the treatment effects of drugs (Torre Diez et al. 2019; Ivascu et al. 2015; Hayati and Suryanegara 2017; Bui and Zorzi 2012; Qi et al. 2017; Patel, Nanda and Sahoo 2016;) and tracking people and objects (Atzori, Lera and Morabito 2010; Hayati and Suryanegara 2017). Monitoring is the first phase of gathering data by connecting to sensor networks, cameras and other terminals.

The result shows that monitoring has a positive and significant influence on both dimensions of VCC. The relationship between monitoring and co-production is statistically positive, with a path coefficient of $\beta = 0.25$, while the connection between monitoring and value-in-use is also found to be positive and statistically significant, with a path coefficient of $\beta = 0.24$.

The findings of this study demonstrate that successful value co-creation heavily depends on how hospitals access, observe, contact, interact and apply their technological knowledge processes. IoT enables the comprehensive smart monitoring of its operations by sensors and other external data sources. Smart monitoring facilitates the compliance of knowledge between actors and continuous patient feedback on services. Previous studies highlighted the direct effect of monitoring capability on the value co-creation between patients and hospitals. IoT-based monitoring capability is able to observe heart trouble, vital signs, mental disorders, panic responses, breathing issues and stress levels. Therefore, monitoring systems of cardiac patients enable the co-creation value to save patient lives (Pevnick et al 2018) in rural areas and in low doctor-to-patient ratio environments (Karkia et al. 2015) through adopting IoT technologies of wireless and wearables sensor technologies. Zois et al. (2016) suggest that an IoT monitoring system models establish platforms of active value co-creation and passive co-creation that require low interaction from patients. They are based on real-time monitoring of patients and personalised treatments and interventions, which meaningfully co-create a real value for patients and doctors by reducing the medical visits and associated cost.

9.2.2 Control and optimization capabilities

Results revealed that there is no significant effect of control capability on value co-creation practices. Hypotheses H2c and H2d predicted a positive effect of IoT control capability on co-production related practices and VIU related practices. However, both hypotheses were not supported by the data analysis of this study. The path coefficient of control effect on co-production was $\beta = 0.02$, whilst the path coefficient of the impact of control capability on VIU was $\beta = -0.01$. Unfortunately, within the constraints of this study, it was not possible to run other tests to confirm this effect because of data limitation.

The findings show that whilst IoT optimization capability is relevant to value co-creation practices that require direct co-working and active interaction with patients, it has no statistical significance for passive co-creation practices that involve less patient-caregiver interaction. This evidence may suggest that in value co-creation between patient and medical organisation through indirect IoT systems an organisation does not impact such practices. Indirect co-creation does not require a high level of interaction, for example, self-service systems. The implication of this finding may suggest that medical organisation focus highly on direct interaction as an outcome of co-creation and use the indirect systems for building relationships (Hoyer et al. 2010).

9.2.3 Collaboration capability cultivates the positive outcomes

The findings also show that efficient co-creation highly depends on how medical organisations communicate, share, remote monitor, remote control, and optimise during their operations. In this study, IoT collaboration capability emerged as an outcome of other IoT capabilities. The results reveal that the impact of collaboration on value co-creation is the highest among the four capabilities. The path coefficient of collaboration-co-production practices is $\beta = 0.34$, while the path coefficient of collaboration and value-in-use connection is $\beta = 0.36$. The value co-creation itself as an overarching concept represents a collaboration style with multiple stakeholders (Prahald and Ramaswamy 2000; Ranjan and Read 2014).

This result is consistent with the findings of Ang (2008) suggesting that collaboration is stronger in technology-intensive organisations. It also endorses the findings of Hagedoorn (1993) who has emphasised technology as a principal factor in creating collaboration and indicated that highly intensive technology adoption has resulted in more intense collaboration. Furthermore, Ding et al. (2010) found that IT adoption enhances collaboration. On the other hand, Ahuja (2000) argues that organisations that adopt high levels of technology are likely to obtain more opportunities to establish collaborations both internally and externally. The findings of this study are congruent with the argument of Iyer (2014), who suggests that technological sophistication leads to extensive collaboration and facilitates sharing of know-how to address challenges of products and services. The emergence of IoT digital health and smart technologies paves the way for collaboration of patients and clinicians by providing easy access to the objective information of patient health. Doctors do not need to rely on the subjective information provided by a neuropathic patient who is unable to sense the deterioration occurring in his own body (Boghossian, Miller and Armstrong 2018). Collaboration may provide organisations with superior performance advantages thanks to efficient routines with partners that streamline the supply chain flows as well as help share knowledge efficiently (Dyer and Hatch, 2006).

