A MODEL FOR CLOUD BASED ELECTRONIC HEALTH ADOPTION AMONG IT PROFESSIONALS IN SAUDI ARABIA HOSPITALS

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DOCTOR OF PHILOSPY
UNIVERSITI UTARA MALAYSIA
2025

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Abstrak

Sektor penjagaan kesihatan di Arab Saudi sedang mengalami transformasi penting yang dipacu oleh integrasi teknologi canggih, khususnya pengkomputeran awan, bagi meningkatkan kecekapan operasi, kebolehcapaian, dan kualiti penjagaan perubatan. Kajian ini meneliti faktor-faktor yang mempengaruhi penerimaan pengkomputeran awan dalam sektor e-kesihatan di Arab Saudi, dengan memberi tumpuan kepada kesan pemoderasi pengasingan jantina dalam rangka kerja Visi Saudi 2030. Pendekatan kuantitatif telah digunakan, di mana data dikumpulkan daripada 304 profesional penjagaan kesihatan melalui soal selidik berstruktur dan dianalisis menggunakan Pemodelan Persamaan Struktur Kaedah Kuasa Dua Terkecil Separa (PLS-SEM).

Dapatan kajian menunjukkan bahawa jangkaan prestasi dan keadaan fasilitasi mempunyai hubungan positif yang signifikan terhadap penerimaan pengkomputeran awan. Walau bagaimanapun, pengaruh sosial menunjukkan kesan negatif yang signifikan terhadap penerimaan pengkomputeran awan, yang mencadangkan bahawa peraturan dan dasar tertentu mungkin menghalang keputusan untuk menerima pakai teknologi ini. Selain itu, pengasingan jantina menunjukkan kesan langsung yang signifikan secara positif terhadap penerimaan pengkomputeran awan, yang menunjukkan bahawa norma budaya dapat membentuk tahap penerimaan teknologi dalam organisasi penjagaan kesihatan.

Analisis pemoderasian selanjutnya mendedahkan bahawa pengasingan jantina memoderasi secara signifikan hubungan antara jangkaan usaha, keadaan fasilitasi dan penerimaan pengkomputeran awan, manakala tiada kesan pemoderasi yang signifikan diperhatikan bagi jangkaan prestasi dan pengaruh sosial. Kajian ini menyumbang kepada literatur inovasi e-kesihatan dengan memperluas rangka kerja **Teori Penyatuan Penerimaan dan Penggunaan Teknologi (UTAUT)** melalui pertimbangan budaya. Kajian ini mengesyorkan agar pembuat dasar dan pengurus penjagaan kesihatan menyelaraskan strategi pengkomputeran awan dengan mekanisme sokongan organisasi dan sensitiviti budaya bagi mempercepatkan kadar penerimaan di Arab Saudi.

Kata Kunci: Pengkomputeran Awan, E-Kesihatan, Pengasigan Jantina, Teori Penyatuan Penerimaan dan Penggunaan Teknologi (UTAUT), Visi Saudi 2030, Transformasi Penjagaan Kesihatan.

Abstract

The healthcare sector in Saudi Arabia is undergoing a pivotal transformation driven by the integration of advanced technologies, notably cloud computing, to enhance operational efficiency, accessibility, and the quality of medical care. This study investigates the factors influencing cloud computing adoption in the Saudi Arabian e-health sector: the moderating effect of gender segregation, within the framework of Saudi Vision 2030. A quantitative approach was employed, with data collected from 304 healthcare professionals through structured questionnaires and analyzed with PLS-SEM. The findings revealed that performance expectancy and facilitating conditions are positively significantly to cloud computing adoption. However, social influence revealed negative significant effect on cloud computing adoption suggesting that regulation and policies may hinder cloud computing adoption decisions.. Moreover, gender segregation demonstrates a direct positive significance on adoption of cloud computing, indicating that cultural norms can shape technology acceptance in healthcare organizations. Moderation analysis further reveals that gender segregation significantly moderates the relationship between effort expectancy, facilitating condition and cloud computing adoption, while no significant moderating effects are observed for performance expectancy and social influence. The study contributes to the literature on e-health innovation by extending the Unified Theory of Acceptance and Use of Technology (UTAUT) framework with cultural considerations. The study recommends the need for policymakers and healthcare managers to align cloud computing strategies with organizational support mechanisms and cultural sensitivities to accelerate adoption in Saudi Arabia.

Keywords: cloud computing, performance expectancy, effort expectancy, social influence, facilitating condition, gender segregation

Acknowledgement

First and foremost, I would like to express my deepest gratitude to Allah Almighty for granting me the strength, patience, and perseverance to complete this PhD journey. Without His guidance and blessings, this achievement would not have been possible.

I extend my sincere appreciation to my supervisors, Associate Professor Dr. Mohammad Shahbani Abdullah and Dr. Maslinda Binti Mohd Nor, for their continuous support, valuable guidance, and constructive feedback throughout the research process. Their mentorship, encouragement, and insightful advice have been instrumental in shaping the direction and quality of this study.

I am also deeply grateful to the faculty members and staff of the Awang Had Salleh Graduate School of Arts and Sciences (AHSGS) and the School of Computing, Universiti Utara Malaysia (UUM) for their academic support and administrative assistance during my study period.

My heartfelt thanks go to all the healthcare professionals in Saudi Arabia who participated in this research and generously shared their time, experiences, and perspectives, which made this study possible.

To my family, I owe an immeasurable debt of gratitude — to my husband for his endless encouragement, to my children for their patience and love, and to my siblings for their constant prayers and belief in me. Their unwavering support has been my greatest motivation.

Finally, I would like to dedicate this thesis to the memory of my late parents, whose endless love, prayers, and sacrifices continue to guide and inspire me every day.

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CHAPTER ONE
Introduction

1.1 Introduction and Background

In recent years, information and communication technology (ICT) has been applied to many different domains. For instance, commerce and education and finance (e.g. banking, insurance) are common examples of domains that utilize ICT in their daily operations. The main drive behind this evolution is the ICT's capability and benefits in harnessing operations. It redefining the methods of providing services: how services are designed, offered, utilized and managed. It is widely perceived to have the capability to improve access and provide a wider range of services, increasing efficiency through enhanced connectivity and exchange of data and knowledge.

This utilization of ICT and other related technologies in healthcare delivery has given birth to the concepts of e-Health (Alahmadi, 1995). E-Health, as defined by Busse et al., (2022) , refers to the field of health information and services provided or enhanced through internet and related technologies, which intersects the edge of medical informatics, public health and business. It is a topic that deals with the devices, clinical guidelines and methods required to improve the quality and management of services and information in the healthcare sector (Eysenbach, 2001; Xiong et al., 2023).

In Middle East, healthcare services have witnessed unprecedented positive changes owing to the advent of ICT, which has revolutionized healthcare representation. Recently healthcare delivery no longer looks like it did in the past; ICT has advanced the capabilities of physicians, caregivers and health organization staff to provide better service to patients and citizens in general. It has facilitated the responsibility of health professionals, physicians and health organisations to provide the health services required by individuals every day (Busse et al., 2022).

In recent years, electronic health (e-health) cloud computing has emerged as a powerful tool for healthcare organizations to streamline care delivery, improve healthcare services and reduce costs. According to Chang et al., E-Health cloud computing refers to integrating cloud computing technologies and digital health services to support efficient management, access, and use of patient-centric healthcare data (Chang et al., 2021). Furthermore, E-health is an emerging field in the intersection of medical informatics, public health and business, referring to health services and information delivered or enhanced through the internet and related technologies. In a broader sense, the term characterizes not only a technical development, but also a state-of-mind, a way of thinking, an attitude, and a commitment to networked, global thinking, to improve healthcare locally, regionally, and worldwide by using information and communication technology.

The future of computing is said to lie in cloud computing technology, where the main objective is to reduce the cost of IT while increasing productivity, availability, reliability, and flexibility and minimizing response times (Alsenea, 2015). Hence, the healthcare sector across Middle East to realize the possible advantages that cloud computing can bring and is willing to apply it. Adoption of cloud clouding in the health care system can give benefits in self-service, scalability, flexibility, pay-as-you-go, and develop time-to-value of technology. Offering of pay- as-you-go services, will give users the opportunity to pay only for the resources they actually utilize, for a specific time period (Hu, 2017).

In addition to that cloud computing offers many advantages, such as economy of scale, efficiency, management, availability, consolidation, cost and energy savings, etc. This helps cloud users to better utilize computing resources and to minimize costs (Hu, 2017). Also, Adoption of cloud computing technology will significantly decreases the cost to government organizations in using information technology (IT) services, and this makes the adoption of this in the public health sector more attractive.

With its immense potential, it has become increasingly popular in the medical and healthcare sectors and is transforming how medical records and healthcare services are delivered and managed. The advancement of healthcare technology and systems continuously provides new opportunities for health institutions worldwide to deliver improved, more cost-effective healthcare services to their communities (Al-Moghrabi et al., 2021; Al-Mutairi, 2022; Idoga, 2018).

The main goal of cloud computing is to reduce cost of IT while increasing productivity and enhancing collaboration (Almazroi et al., 2019; Brian, 2008). Cloud computing offers healthcare organizations an array of benefits; economic, operational and functional benefits. The economic benefits of cloud computing include less capital expenditure, lower maintenance cost, reduced IT labour costs and energy savings. The operational benefits include unlimited computing resources, enhanced collaboration, a 24 hour platform and improved security. Lastly functional benefits is the potential for broad interoperability and integration (Cloud council, 2017; Saslow, 2014).

Al-Mutairi et al. indicated that electronic health is an area that has received growing attention from healthcare professionals, health system administrators, and technology providers in recent years, and its increased use is rapidly changing the face of healthcare around the world (Al-Mutairi, 2022; Okikiola, 2020). Cloud computing offers an enormous opportunity for the healthcare system in Saudi Arabia to become more productive and successful, especially for e-Health solutions (Ibrahim et al., 2022).

The primary objectives of any health delivery system are to enable all citizens to receive health care services whenever needed, and to deliver health services that are cost- effective and meet pre-established standards of quality according to World Health Organization (WHO, 2010). The health care delivery in both high, low and middle income countries have been shown to fall short of these ideals (Brandeau, Sainfort & Pierskalla, 2008; Xiong et al., 2023).

In an effort under the Saudi Vision 2030 initiative to enhance healthcare efficiency and digital transformation within the country, Saudi Arabia introduced cloud computing to the healthcare sector in 2016.

Furthermore, the Vision 2030 plan, which was launched by the Saudi government in 2016, includes a comprehensive strategy for transforming the healthcare system. Saudi Arabia, with its ambitious Vision 2030 initiative, is actively embracing digital innovation in the healthcare sector. The plan aims to create a healthcare system that is more patient-cantered, innovative, and accessible to all citizens. It also emphasizes the importance of preventive healthcare and health education.

Saudi Arabia has been undergoing significant social reforms, particularly related to women's rights and the adoption of cloud computing. While gender segregation in public spaces was once a common practice, recent policies have aimed to relax these restrictions, particularly in restaurants and public events. Concurrently, Saudi Arabia is actively promoting cloud computing adoption through its "Cloud First Policy. Thus, The Kingdom has implemented gender-inclusive policies and laws at a local level by the 2030 Vision. These measures aim to provide women with equal rights and opportunities in all disciplines and sectors without any discrimination based on gender.

Gender is one of the factors that attracted the attention of various researchers especially in the context of developing countries and KSA is no exception, a number of enquiries were conducted in the KSA context, for instance a technology acceptance study in KSA context found that there is a significant difference between male and female acceptance on technology where male citizens were found to be more accepting to technology compared to their female counterparts. (Al-Gahtani, 2004; Almazroi et al., 2019). In contradiction, another study reports that gender has no significant impact on technology acceptance in KSA context (White Baker, Al-Gahtani, & Hubona, 2007).

Under vision 2030, led by Crown Prince Mohammed bin Salman, aims to modernize the kingdom socially and economically, which includes significant easing of gender segregation laws: Women in the Workforce: One of the major goals is to increase female participation in the labor force from 22% to over 30%, which was already surpassed by 2021. Gender-mixed workplaces are now permitted in many sectors, including retail, finance, hospitality, and government offices.

As more countries keep going to cloud computing for e-Health, there is the possibility for the whole health sector in Saudi Arabia to transform for the better and meet the increasing need for quality care. Therefore, this research will evaluate the adoption of e-Health cloud computing systems in Saudi Arabia.

As of recent reports, approximately 38.6% of hospitals in Saudi Arabia have adopted cloud computing technologies, driven largely by initiatives from the Ministry of Health to enhance operational efficiency and data management, especially in response to the COVID-19 pandemic (Alaboudi et al., 2016; GMI Research, 2022).

However, this adoption rate lags behind other sectors such as banking and industry. The banking sector, for instance, has a cloud adoption rate of about 74%, utilizing cloud services for enhanced security, scalability, and improved customer service (IDC, 2023). Similarly, the industrial sector, including IT and telecom, shows a cloud adoption rate of around 65% (IDC, 2023). The slower adoption in healthcare is attributed to concerns over data privacy and security, challenges with digital infrastructure, and the high initial costs of transitioning to cloud systems (Alaboudi et al., 2016; Mogeb. Alshahrani et al., 2024). Additionally, the unique environmental and cultural context of Saudi Arabia further complicates the adoption process.

The cultural norms, particularly the strict regulations on gender segregation and separation, create logistical challenges for implementing unified digital systems that require seamless interaction between male and female healthcare professionals (Goniewicz et al., 2024; Alaboudi et al., 2016). This cultural aspect demands additional layers of security and privacy, thereby increasing the complexity and cost of cloud computing solutions in healthcare. Addressing these multifaceted challenges is essential to accelerate cloud adoption in the healthcare sector and bridge the gap with other more agile sectors.

Several studies in various fields have revealed that revealed gender segregation to have influences on performance. For instance, previous studies revealed that gender diversity have positive influence on performance; there are studies also that report a negative relationship or no relationship at all (Andrieș et al., 2017; Andries & Capraru, 2013). Riquelme and Rios, (2010) studied the moderating effect of Gender in the adoption of mobile banking. (Presbitero et al., 2014) also investigated that gender-based discrimination in credit markets. Gender difference is also studied in entrepreneurship and financial inclusion (Saviano et al., 2017).