The finding of this research supports the organisational capability theory by demonstrating that emergent technologies improve the collaboration capabilities that make organisations more capable of achieving high level of innovation capabilities. This research embodies the implementation of IoT technologies as an organisational capability that involves four different capabilities working together to leverage the internal and external operations to a high level of efficiency and maturity. From the perspective of RBV and organisational capability theory, value co-creation is a capability (Marcos-Cuevas et al. 2016) that is supported by the technological resources of IoT. Drawing upon organisational capability theory, this study conceptualises IoT capabilities as an extension of ICT capabilities, which enable a higher level of organisational capability. Higher-order organisational capability is related to RBV theory and is suggested as a source of performance (Rai, Patnayakuni and Seth 2006). According to organisational capability theory, firms develop their core capabilities to enhance their innovation capability. Organisational capabilities perspective suggests that an organisation has to develop capabilities in order to obtain, integrate and re-allocate resources that are socially and culturally embedded (Rai, Patnayakuni and Seth 2006). This study draws upon the resource-based view and the organisational capabilities theory to suggest that organisations that develop IoT capabilities and leverage them to create a higher-order organisational capability, generate significant performance gain (Rai, Patnayakuni and Seth 2006). However, organisational capability perspective and RBV theory do not see technological capabilities as being capable themselves at developing a sustainable performance (Bharadwaj 2000; Powell and Dent-Micallef 1997).

Overall, the results of the analysis reveal that there are four managerial capabilities for IoT technology: monitoring, control, optimisation and collaboration. However, the influences and interactions of these capabilities with service innovation and value co-creation practices are not equal, and for control capability, the relationship was not supported.

9.3 What is the relationship between IoT-enabled co-creation and the performance of service innovation?

This study investigates the impact of value co-creation on service innovation and explores the role of IoT as an enabler for VCC to influence service innovation in the context of healthcare. This thesis confirms the positive influence of IoT-enabled co-creation on the performance of service innovation (H4a and H4b). However, the impacts of the two co-creation dimensions are not equal. Value-in-use related practices were found to have more impact on service innovation than co-creation related practices.

The result is consistent with the findings of Kim et al. (2020) who posited that value co-creation has a significant and positive impact on the organisational performance of large, small and medium organisations. Wu, Xiao and Xie (2020) found that information technologies enhance the co-creation of service innovation through customer interaction resource sharing and digital engagement. In their findings Yao Wu et al. (2020), highlight the importance of information technology as an integrator of resource heterogeneity to facilitate service innovation.

Unlike Lee (2018) who studied the influence of key VCC elements in healthcare technology from the patients' perspective; this study primarily focuses on the service providers' perspective to examine how technology enables interactions of value co-creation to improve quality and safety of patients. is the results are consistent with the findings of Hsieh and Hsieh (2015) suggesting that dialogue-based co-creation is an effective factor in order for service users to feed organisations with valuable information and knowledge. Chen, Tsou and Ching (2011) argue that adopting dialogue-based co-creation that opens up opportunities for service users to share ideas is a key factor for organisational service innovation.

The findings of this thesis are consistent with the argument of Bitner, Zeithmal and Gremler (2010) that technology has extensively changed the way customers learn about services and it has transformed the nature of service provision and impacted how service is delivered and modified. Technology also plays an important role in resource integration. It provides a dynamic contribution of resource integration and improves individual skills and ecosystem knowledge (Storbacka et al. 2016). In line with this argument, Barile et al. (2020) discuss the role of technology in boosting the synergy of value co-creation processes to produce multiple forms of novelties in products and services. In the same vein, Wang et al. (2013) argue that technology-based services have a direct and positive impact on patient satisfaction and hospital image, and highlights the importance of technology in enabling comfortable service delivery and favourable interactions by using an online appointment system.

This study conceptualises the nature of the value co-creation process as a set of sequence interactions (Breidbach and Maglio 2016) between actors in the ecosystem and their contribution to the process based on their roles. In contrast to Gronross (2011) who argues that the provider and customer work together in an unspecified, all-encompassing value creation process, the analysis and findings of this study show that the provider (caregiver) and the beneficiary (patient) have identified roles in the healthcare co-creation process. This thesis demonstrates that IoT capabilities have transformed the structure of healthcare service delivery through internal collaboration between patient and clinical. In service encounters, patients and caregivers use their operant resources to utilise IoT technologies to co-create value (e.g. obtaining high accuracy of diagnosis to improve care quality). Actors in the healthcare ecosystem co-create value through both direct and indirect interactions (Sweeny et al. 2015, Yi and Ging 2013). Technology supports both ways of interaction through assisted systems for service encounters and an interactive exchange of information (e.g. Mobile apps).

The findings of this thesis are consistent with the argument of Saunders and Baeck (2015), that advanced technology improves the quality of life through a collaborative economy and collective decision-making. It is also consistent with Hoyer et al. (2010) in showing that advanced technologies provide valuable opportunities for value co-creation and work as a motivator for consumer co-creation. Lehrer et al. (2018) conducted multiple case studies to explore the connection between big data technologies and service innovation through the lenses of S-D logic framework. Their main argument is that big data analysis technologies work as key organisational sources of service innovation by enabling service processes that provide value propositions for the customer.

Balaji and Roy (2017) conducted an empirical study that connected IoT technology with VCC to understand customer's interactions with IoT applications while shopping at retail stores. They found that IoT-enabled value co-creation impacts customer continuance intentions and word-of-mouth intentions. The findings of this research emphasise the positive role of technology in human life. Hong and Lee (2018) suggested that the adoption of information technology systems is associated with providing a high quality of care service to patients. It also highlights the role of technology in facilitating collaboration. Carrubbo et al. (2015) argue that IT technology enables the information sharing process by linking researchers, medical staff, patients and industries and enables them to interact, without restrictions of time, location and space. Bharadwaj (2000) argues that information and communication technologies positively influence the organisational performance if associated with human and financial resources. Laurenza et al. (2018) argue that the adoption of digital technologies positively impacts the performance of healthcare business processes. The transformational impact of advanced technology on value co-creation between actors is not new in the literature (Neuhofer et al. 2012; Tilaar and Novani 2015; Storbacka et al. 2015; Breidbach and Maglio 2016; Jiménez-Barreto and Martínez 2018). Neuhofer et al. (2012)

argue that technology should be conceptualised as the key source of innovation and competitive advantage for enhancing effective co-creation process.

The effect of technology in value co-creation has been overlooked in prior research (Storbacka et al. 2016). This thesis extends the managerial perspective on IoT technology and value co-creation literature. The fast pace of developing advanced technologies and its new ways of interaction makes technologies a key part of the co-creation equation (Brynjolfssin and McAfee 2014; Strobacka 2016). IoT and other autonomous technologies offer opportunities for transforming the actor-to-actor interaction. The new form of interaction replaced the human-based interaction with customized and contextual forms human-to-machine interaction (Storbacka et al. 2016).

IoT health technology enables hospitals to manage relationships with patients over distance and time. The results of this research show that IoT monitoring capability has a significant and positive influence on value co-production and value-in-use related practices which emphasises the argument of Lusch, Varg and Tanniru (2010) that digitalization liquefies resources by allowing them to move freely in time and space and affording a profusion of opportunities for connecting resources among actors in novel ways (Nenonen and Storbacka 2018).

This thesis extends the present literature on social exchange theory in the field of IoT technology and healthcare. Social exchange theory has been widely used as a theoretical base in the context of technology, such as e-learning (Zhang et al. 2018), ICT (John et al. 2016; Gal, Jensen and Lyytinen 2014) and online health communities (Yan et al. 2016). The results of the study demonstrate the importance of the role of IoT-enabled VCC in facilitating new and simple ways of exchange between actors to foster service innovation performance. This study demonstrates how technology can support patients who are eager to proactively participate in order to gain intrinsic or extrinsic rewards, as long as they believe that they will obtain higher value-in-use from participation in the delivery of healthcare service, which supports the idea of social exchange theory. This study argues that IoT technology has enhanced the actors' view on the "cost and benefit" feature of social exchange theory. This setting positively influences the relationship between the patient and the hospital, by enabling the patient (who is satisfied with the service provided) to reward the hospital through the value co-creation process. It is not certain that rewards are related to intention to return but include feedback through software applications, word of mouth and participation in hospital social media activities.