Gender is also measure as mediator variable by Tan et al., (2025) while investigation the mediating effect of digital financial inclusion on gender differences in digital financial literacy and financial well-being: Evidence from Malaysian households. Furthermore, Almarazroi et al., (2019) investigated gender effect on cloud computing services adoption by university students: Case study of Saudi Arabia. Hence this study will measure gender segregation as a moderating variable between factors influencing E-health and cloud computing adoption in Saudi Arabia.

For several years, Saudi Arabia has been actively striving to transform its healthcare system into an effective one that uses cutting-edge medical technology and information systems (AlQudah, 2021; Mekawie, 2021). One of the central objectives of the Saudi National eHealth Strategy is to establish a thorough, interconnected national e-health platform with cloud computing at its core. This plan entails using cloud computing for functions such as electronic health records, e-prescription systems, and telemedicine, among other e-health services.

There has been a considerable surge in the use of e-Health cloud computing systems in Saudi Arabia over recent years (Sadoughi et al., 2020; Abrar, 2018). As noted by Sadoughi et al. (2020), the key advantage of applying cloud computing in e-Health lies in its potential to cut down costs. Specifically, cloud computing will help the Saudi healthcare system save money by eradicating hardware and IT maintenance expenses, since it does away with the necessity for physical data centers and simplifies access to medical records, e-prescriptions, and other e-health tools. In addition to that, cloud computing provides more flexibility since cloud-based software can be adjusted or modified to address changing patient demands and present prerequisites for e-Health services (Ibrahim et al., 2022). Consequently, various healthcare institutions are progressively abandoning traditional methods and embracing this new technology to tap into the numerous benefits it offers for e-Health cloud computing.

In addition, deploying cloud-based solutions and services for e-Health enables rapid deployment of solutions with fewer errors and less time than traditional development (Al

Otaibi, 2019). Al Otaibi says this allows healthcare entities to provide quicker and more efficient services, especially with the growing demand for quality care. Cloud computing will also allow data sharing among health providers and across the region. Healthcare data can be stored on a secure and centralized cloud-based system that allows access and sharing of data among providers and other healthcare stakeholders (Noor, 2019). Healthcare data interoperability across various healthcare providers allows more effective patient care and reduces administrative costs and redundancy (Alharbi et al., 2015). Therefore, cloud computing solutions in e-Health allow better integration with other solutions and systems, providing better visibility and accessibility to data from a range of solutions and systems.

Joining e-health into the Saudi healthcare system is a Monument-like duty with enormous possibility to enhance the lives of limitless people all over the country. Semwanga et al. (2021) observed that the use of e-health in healthcare institutions can improve performance and more precise data access. To do such achievements, an organized and clearly outlined model for implementation is required (Alharbi et al., 2015). The primary goal of integrating e-health technology into Saudi's healthcare system is to optimize its benefits for the people, which indicates that cloud computing must be element of the plan.

According to Alharbi et al., cloud computing allows the fast and useful exchanging of healthcare data from one institution or country to another. It can also better organize resources, specifically if all related teams (patients, physician, and insurers) can access patient data stored in the cloud. Furthermore, by utilizing cloud computing, Saudi healthcare organizations will have access to creative health applications, assisting them to use digital medical technology such as artificial intelligence, the Internet of Things (IoT), and predictive analytics to treat complicated medical tasks and data management (Noor, 2019). Alharbi et al. (2015) suggested that the main side of the model for application is to set a proper set of rules and regulations. By providing secure systems with specific privacy regulations and technological protections, Saudi authorities will ensure the secure use of data while at the same time respecting the privacy of users.

Furthermore, technological and structural preparedness should be strong-willed to understand the readiness of each healthcare institution for utilizing e-health services (Elkhalifa et al., 2022). Elkhalifa et al. indicated that this process should identify the strong points and weak points of each institution, as well as possible Struggles and Demands. To complement this assessment, capacity-building programs are needed to prepare staff to properly operate and utilize new technology. The formation of networks of regional healthcare centers can further benefit by allowing regional collaborations and resource sharing, leading to improved data quality, better training for professionals, and faster access to care.

The effective utilization of e-health technology into the Saudi healthcare system will possibly include forming both infrastructure and definite policies (Noor, 2019). To confirm this, all interested parties must collaborate to ensure the seamless and successful implementation of cloud computing technologies, legal regulations, and organizational prepared status. Such an initiative can significantly contribute to the health and welfare of the Saudi population.

Utilizing cloud computing in the Saudi Arabian e-health sector could substantially improve patient care, according to Al-Mutairi (2022). Cloud computing can enable quicker diagnoses and treatment processes by providing healthcare providers with easier and faster access to medical data. Furthermore, this technology enhances patient involvement, which could result in more personalized healthcare services and possibly even cost reduction.

Notably, the integration of cloud computing could decrease paperwork, minimize errors, and promote teamwork among healthcare entities and professionals.

Elkhalifa et al. (2022) state that incorporating cloud computing into the Saudi Arabian e-health infrastructure is an appealing proposition. It presents numerous benefits including reduced costs, elevated patient involvement, speedier and more precise access to healthcare data, along a decrease in paperwork and errors. Importantly, it aids Saudi Arabia in its pursuit of digital healthcare objectives of offering high-quality care and establishing a modern healthcare system for its populace. This study is geared towards equipping the Saudi Arabian government with an understanding of the benefits and drawbacks associated with the integration of cloud computing into their healthcare sector.

Furthermore, it seeks to provide insight into how the implementation of cloud-based e-health systems could enhance the efficiency and cost-effectiveness of the country's healthcare sector. Therefore, the primary objective of this research is to evaluate the factors affecting the adoption of clod computing in Saudi Arabia health sector.

1.2 Problem Statement

The Saudi Arabian healthcare sector is facing the difficulties of understanding the possible benefits and challenges of adopting cloud computing systems. The healthcare system in Saudi Arabia faces various issues such as poor quality of services and low health literacy, though the government has financial resources (Kumar, 2023). Healthcare resources in Saudi Arabia are frequently concentrated in urban regions, leaving rural and distant places with limited access to quality healthcare services (Saeed et al., 2023).

There is also deficiency of healthcare experts, particularly in specialized professions. This shortage might lead to long wait periods and delays in accessing healthcare. Although

Saudi Arabia has made progress in implementing technology in healthcare, there is still considerable opportunity for improvement. For instance, telemedicine is not yet commonly utilized; limiting access to healthcare services for persons in remote locations, some individuals may find it challenging to purchase vital healthcare services in Saudi Arabia due to the country's high healthcare prices (Saeed et al., 2023).

The Saudi Arabian government has started a number of initiatives to improve the healthcare sector in response to these difficulties (Saeed et al., 2023). These objectives include improving access to healthcare services in rural and isolated locations, boosting the number of healthcare professionals, and investing in technology (Rahman & Al-Borie, 2020). However, the Saudi Arabian government is taking steps to address these challenges and transform the healthcare system into a more efficient and effective one. One of the key initiatives is the National Transformation Program 2020, which aims to improve the quality of healthcare services, increase access to care, and reduce healthcare costs. The program includes several measures such as increasing the number of healthcare providers, enhancing healthcare infrastructure, and implementing new healthcare technologies. The plan aims to create a healthcare system that is more patient-centred, innovative, and accessible to all citizens. It also emphasizes the importance of preventive healthcare and health education (S. Chowdhury et al., 2021).