The study extends the notion of social exchange theory by emphasising the new social forms of exchange that are developed by the potential benefits of IoT adoption and open up new opportunities of co-production and value-in-use practices. This study contributes to the IoT, healthcare and marketing literature by applying the S-D logic framework of value co-creation and examining the application of social exchange theory to explain the likely relationship between these variables. The findings demonstrate that value co-creation has a significant statistical association with IoT technological capabilities and service innovation performance.

9.4 Theoretical Contribution:

First, the study extends the current literature of RBV by providing a unique insight into IoT capabilities' role through the lens SD logic framework, which contributes to the stream of digital technology research focused on understanding IoT capabilities archetypes and how they interact with value co-creation practices to enhance the organizational performance. IoT should be conceived as an effective mechanism to increase the positive impacts of disruptive and open innovation within the organisation (Shin 2017). The study also, proposes an empirical evidence for IoT capabilities' direct and interactive effect on value co-creation practices (Barney, 1991, Burgelmn, Maidique and Wheelwright, 2004, Sjödin, Parida and Kohtamäki 2016; Porter and Heppelmann 2014). It also, broadens a set of technology's capabilities considered earlier (Porter and Heppelmann, 2014; Wolf, Stumpf-Wollersheim and Schott, 2019; Suppatvetch Godsell and Day, 2019) by drawing on the smart technology field to identify particular capabilities (monitoring, control, optimisation and collaboration) that is related to the IoT and consistent with resource-based logic. It also examines the value of these capabilities within the healthcare context. It complements the findings of (Wetering, Versendaal and Walraven 2018) that medical organisations that invest in information technology will outperform other medical organisations in terms of digital capabilities. Drawing on the resource-based view, Mata et al. (1995) found that managerial information technology capabilities have a high potential to be a source of sustainable competitive advantage. The RBV theory has spread to various management fields, which creates some opportunities for "cross-fertilising" insights from several contexts (Lioukas, Reuer, and Zollo 2016). Therefore, this study represents an early step in this direction.

Second, the study provides analyses of the relevance of specific digital technological capabilities and resources available for innovative value co-creation, which has remained relatively unexplored in the smart technology literature in the framework of resource-based view theory. The sustainability of digital technologies permits organisations to detect and respond to opportunities and threats in the market, such as securing resources against imitation, transfer, or substitution (Wade & Hulland, 2004). This shed light to the importance of business and technology combination and extends the argument of (Choe, 2003; Liang & You, 2009; Tang, Seng Ee and Phang 2018) that the factors of sustainable competitive advantages of technological systems can be achieved by the greater alignment between business and technological system strategies. The findings of the IoT collaboration capability are in agreement with previous studies of corresponding synergies with internal and external organisational resources (Hulland et al., 2007; Ravichandran & Lertwongsatien, 2005). Moreover, the study adds knowledge on the management of smart technology in a new context of analysis, (the medical IoT capabilities), which present a highly innovative technology mechanism with a wide variety of benefits (Chen, 2014, Raji, Jeyasheeli and Jenitha, 2016; Zois, 2016; Kim and Chung, 2017). The results of the study are strongly consistent with Porter and Heppelmann (2014). They argue that monitoring, control, optimisation and automation capabilities should be considered one group, each builds on the preceding one, to capture the maximum value and influence the boundaries of the industry. The findings of this research statistically show that collaboration capability represents the outcome of all other IoT capabilities and endorses the findings of Ang (2008) that collaboration capability is greater in technology-intensive organisations than other types of organisations.

Third, this study contributes to the literature on value co-creation by establishing empirical evidence to show that IoT capabilities are an antecedent of value co-creation. The study arrived at this conclusion by using a validated scale for value co-creation in services. The study shows that introducing IoT technology to the domain of healthcare influences the providers' and customers' joint sphere of value co-creation in multiple ways that are empowered by the potential benefits of IoT. These methods include interaction, access to customer processes and decision-making power (Schüritz et al. 2019). IoT can provide a wide range of interactions, which offer opportunities for more and deeper understanding of patient needs. The results of this study demonstrate that IoT monitoring, optimization and collaboration capabilities significantly and positively influence value co-creation related practices. It also shows that IoT establishes a new language of interaction and a new way of accessing customers' processes and behaviour and collectively share the decision-making power among actors. Consequently, IoT technologies greatly contribute to the expansion of the joint sphere and real value co-creation activities.

Fourth, the study is distinctive because it is the first research that provides a clear identification and an in-depth analysis of the "Internet of Things" capabilities and their impact on the value co-creation practices in healthcare organisations. The study develops and tests a measurement scale for the four IoT capabilities of monitoring, control, optimization and collaboration. This thesis describes the managerial capabilities of IoT and how they support the service innovation in healthcare through facilitating value co-creation and developing adaptive capability. Prior literature focusses on IoT capability as one-dimensional construct (De Vass, Shee and Miah 2018; Shafique et al. 2018; Yu, Nguyen and Chen 2016). This study outlines and deeply analyses four IoT capabilities based on an extensive review of the relevant literature.

Fifth, the study adopted a comprehensive approach, where the two types of resources (technological and social capital) were analysed and offers an enhanced view of the determinants of healthcare service innovation. In fact, the study illustrated the impact of digitalization and smart technology (IoT) on service innovation, directly and indirectly via the S-D logic framework. Therefore, this thesis responds to the calls of several researchers (Zheng et al. 2018; Andersson and Mattsson 2016) to address this gap in service innovation literature particularly in developing countries. This study demonstrates that IoT is not just a tool for automating existing healthcare practices and processes nor a hardware or software technical fixes. IoT is a true enabler of healthcare service outcomes and a smart system that creates real reform, which has considerable benefits for the whole healthcare ecosystem. In the same vein, the study highlights the importance of effectively managing service innovation and using information and communication technology tools and competencies to increase the gains of organisational knowledge management orientation (Darroch 2005). The study also, complements prior studies on the effects of IoT capabilities on organisational innovation performance. Actually, despite many studies and arguments, the empirical evidence of the effect of IoT capabilities on performance is rather limited (De Vass, Shee and Miah 2018).

Sixth, the study proposes a conceptual framework on how IoT, as a new smart technology in developing countries (e.g. Jordan), reshapes the dyadic relationship between actors and redefine their roles by promoting a new digital service delivery, which, in turn, enhances the service innovation performance in the healthcare context. The methodology of this study is different from previous studies. Most of IoT technology studies are conceptual (Gubbi et al. 2013; Kawsar et al. 2010) and qualitative (Balta-Ozkn et al. 2013), but quantitative studies are rare (Balaji and Roy 2017).

In summary, this study has made theoretical and practical contributions to knowledge on RBV, value-co-creation, IoT and innovation. The results and implications of the findings go beyond value co-creation practices and service innovation performance in the healthcare context, but they are also applicable to any organisation that installs, develops and implements IoT technologies in its operations.

9.5 Managerial Implication

This study has implications in terms of how healthcare organisations develop mutual values by leveraging IoT capabilities and organisational adaptive capability. First, considering that value co-creation with customers and obtaining the benefits from the value created is a concern for medical organisations, the study has demonstrated that possessing IoT smart technological capabilities is important for developing a potential value through co-creation. This thesis highlights the significant contribution of IoT capabilities to value co-creation practices and finds that monitoring capability and collaboration capability are important capabilities that organisations should obtain and develop to co-create real value with their customers.

Second, managing the interaction between the organisation and the beneficiary through IoT technology is a key capability that contributes to increasing the competitive capacity of the organisation. The use of this emerging technology does not entail shifting the responsibilities from the organisation to the patient in particular tasks, rather, it provides patients with the opportunity to effectively co-create value. Healthcare organisations should maintain highly trained staff capable of managing IoT effectively, and promptly responding to patients' needs. The adoption of IoT technology enables organisations to co-create a unique value when they work together closely with their customers by utilising IoT's collaboration capability.

Third, by establishing the connection between IoT capabilities and organisational performance innovation, this study serves to inform managers and practitioners that investment in IoT and smart technologies alone is not sufficient. They should work on creating organisation-wide IoT capabilities. Through theoretical arguments and examples, this research shows that building IoT capabilities is complicated and requires time and effort. Although there is an increasing number of studies relevant to IoT technology, there is little attention on approaches of IoT adoption.