Another step taken in Saudi Arabia healthcare system is the adoption of cloud computing solutions, which have the potential to revolutionize healthcare by improving efficiency, reducing costs, and enhancing the quality of care. Hence, health sector transformation programme under the Saudi vision 2030 was launched in 2021 with sight for next 5 years aimed at restructuring the health sector to be a comprehensive, effective and integrated health system based on the health of the individual and society, that includes citizens, residents and visitors (Alasiri & Mohammed, 2022; Government of Saudi Arabia, 2020).

The programme depends on the principle of value-based care, ensuring transparency and financial sustainability by promoting public health and preventing diseases (Alasiri & Mohammed, 2022). The specific aims of the programme is to improve access and quality of health services through optimal coverage and comprehensive and equitable geographical distribution by expanding provision of e-health services and digital solutions.

Both the National Transformation Program (NTP) 2020 and Saudi Vision 2030 are on track, with significant achievements in digital transformation, economic diversification, and societal reforms. For instance, the NTP has achieved 34 of its 96 strategic goals, and Saudi Vision 2030, launched in April 2016, is a comprehensive blueprint to diversify the economy, reduce oil dependency, and enhance societal and governance structures. It is structured in three phases, with the NTP being a key driver. Vision 2030 is progressing through its second phase, with the third phase set to begin in 2026 focusing on stabilizing and sustaining achievements

In Saudi Arabia, adoption of cloud computing can assist the healthcare in the areas like medical diagnoses, help healthcare providers diagnose diseases accurately and quickly, and patient care. Hence, adoption of cloud computing can reduce the burden on healthcare providers and improve the accuracy of diagnosis, leading to better patient outcomes.

For several reasons, Saudi Arabia was selected as the focal point of this investigation. This nation's distribution of healthcare services represents a strong challenge for the Saudi government due to its many rural areas and vast geographical land (Alaboudi et al., 2016).

Moreover, it is Worthy of note that healthcare services are provided free of cost to all Saudi Citizens (Asmri et al., 2020).).

This, in turn, causes the fragmentation of healthcare systems within the country (Alqahtani et al., 2017), mandating additional financial resources to maintain good healthcare services. Furthermore, it is important to understand that the sociocultural milieu common in Saudi Arabia holds potential implications for adopting and implementing cloud computing in this region. As a conservative Muslim-majority country, Saudi Arabia's cultural context intricately influences daily life, encompassing technology adoption.

The influence of cultural and societal norms on cloud computing in Saudi Arabia cannot be undervalued. Saudi Arabia's precise gender segregation has significant cconsequences for application cloud computing, particularly within the healthcare sector. The enforcement of gender segregation in job sites requires the establishment of separate cloud infrastructures and access controls to respect the cultural norms (Idoga et al., 2018). As a result, this gender-based segregation impacts cloud computing in many ways.

Firstly, gender segregation in Saudi Arabia's e-health sector can influence cloud computing adoption by making security even more critical factors. Cloud-based platforms, particularly for telemedicine, allow for consultations between male patients and female doctors, or vice versa, without a physical meeting, which can be culturally and socially preferable for some individuals. Studies suggest that for female users in particular, privacy and security of the cloud system is a significant determinant of their willingness to adopt new e-health services. Therefore, successful cloud adoption in this context isn't just about technological capability; it's about building a robust, transparent framework that assures users their data is safe and their privacy is respected in accordance with cultural norms.

Secondly, the influence of gender segregation on cloud adoption also encompasses design and delivery of e-health services. For example, some healthcare organizations have implemetnted thumbprint verification systems for female patients to ensure their identity is verified without requiring a photograph, which aligns with cultural values while maintaining security. Cloud computing facilitates such specialized solutions by providing a flexible and scalable infrastructure that can be customized to meet specific cultural needs. Furthermore, the use of cloud-based telemedicine can help overcome physical barriers to care for women, such as transportation issues or the need for a male guardian to accompany them to appointments. This not only improves healthcare access but also demonstrates how cloud technology can be a powerful tool for navigating and even mitigating the logistical challenges that gender segregation can present in a traditional healthcare setting.

Thirdly, gender segregation often results in restricted access to resources and infrastructure needed to employ cloud computing solutions effectively in healthcare organizations. The separation of facilities and work place settings for male and female cause difficulties when managing and utilizing cloud-based systems. Fourthly, gender segregation may result in a limited number of skilled workers available for cloud computing initiatives, thus preventing development, implementation, and management (Al-Bakr et al., 2017). If certain technical roles are restricted to women or opportunities for professional growth are denied, the expertise available for cloud computing projects diminishes.

Furthermore, in a gender-segregated environment, communication barriers may develop, requiring extra approvals or restricting communication between male and female workers (Al-Bakr et al., 2017). These can Impedes collaboration and teamwork, thus effecting decision-making and problem-solving processes essential for the success of cloud computing utilization. Moreover, gender segregation may require stricter access controls and security measures to comply with cultural norms and regulations. For example, healthcare organizations may need separate storage and access protocols for male and female patient data. However, implementing such gender-specific data segregation within cloud computing systems introduces complexity and potentially increases security risks.

Lastly, training and education on cloud computing technologies may be hindered in a gender-segregated environment. Limitations on interaction between male and female trainers or trainees can undermine the quality and effectiveness of training programs focusing on cloud computing skills (Jurado Pérez & Salvachúa, 2021). Therefore, the influence of gender segregation on cloud computing in the Saudi Arabian healthcare sector cannot be overlooked. These limitations necessitate the development of strategies that account for and mitigate the impact of cultural and societal norms on cloud computing implementation.

Current researches have neglected mainly to examine the complexities of integrating cloud computing systems in Saudi Arabian healthcare, including examining the legal frameworks (Ibrahim et al., 2022). Upon evaluating the existing frameworks and models for Cloud Computing adoption, it is apparent that they are not without limitations. Current models and frameworks mainly concentrate on only the operational and tactical level and are restricted in scope, neglecting other pertinent aspects.

Additionally, while most of them emphasize the technical facet of Cloud Computing, cultural and organizational factors may play a significant role in how various countries implement Information Technology projects (Chang et al., 2021). Therefore, there is a need to examine the impact of such factors across different sectors and countries in order to advance the knowledge surrounding the adoption of cloud computing. Despite previous research suggesting that environmental and organizational factors influence Cloud Computing adoption vary across different contexts; frameworks tend to be too general and not focused on specific sectors, such as the healthcare industry (ALMutair & Thuwaini, 2015).

This challenges different countries, which may exhibit varied industry environments that need to be approached individually, case-by-case. As such, more research must be conducted to establish an appropriate model that accommodates cultural and organizational diversity in order to enhance Cloud Computing adoption globally (Gupta et al., 2019).

Also, the lack of adoption model for cloud computing suitable for the culture and society of Saudi Arabian healthcare sector (Gao and Sunyaev 2019). Specifically, a greater understanding of the legal implications and risks of integrating cloud computing in healthcare and examining the specific technical needs, flexibility, and scalability required by different health facilities to utilize the full capabilities of cloud computing is needed. Moreover, more research is needed to evaluate the cost-effectiveness and security of cloud computing compared to traditional information systems (Kamruzzaman et al., 2022).

Consequently, a lack exists in understanding of the efficacy and implications of cloud computing in the Saudi Arabian healthcare sector. As a result, the research gap becomes evident wherein the implementation of electronic services in healthcare lags behind other sectors such as banking and industry (Alsulame et al., 2015; Alqahtani et al., 2017).
Alassafi conclude in his study that the adoption rate of cloud computing in health care sectors in Saudi Arabia is very low (Alassafi, 2021). Another study conducted for private hospitals in Saudi Arabia conclude that the use of cloud technology in the Saudi Arabia private hospitals is the lowest in the nation (Alshahrani, Beloff, & White, 2023.). A survey highlights that a mere 16 out of 19 hospitals in the eastern region of Saudi Arabia have unsuccessfully incorporated the Information Technology (Alqahtani et al., 2017).

Similarly, a study conducted in 2013 across two hospitals identified various obstacles to the effective implementation of information technology in the Kingdom of Saudi Arabia. These challenges included human factors, technical issues, and organizational difficulties (Khalifa, 2013). Additionally, Aldosari (2014) conducted a study examining the rates, levels, and determinants of information technology adoption in 22 hospitals in Riyadh, Saudi Arabia he found that 50% of the hospitals had fully implemented IT systems, 50% in progress, or had not implemented it.

Another study conducted by AlSalman and Haider (2021) examined the implementation status of health information systems in 18 hospitals in the eastern province of Saudi Arabia, found that about half of the hospitals in the study had fully implemented the HIS in their hospital, while the other half were not in place. Moreover, a significant portion, around 75%, of healthcare IT projects in the country either remains incomplete or fails altogether (Abouzahra, 2011).

Additionally, The integration of cloud computing into the Saudi Arabian healthcare sector is hindered by a unique set of cultural, legal, and organizational challenges, with gender segregation standing out as a critical factor. The Unified Theory of Acceptance and Use of Technology (UTAUT) provides a useful framework for examining how performance expectancy, effort expectancy, social influence, and facilitating conditions drive or inhibit adoption (Gu et al., 2021). Its shaped by segregation, these constructs are reframed: social influence is restricted by limited cross-gender collaboration, facilitating conditions are shaped by legal requirements, and performance benefits may be perceived differently by male and female professionals (Mongwe, 2023). Thus, UTAUT underscores how social and legal environments shape user perceptions of cloud computing technologies.

In addition, the Diffusion of Innovation (DOI) theory highlights how innovations spread within a society, emphasizing attributes such as relative advantage, complexity, trialability, and observability (Adlung et al., 2025). In the Saudi healthcare system, the compatibility of cloud solutions is tied not only to organizational processes but also to social and gender interaction. Trialability and observability are constrained by legal restrictions, where opportunities for shared experimentation between male and female practitioners are limited.

These constraints slow the pace of diffusion, as adoption must negotiate the dual demands of technological efficiency and cultural legitimacy. DOI thus illuminates how systemic cultural and organizational barriers can impede the diffusion of healthcare innovations in highly conservative environments. Recent reforms under Saudi Vision 2030 are reshaping these dynamics, reducing rigid gender segregation while accelerating digital transformation across sectors, including healthcare (Aldossary, 2019). These changes create an unprecedented opportunity to modernize healthcare delivery through cloud computing, improving efficiency, access, and patient outcomes.

This influences how healthcare facilities design their cloud-based systems to ensure that they respect these norms, which can add layers of complexity to the system design and integration processes (Alkhater, Walters, & Wills, 2018). The adoption of cloud computing in Saudi Arabia's healthcare sector is shaped by various cultural factors, including gender segregation and heightened privacy concerns. Addressing these issues requires culturally sensitive approaches to system design, robust security measures, and inclusive training programs. By considering these factors, Saudi Arabia can continue to advance its healthcare sector through effective cloud computing solutions.

Gender segregation in Saudi Arabia's e-health sector can influence cloud computing adoption by making security even more critical factors. Cloud-based platforms, particularly for telemedicine, allow for consultations between male patients and female doctors, or vice versa, without a physical meeting, which can be culturally and socially preferable for some individuals. Studies suggest that for female users in particular, privacy and security of the cloud system is a significant determinant of their willingness to adopt new e-health services. Therefore, successful cloud adoption in this context isn't just about technological capability; it's about building a robust, transparent framework that assures users their data is safe and their privacy is respected in accordance with cultural norms.

The influence of gender segregation on cloud adoption also encompasses design and delivery of e-health services. For example, some healthcare organizations have implemented thumbprint verification systems for female patients to ensure their identity is verified without requiring a photograph, which aligns with cultural values while maintaining security. Cloud computing facilitates such specialized solutions by providing a flexible and scalable infrastructure that can be customized to meet specific cultural needs. Furthermore, the use of cloud-based telemedicine can help overcome physical barriers to care for women, such as transportation issues or the need for a male guardian to accompany them to appointments. This not only improves healthcare access but also demonstrates how cloud technology can be a powerful tool for navigating and even mitigating the logistical challenges that gender segregation can present in a traditional healthcare setting.

However, one of the key limitations of this study is its reliance on health sector professionals as the sole respondents, which may restrict the generalizability of the findings. While healthcare professionals provide valuable insights into organizational, technical, and cultural factors influencing cloud computing adoption, the perspectives of other key stakeholders such as patients, policymakers, IT vendors, and regulatory authorities were not considered. This narrow scope may overlook broader systemic challenges, including patient trust, legal compliance, and infrastructure readiness, which are equally critical to successful e-health cloud adoption in Saudi Arabia.

1.3 Research Significant

The primary contribution of this study is the development of a comprehensive model to facilitate cloud computing adoption in healthcare settings. Recognizing the need for such a model, which has been highlighted by many scholars in healthcare IT research, this thesis offers an assessment tool tailored for healthcare organizations. The model considers various factors that influence the decision-making process, including the effects of unique environmental aspects of Saudi Arabia, “gender segregation” on these factors and the adoption decision.

This approach aims to bridge the gap between theoretical frameworks and practical implementation, addressing the shortcomings of previous studies that referenced these factors without providing a detailed plan. The proposed model assesses readiness for cloud computing adoption by incorporating multiple perspectives and specific regional considerations, thereby providing a practical guide for healthcare organizations in Saudi Arabia. This study provides valuable insights and practical guidance for healthcare organizations seeking to implement Cloud Computing technology.

1.4 Research Objectives

1. To identify the factors necessary for the successful adoption of cloud computing in the Saudi Arabian healthcare sector.

2. To examine the moderating effect of gender segregation on the relationship between the identified factors and cloud computing adoption in the Saudi Arabian healthcare sector.
3. To evaluate the proposed model's constructs in explaining and predicting cloud computing adoption in the Saudi Arabian healthcare sector.

1.5 Research Questions

RQ1. What are the factors necessary for the successful adoption of cloud computing in the Saudi Arabian healthcare sector?

RQ2. Does gender segregation moderate the relationship between the identified factors and cloud computing adoption in the Saudi Arabian healthcare sector?

RQ3. Does the proposed model constructs significantly explain and predict cloud computing adoption n the Saudi Arabian healthcare sector?

1.6 Summary

This chapter starts with introduction and background of the study to provide a reader glimpse in to the problems and a representation of the research environment. Then, the research issues are presented at the problem statement section. Moreover, the significance of conducting this study was discussed, followed by the research questions and objectives. Finally, the chapter ends with a summary.