The findings of this research show that the adoption of IoT technology is an important decision that enhances the performance of organisational innovation and enables organisations to compete against rivals. Li et al. (2012) propose the "topology of IoT strategic decision" to guide management while implementing IoT technology. They present two approaches of IoT adoption from the strategic management perspective to achieve organisational innovation get-ahead and catch-up. In their argument, they describe the IoT get-ahead approach as a set of plans and actions that are designed and implemented earlier than other competitors, therefore, organisations obtain a competitive advantage in IoT technology by being a first-mover. On the other hand, a catch-up strategy is a set of plans and actions that are developed and implemented to create IoT capability through imitating and learning from industrial leaders' strategies. Management should be aware that building IoT capabilities implies an efficient strategic decision. The implementation of IoT technology enables organisations to recognize new business opportunities and threat possibilities and obtain competitive advantage (Yu, Nguyen and Chen 2016).

Fourth, the findings of this study show that a patient's value plays an important role in healthcare organisation value. As a result, caregivers who endeavour to deliver superior value and offer high-quality benefits to their patients must ensure that they have a full understanding of their patient's value and then utilise IoT capabilities to support the delivery of such value. At the same time, organisations should ensure that the patient is effectively engaged in the service interaction and understand what to do and how to do it (Payne et al. 2008). The findings of this study show that the main reason for co-creation is that the healthcare provider and patient collaboratively work together in a manner that creates value for the medical organisation as well as the patient.

9.6 Limitations and recommendations for future research

While this study offers important insights into IoT-enabled value co-creation in healthcare services, it is not without limitations, which may offer avenues for future research. First, this research has investigated value co-creation at organisational level. The results of this study suggest very insightful implications from focal organisations' perspective. However, the study uses a single key informant (health caregiver) to evaluate value co-creation in an IoT adoption environment, which may not capture the aspects of the whole healthcare ecosystem that might have an impact on innovation performance. This can be an opportunity for future research to incorporate the perspectives of the patient and the other actor's such as family, friends, and administration and examine value co-creation at various levels of analysis considering the industry level and the whole ecosystem.

Second, this study has focused on the positive impacts of value co-creation, with emphasis on organisation and patients value. However, the implicit risk of value co-destruction (Echeverri and Skålén 2011; Harris et al. 2010) was overlooked. Value can be destroyed through interaction between actors because of resource misuse either accidentally or deliberately (Harris et al. 2010). Therefore, exploring the potential effects of co-destruction practices would be an interesting extension of this work.

Third, the research methodology of this study is a cross-sectional research design, and the collected data did not examine time as a variable in this study. Although this study provides a solid cross-sectional framework that can be considered as a basis for future research to establish causality between IoT capabilities and service innovation performance; readers should apply caution when drawing the inferences about the cause-effect relationships and the outcome of this research should be interpreted as supporting a prior cause-effect framework, not as evidence of an underlying causality relationship. Hence, it would be an opportunity for future work to design a longitudinal research study to obtain a deeper insight and confirm the cause-effect relationships and assess the innovation performance over time.

Fourth, future research studies could build on this work and examine the potential effects of IoT capabilities (monitoring, control, optimization and collaboration) on the relationships with outside partners of the organisation. The IoT technology is a network system that can effectively connect an organisation with external partners such as suppliers, communities, government, universities, institutions and R&D labs.

Fifth, the study has focused on IoT technological adaptation mostly during the short period after the adoption. It would be an opportunity for future work to investigate how organisations develop technological adaptation over time.

Lastly, the limitation of this research is the relatively small sample size of 208 organisations. Even though this sample was sufficient to accomplish the objectives of this study, a larger scale survey would do better in solidifying the findings and results. Also, the study was restricted to one country (Jordan) and to the context of healthcare. Therefore, future research could extend this work by evaluating the conceptual model in other research contexts.

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Appendices

Appendix A, the research questionnaire

Research Questionnaire

Technology in Healthcare service

Medical technologies are the devices and systems developed to solve a health problem and enhance the quality of lives.

You are invited to participate in this study that investigates how "health technology supports the innovation performance of healthcare services. We have estimated that it will take you approximately 20-25 minutes to complete this survey. Participation in this survey is voluntary; **all information will be confidential**, and your organization will not be identified; only the researcher will have access to the information of the survey.