CHAPTER TWO
Literature Review

2.1 Introduction

Today, there are a multitude of digital technologies that support e-health systems in the world that are dictating the way healthcare services are delivered all over the globe. In addition to improving patient outcomes, electronic record data management systems combined with other useful applications help maintain patient privacy and improve clinical outcomes (Ahmed Kamal et al., 2023). As a result of technological advancements in recent times, cloud-based systems have allowed healthcare service providers globally to access cloud platforms that offer more affordable solutions while remaining flexible enough to store vast amounts of medical records and associated applications (Razi & Batan, 2023). E-health cloud computing has enabled organizations to store and access medical records and associated applications more efficiently, providing cost savings and improved outcomes. This section provides an overview of the history of e-health cloud computing, encompassing a general perspective. It delves into the adoption of e-health and cloud computing specifically within Saudi Arabia, offering an in-depth analysis of adoption rates and the influencing factors. Furthermore, it elucidates the theoretical background underlying technology adoption.

2.2 E-health literacy

As the focus of healthcare has shifted from treating illnesses to preserving health, health promotion has emerged as a societal issue that affects individuals in general as well as healthcare professionals. Electronic health (e-Health) has become a new concept of service delivery in healthcare by consolidating technology, commerce, and health (Alshammari et al., 2021; Hakeem et al., 2023). E-Health has been defined as healthcare services and health information provided and obtained using electronic and digital means (da Fonseca et al., 2021; Shaw et al., 2017). E-health literacy is a degree of individual skills and competencies, which are needed to provide, connect, process, and understand basic health information, and services required for making appropriate health decisions (Dickson-Swift et al., 2007; Ghaffari et al., 2020).

E-Health benefits include increasing the effectiveness and accessibility of medical and dental services; for example, the implementation of various mobile health applications and social media (Alshammari et al., 2021).

Saudi Arabia has undergone rapid socioeconomic development and related lifestyle modifications, but the prevalence of poor oral health in Saudi Arabia is still rising (Ghazal et al., 2022). Hence, understanding the level of e-Health literacy among the population and addressing the disparities in e-Health literacy can improve health outcomes and reduce healthcare costs. Healthcare providers, policymakers, and health educators should work together to develop and implement e-Health education programs targeting disadvantaged groups with low e-Health literacy.

When individuals have low e-Health literacy, they may face challenges in effectively using health information from the internet. They may encounter difficulties in finding the reliable information they need, or they may come across distorted or inaccurate information that can lead to health imbalances and disparities. Therefore, it is essential to improve the level of e-Health literacy among individuals, enabling them to discern and use accurate information (Kim & Lim, 2022).

Health literacy includes different skills, which enable individuals to engage in the community more completely and apply further control over their health measures and decisions. This literacy can significantly affect the health outcomes, health promotion behaviours, and patient-physician relationship and lead to the significant improvement in physician-patient communication skills and their self-efficacy and self-care behaviours (Ko & Kang, 2018; Parthasarathy et al., 2014).

2.2.1 History of E-health cloud computing

Over the past decade, healthcare communities have adopted e-health cloud computing more widely due to the advantages of cloud platforms. These include its ability to scale up or down, affordability and reliability as Ahmed Kamal et al. (2023) noted. The use of e-health cloud computing records as well as remote monitoring systems in hospitals was initially developed for online appointment scheduling and telemedicine applications. Adler-Milstein et al. (2021) reported the inception of the Health Information Exchange (HIE) which outlines efforts made in 2010 towards encouraging adoption of cloud-based health information-sharing networks within the government.

E-health cloud computing have been utilized to make remote monitoring and the use of cloud-based electronic health records possible (Jabbar et al., 2020). This paved the way for the emergence of varied e-health cloud platforms including essential tools for clinical decision support, patient monitoring, and healthcare analytics among others. Following is a summary of the evolution and acceptance phases of implementation & development.

Remote access applications have transformed healthcare provision with patients able to schedule appointments online or consult specialists easily according to El-Sheriff et al. (2022). Limited initial penetration of telemedicine technology was due to prohibitive equipment costs coupled with unreliable network connectivity, according to El-Sheriff et al.'s research. Moreover, since its initiation early around 2000, e-records were sufficient impetus for e-health cloud computing adoption, facilitating easy provider surveillance as inclusive patient data files comprising medical histories test results, prescriptions medications & allergies can be retrieved from any location (Pai et al., 2021).

This use case allows caregivers' access to a comprehensive range of metrics understood in turn using data analysis systems enabling beneficial clinical decisions resulting in superior patient outcomes. To make the process easier, the use case leverages e-health cloud computing technology to deliver real-time access to patient data (Abdalla & Varol, 2019).

This allows caregivers to quickly analyze the data and make informed decisions that will improve patient outcomes. By leveraging e-health cloud computing technology, caregivers are able to quickly analyze patient data and make decisions that will ensure superior patient outcomes, making the process easier and more efficient.

Technological advances continue shaping healthcare practices necessitating secure modes for affordable delivery methods such as e-health cloud computing (Sadoughi et al., 2020). However prior utilization approaches deployed on these cloud service platforms encountered difficulties cantered around lack of necessary frameworks to protect privacy adequate risks controlled measures compatibility breakdowns between comprehensive health data exchange systems alongside bandwidth limits affecting service delivery ensured caution concerning offerings (Ksibi et al., 2022).

Nonetheless, recent technological involutions particularly machine learning which currently supports blockchain technology fundamentally improve care anytime through impressive encrypted system execution offering simplified and effective cloud-based administration solutions (Sadoughi et al., 2020). E-health cloud computing platforms are examples of solutions that allow healthcare providers to access high-quality, comprehensive care anytime, anywhere (Chhabra, 2023). These platforms offer secure, encrypted systems that enable providers to quickly and easily access patient data and healthcare information. In addition, they enable providers to manage care delivery in real time.

In modern health care delivery systems, advanced analytical and data-driven technologies have revolutionized risk management capabilities significantly. These advancements are further complemented by enhanced communication networks that effectively transfer sensitive patient information throughout various care points. Such developments have allowed experts in the field to predict future illnesses and emerging health trends more accurately than ever before. This is based on increased access to large medical data pools.

Moreover, Tahirkheli et al.'s (2021) report details how e-health cloud computing technology now offers health care providers an alternative with enhanced scalability potential and cost effectiveness compared to traditional IT platforms. This virtual storage environment provides scalable computational power on demand while ensuring patient data safety. Ishak et al.'s (2021) study cites e-health applications as among the biggest beneficiaries of cloud computing technology progress.

As a significantly cost effective and secure way to manage medical records, cloud-based systems now allow streamlined communication and collaboration between different healthcare providers without administrative hassles making it one of the defining advances in modern e-healthcare solutions today. As such, E-health cloud computing offers access to medical records, data, and applications from anywhere in the world, providing enhanced flexibility and scalability to the medical industry (Jabbar et al., 2020).

Healthcare providers can enjoy access to constantly updated, vast databases of reliable information available in real-time. This real-time access to vast amounts of reliable data allows healthcare providers to make more informed patient decisions and quickly adapt to industry changes.

2.2.2 E-Health in Saudi Arabia

The Saudi government acknowledges the crucial role of Information and Communications Technology (ICT) in providing quality services to Saudi citizens and launched the first national E-government strategy in 2005. In response, healthcare service providers began incorporating some ICT solutions in their facilities, while the Ministry of Health (MOH) established the National E-health Strategy in 2011 to support the primary MOH business objectives.

However, the implementation of Health Information Technology (HIT) in Saudi healthcare organizations remains relatively low for various reasons, as revealed by researchers. Previous research such as Alsulame et al., 2016; Khudair 2008; Magd, 2016 reasoned that ineffective leadership, insufficient system infrastructure and support, and lack of strategic planning from physicians' viewpoints were to blame for the unsuccessful outcomes. Similarly, Alasiri and Mohammed, (2022); Khalifa (2013): Majrashi, (2023) indicated several barriers towards the successful adoption of Electronic Medical Records (EMRs) in Saudi Arabia.

This includes factors like limited specialists in health informatics, deficient computer applications and insufficient expertise and know-how on EMRs. Khalifa (2013) also mentioned high costs related to implementing and maintaining EMRs as a substantial financial impediment, particularly for Saudi hospitals.

Similarly, Alkraiji, Jackson, and Murray (2017) also acknowledged the existence of various challenges to the adoption of health data standards in Saudi Arabia, including the issues relating to technology context such as complexity, compatibility, system fragmentation, and inadequate IT infrastructure. Moreover, Hasanain and Cooper (2014) indicated that social barriers, including gender segregation, further complicated the EMR implementation in Saudi hospitals, coupled with technical and environmental barriers like unstable EMR vendors and insufficient computer supply for the staff.

Generally, these studies reveal the obstacles that impede the adoption of HIT and health data standardisation in Saudi Arabia's healthcare system. These barriers must be addressed adequately to support the successful integration of technology in healthcare, improve quality service delivery, and enhance patient outcomes.

2.2.3 Studying Cloud Computing Adoption in Saudi Arabia

From 2013 onwards, there has been an increasing interest in Cloud Computing in Saudi Arabia (Al-Hujran et al., 2018). Before this, limited research had been conducted on implementing Cloud Computing in the country. This section delves into the existing studies that have explored this topic. Alharbi (2012) and Alotaibi (2014) conducted studies on users' acceptance of Cloud Computing in Saudi Arabia, using the Technology Acceptance Model (TAM).

While these studies shed light on the factors influencing the adoption of Cloud Computing in Saudi Arabia, they focused solely on the user level and utilized TAM to predict users' acceptance. At the organizational level, Al-Hujran et al. (2018) surveyed to gauge the level of awareness of Cloud Computing in Saudi Arabia. The study revealed a rising trend towards the adoption of cloud technologies within Saudi organizations. However, the research did not extensively delve into the specificities of incorporating Cloud Computing within the Saudi context, thus presenting a broad outlook.

The research by Alkhater et al. (2014) sought to determine the key elements that influenced a wider adoption of Cloud Computing. Notable findings from their study were factors such as trust, perceived benefits, and readiness for technology, all of which play a role in the utilization of cloud computing. However, they neglected to scrutinize the effect of two major factors - the human element and business perspective - in the integration of Cloud Computing. The sample size in their study was also quite limited, encompassing only 20 specialists.

On the other hand, Almazroi and Shen, 2019; Alsanea (2014); directed his research towards understanding the adoption of Cloud Computing in Saudi Arabian government institutions. The study revealed an optimistic outlook towards the uptake of Cloud Computing, with 86% of respondents supporting its implementation. Other influential elements revealed in the study included indirect benefits, sector of industry, cost-effectiveness, trust, and feasibility (Alsanea, 2014). Despite the rich findings, the study did not adequately delve into the specific nature of the organizations studied and overlooked human aspects.

Thus, although some research has been undertaken on cloud computing adoption within Saudi Arabia, existing studies are not without their shortcomings, failing to give an exhaustive insight into the factors affecting its adoption.

Tashkandi and Al-Jabri's (2015) research delved into the usage of cloud computing in higher educational institutions in Saudi Arabia. Their study specifically evaluated how technology, organizational, and environmental factors affect the decision to adopt this form of computing, their investigation revealed that the relative advantage of Cloud Computing has a positive effect on the inclination to adopt this technology.

In addition, it was observed that complexity and vendor lock-in have a negative impact on the adoption decision. It should be noted that the study possesses certain limitations, as it primarily concentrated on higher education organizations, thereby neglecting the crucial business dimension of adopting Cloud Computing. On a similar note, Alhammadi et al. 201); Karim and Rampersad, (2017) explored the determinants of Cloud Computing adoption in Saudi Arabia.

Their study examined the factors influencing the decision-making process: security concerns, organization readiness, top management support, firm status, government support, and compatibility. It is worth mentioning that this study was conducted at an organizational level, refraining from a specific industry focus or providing detailed information regarding the roles of the participants.

Furthermore, Alkhlewi et al. (2015) identified 15 factors contributing to the successful implementation of a private government cloud within Saudi Arabia. It should be highlighted that their study exclusively concentrated on government organizations, displaying a rather limited sample size of merely 30 experts, predominantly comprised of IT professionals. Lastly, AlBar and Hoque (2015) proposed a theoretical framework to examine Cloud ERP Adoption in Saudi Arabia; however, the application of said framework was not carried out within their study.

In a comprehensive investigation by Noor (2016), the utilization of Cloud Computing in Saudi universities was scrutinized. The study involved 300 participants hailing from five distinct universities. Findings revealed that the primary motivators behind IT department employees' adoption of cloud technology were the ability to access the cloud from any device and the convenient self-service feature of Cloud Computing.

Conversely, the study highlighted a number of obstacles that hindered the adoption of Cloud Computing, namely concerns pertaining to privacy, compliance, security, reliability, and availability. It is worth noting that the scope of the study was limited to Saudi universities and predominantly focused on the user perspective, neglecting to explore additional facets such as the financial implications associated with adopting this technology.

Almutairi and El Rahman (2016), on the other hand, examined the impact of IBM Cloud Solutions on Saudi students, revealing that a majority of the participants possessed awareness regarding Cloud Computing; however, only 56% had personally experienced cloud solutions. Equally, Albugmi et al. (2016) presented a conceptual framework for the adoption of cloud computing by Saudi government overseas agencies. Still, they refrained from conducting specific surveys or analyzing case studies to test the viability of the proposed framework.

Similarly, Mreea et al. (2016) formulated a Cloud Computing value model intended for public sector organizations in Saudi Arabia, without conducting specific surveys or analyzing case studies to validate the model. Alharthi et al. (2017) further investigated critical success factors in cloud migration within Saudi universities and identified various factors, including security, reliability, migration planning, regulation compliance, and technical support incorporating the Arabic language. However, the study omitted discussion on business factors, such as cost, and technical factors, such as infrastructure readiness.

2.2.4 Cloud Computing in the Saudi Healthcare Context

Studies have explored the implementation of E-health cloud computing in Saudi Arabia's healthcare sector. The Saudi Vision 2030 initiative has been a key driver of digital transformation across various sectors, including healthcare. In 2020, the Saudi government allocated approximately $1.5 billion for digital health initiatives, which includes the integration of E-health cloud computing solutions in hospitals and clinics nationwide (Saudi Vision 2030, 2020).