For more information:

Please contact the director of studies Professor Halim Boussabaine, telephone 00971 4 279 1400 Ext: 437, email halim@buid.ac.ae, or the student researcher Radwan Al Jbour 00971563398681, email 20170032@student.buid.ac.ae

Part one

Q1.1 Please rate your level of agreement with the following statements on healthcare technology support

	Statement	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
MON1	Tracking individual items							
MON2	Track behavior of individuals							
MON3	Observe the environmental condition							
MON4	Observe the performance of individuals							
MON5	Observe the performance of equipment							
MON6	Observe the performance of service							
MON7	Provide real-time information							
MON8	Provide vitals observations							
MON9	Provide real-time analytics							
MON10	Quickly identify performance issues							
MON11	Detect potential security vulnerabilities							
MON12	Predict patients flow							
MON13	Observe and track medical assets							
MON14	Observe waste reduction							
MON15	Log patients' complaints							
MON16	Detect patterns and anomalies in collected data							

Q1.2 Please rate your level of agreement with the following statements on healthcare technology support

	Statement	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
CON1	Control performance KPIs							
CON2	Control the extent to which organization attain performance goals							
CON3	Enable management to control healthcare service activities							
CON4	Evaluation of the quality of healthcare service							
CON5	Support swift corrective action							
CON6	Identify problems							
CON7	Enhance the troubleshooting process							

CON8	Enhance the business performance							
CON9	Enhance business insights							
CON10	Support the efficiency/productivity gain.							
CON11	Control expectations							
CON12	Control progress							
CON13	Evaluate staff activities							
	Statement	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
CON14	Appraising work in progress							
CON15	Improving results							
CON16	Regulating performance							
CON17	Correcting deviations from standards							
CON18	Measuring performance against the standards							
CON19	Predict future performance							

Q1.3 Please rate your level of agreement with the following statements on healthcare technology support

Statement	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Provide enough information to use resources efficiently							
Provide real-time information for efficient operations							
Provide real-time information to improve practices							
Provide large volume-variety of data to improve processes							
Provide large volume-variety of data to minimize the cost							
Provide real-time information to reduce waiting time							
Immediately detect an automaton-based situational event (e.g. gas alert)							
Enhance the prediction of demand and inventory							
Increase customer retention							
Increase service reliability							
Support process re-engineering							
Support change management							
Accelerate innovation							
Potential of new health care delivery models							

Q.1.4 Please rate your level of agreement with the following statements on healthcare technology support:

Statement	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Strengthen information sharing within the organization							
Facilitate interaction among parties within/out of the organization							
Facilitate relationships among parties within/out of the organization							
Provide real-time communication							
Statement	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Provide real-time collaboration							
Facilitate the participation of patient and staff							
Facilitate cooperation of parties with and out of the organization							
Improve patient satisfaction							
Provide information on network performance							
Provide real-time visibility of activities Provide							
Provide real-time visibility of service status							
Improve service insights and patient experience							

Part two

Q2.1 Please rate your level of agreement with the following statements:

Statement	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
My organization is open to the patient's ideas and suggestions about existing services or towards developing a new service.							
My organization provides sufficient illustrations and information to the patient							
In my organization patient would willingly spare time and effort to share his ideas and suggestion in order to help it improve its services and processes further							
My organization provides suitable environment and opportunity to the patient to offer suggestions and ideas							
My organization provides easy access to information about the patient's preferences							
The processes of service development are aligned with patient requirements (i.e. the way we wish them to be)							
My organization consider patient roles to be as important in the process of service creation							

My organization share an equal role with patients in determining the final outcome of the treatment process.							
During the process of service development, patients could conveniently express their specific requirements							
My organization convey to its patients the relevant information related to the treatment process							
My organization allows sufficient patients interaction in its healthcare processes (healthcare service development, assisting other patients)							
In order to get the maximum benefit from the treatment process, my organization plays a proactive role during interaction with patients							

Q2.2 Please rate your level of agreement with the following statements:

Statement	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
My organization creates a memorable experience for patients.							
Depending upon the nature of individual participation, patient experiences in the process might be different from other patients							
It is possible for a patient to improve the process by experimenting and trying new things							
The benefit, value, or fun from the process (or, the service) depend on the user and the usage condition							
My organization tries to serve the individual needs of each of its patients							
Different patients, depending on their taste, choice, or knowledge, involve themselves differently in the process (or, with the service)							
My organization provides an overall good experience, beyond the “functional” benefit							
In my organization, the extended facilitation is necessary for patients to enjoy the process (or, the service) fully							
Our employees feel an attachment or relationship with the patients							
There is usually a group, a community, or a network of patients and customers who are a fan of my organization							
My organization is renowned because its patients usually spread the positive word about it in their social networks							

Part Three:

Q3.1 Please rate your level of agreement with the following statements:

Statement	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
In my organization, the average cost of developing a new service is less than those of other competitors							
In my organization, the number of new services developed annually is more than those of competitors.							
In my organization, the costs of new services are less than those of competitors.							
Statement	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
In my organization, the time to develop a new service model is less than those of Competitors							
In my organization, the time from development of new service models to entry is less than that of competitors.							
My organization achieved better cost efficiency than competitors							
My organization is exceeding the growth target (e.g. obtained more new patients than planned)							
My organization seeks to obtain competitive advantages (e.g. new offerings, innovative services)							
In my organization, the service quality we provide is better than those of competitors.							
In my organization, we provide higher reliability service than those of competitors (e.g. patients never seek for different treatment by other competitors)							
In my organization, the service provided has higher customer satisfaction than competitors.							

Q3.2 Please rate your level of agreement with the following statements:

Statement	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
My organization regularly analyze a wide variety of opportunities for improvement and adapt our business model accordingly.							
In my organization, managers at all levels actively and visible support innovation.							
In my organization, changes are simple, focused and clearly communicated.							
In my organization, we view incongruities and inconsistencies as opportunities. (e.g. disagreement of opinions)							

In my organization, senior management recognizes innovation as everyone's responsibility.							
In my organization, we often reject easy answers and search for more deep ones.							
In my organization, we believe that doing business in a normal way is not sufficient.							
In my organization, change opens opportunities for growth and gain.							
Learning is one of our core values.							
In my organization, incentives reinforce change; they do not drive it.							
I know what is important to me and use this knowledge in making decisions							
Statement	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I assess my strengths and weaknesses, outline ways to grow, and establish short- and long-range goals for my career.							
I can organize my surroundings and prioritize tasks, even in stressful times.							
I can usually think of several alternatives to solving a problem.							
I believe that I always have options and choices, even in difficult situations.							
I regularly spend time keeping my knowledge and skills current.							

Demographic

Please provide the details below:

1. Type of your organization
☐ Public ☐ Private ☐ Semi-Government ☐ Not for profit

2. Size of your organization (number of employees)
☐ 1 - 49 ☐ 50 - 999 ☐ 1,000 - 4,999 ☐ 5,000 or more ☐ Don't know

3. Job level
☐ Employee ☐ Middle Management ☐ Top Management

4. No. of total years of work experience
☐ 0 – 2 ☐ 3 – 5 ☐ 6 - 10 ☐ 11- 19 ☐ 20 or above

5. Educational level
☐ High school graduate or Less ☐ College degree
☐ Higher Diploma/Bachelor degree ☐ Masters ☐ Doctorate or above

6. Your email (Optional) if you want to receive a summary and key finding of the study

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Thanks for successfully completed the questionnaire

Appendix B:

Items dropped through IoT scale validation stages

Item code	Items dropped after expert review
MON9	Quickly identify performance issues
MON15	Log patients' complaints
MON16	Detect patterns and anomalies in collected data
CON1	Control performance KPIs
CON6	Identify problems
CON8	Enhance the business performance
OPT12	Support change management
Item code	**Items dropped after EFA**
MON6	Observe the performance of service
MON7	Provide real-time information
MON8	Provide vitals observations
MON10	Provide real-time analytics
MON11	Detect potential security vulnerabilities
MON12	Predict patients flow
MON13	Observe and track medical assets
MON14	Observe waste reduction
CON2	Control the extent to which organisation attain performance goals
CON3	Enable management to control healthcare service activities
CON4	Evaluation of the quality of healthcare service
CON5	Support swift corrective action
CON7	Enhance the troubleshooting process
CON9	Enhance business insights
CON10	Support the efficiency/productivity gain
CON11	Control expectations
CON12	Control progress
OPT5	Provide large volume-variety of data to minimize the cost
OPT13	Accelerate innovation
OPT14	Potential of new health care delivery models
COL5	Provide real-time collaboration
COL8	Improve patient satisfaction
COL9	Provide information on network performance
COL10	Provide real-time visibility of activities Provide
COL11	Provide real-time visibility of service status
COL12	Improve service insights and patient experience
Item code	**Items dropped after CFA**
OPT1	Provide enough information to use resources efficiently
OPT2	Provide real-time information for efficient operations
COL2	Facilitate interaction among parties within/out of the organisation
COL3	Facilitate relationships among parties within/out of the organisation