This investment aims to improve data management, enable telemedicine, and support advanced healthcare analytics. As of 2023, over 70% of healthcare providers in Riyadh Saudi Arabia have adopted cloud-based electronic health records (EHR) systems. This shift has significantly reduced administrative burdens, improved patient data accessibility, and streamlined workflows. The Ministry of Health (MoH) reported a 25% increase in patient satisfaction and a 30% reduction in operational costs due to cloud implementation (Ministry of Health, 2023).

During the COVID-19 pandemic, the Saudi MoH rapidly expanded its telemedicine services using cloud infrastructure. Over 2 million teleconsultations were conducted in 2020 alone, providing critical healthcare access to remote and underserved areas (Saudi Ministry of Health, 2021). This initiative not only showcased the scalability of cloud solutions but also highlighted their role in crisis management.

King Faisal Specialist Hospital & Research Centre (KFSHRC) has successfully implemented a cloud-based EHR system, resulting in improved patient data management and streamlined clinical workflows. The hospital reported a 15% reduction in readmission rates and a 20% improvement in patient care coordination (KFSHRC Annual Report, 2022). In addition, King Abdulaziz City for Science and Technology (KACST) implemented Cloud Computing to help the Saudi Genome Project (2015) and Azzedin et al. (2014) created the Disease Outbreak Notification System (DONS).

However, these studies only focused on the technical implementation of cloud computing, neglecting the factors that contribute to its adoption within Saudi healthcare organizations. Adopting e-health cloud computing in healthcare organizations could prove advantageous in alleviating some of the management challenges encountered by healthcare organizations in Saudi Arabia. These benefits include economic savings, the reduction of IT and health informatics technicians, better integration and exchange of medical records across multiple organizations, and the provision of sufficient computing resources for data created by e-health services.

Moreover, by collaborating with other technologies such as the Internet of Things, m-health, and Big Data, E-health cloud computing will contribute to reshaping healthcare services in Saudi Arabia. The academic community has yet to examine the non-technical factors that affect the adoption of E-health cloud computing in Saudi healthcare organizations, making it a topic ripe for exploration and investigation.

Generally, the integration of E-health cloud computing within Saudi Arabia's healthcare system offers significant advantages that require further exploration and investigation to determine how its adoption can be fully optimized.

The existing research suggests that there is a requirement for more in-depth study about the uptake of Cloud Computing in Saudi Arabia, particularly within the realm of healthcare. Scholars have proposed that the research should encompass a broad range of cultural, social, technical elements, and also consider financing methods. The variation in healthcare setups in diverse countries underscores the necessity for an approach tailored to the specific context when assessing healthcare systems.

For instance, while the United Kingdom and Australia rely on general taxes as their primary source of funding, social insurance schema serves as the primary source in countries such as France, Germany, and Japan. Government regulation and its role in healthcare provision is another important factor to consider.

The differences in healthcare IT maturity levels across countries add further complexity to the analysis. For instance, while Taiwan implemented e-healthcare in 1995, Saudi Arabia only recently launched its National E-health Strategy in 2011. Additionally, cultural differences play an integral role in the adoption of IT in healthcare systems across the world. Studies have found that gender segregation is one of the factors affecting the implementation of Electronic Medical Records in Saudi Arabian hospitals. Therefore, each country's healthcare system must be studied as an individual case, taking into account its unique characteristics and contextual factors.

2.2.4.1 Current State of E-health Cloud Computing in Saudi Arabia

Saudi Arabia continues to adopt e-health cloud computing at a promising rate despite some obstacles outlined by Alkurdi (2022), including inconsistent standards across different healthcare providers for sharing electronic information, patient data privacy concerns due to varied local regulations and requirements, plus more standardization challenges for all compliant platforms' governance policies. Adoption of SaaS cloud computing would allow users to access software applications and services remotely over the internet (Chhabra, 2023). This type of e-health cloud computing is becoming increasingly popular in the healthcare sector. This is due to its cost effectiveness, scalability, and ability to offer secure access to services on demand.

Cloud computing offers many advantages, including cost savings, scalability, and flexibility (Abdalla & Varol, 2019). Additionally, it provides secure access to services on demand, which is especially important in the healthcare sector. Furthermore, it is easy to use and provides 24/7 access to data and applications. With this type of technology, the government remains committed via investment into a national strategy for e-healthcare and initiatives such as establishing guidelines for data security compliance issued by Saudi Standards, Metrology and Quality Organization (SASO) and ensuring quality service levels according to documented policy. Continued commitment to enhancing the digital infrastructure holds vast potential for expansion and evolution within e healthcare. This bodes well for patients and healthcare professionals who stand to benefit greatly from these advancements.

The relevance of the study on e-health cloud computing in the healthcare landscape of Saudi Arabia cannot be overemphasized. In spite of the hurdles previously identified by Alkurdi (2022), Saudi Arabia has made considerable strides in adopting e-health cloud computing solutions in the healthcare industry. The particular focus on cloud computing allows researchers to tackle the obstacles and harness the advantages that align with the healthcare ecosystem in the country. Cloud computing technology allows users to access software applications and services remotely over the internet. The healthcare sector is increasingly embracing cloud computing due to its affordability, ability to scale, and its secure provision of on-demand services (Chhabra, 2023).

These advantages are crucial to Saudi Arabia's healthcare system, helping practitioners to address issues inherent to conventional computing solutions. Utilizing cloud computing, Saudi Arabia's healthcare sector can optimize efficiency, reduce costs, and increase productivity, thereby delivering superior healthcare to its population.

The importance of cost-efficiency cannot be understated for healthcare institutions in Saudi Arabia. This could be achieved through the use of cloud computing solutions (Sharif & Datta, 2019). By opting for cloud computing these providers can evade the high initial costs that accompany infrastructure setup and software licensing. Instead, they can pay solely for the services they utilize, which promotes optimal use of resources and careful budgeting.

The healthcare industry is inherently fluid and as such, adaptability is crucial. With the introduction of e-health cloud computing, Saudi Arabian healthcare establishments are empowered to easily alter their software and services, in response to evolving needs. The adaptability provided by e-health cloud computing enables healthcare providers to cope with fluctuations in patient volumes and evolving technological requirements without causing any significant investments or disruptions (Abtahi & Abdi, 2018).

According to Abtahi and Abdi, the security of services is a paramount concern in the healthcare industry, especially when dealing with confidential patient information. cloud computing providers usually implement robust security measures and certifications, guaranteeing patient information's confidentiality, integrity, and availability, ensuring secure access to services on demand. The adoption of e-health cloud computing in Saudi Arabia's healthcare industry will optimize resource utilization, boost budgeting, and ensure security and flexibility, eventually improving patient outcomes and enhancing healthcare delivery.

The deficiency of data on current conditions impacting E-health cloud-computing adoption rates raise a challenge when building a model encompassing all necessary criteria and context-specific requirements (Alkurdi, 2022). However, within the available circumstances, a deficit of information regarding important factors including the cultural-social, technical complexities regulation and policies leaves designing appropriate strategies problematic. To address this issue of whether to develop a model further exploration is needed focusing on e-health cloud computing adoption in Saudi Arabia. Methodologies should center on assessing levels of awareness concerning available information and taking into account specific challenges encountered throughout the adaptation process (Noor, 2019). The complexities of implementing e-health solutions in healthcare institutions are highlighted by the eight distinct factors that must be considered in Saudi Arabia, as presented in Figure 2.1. Nevertheless, despite these significant hurdles, the healthcare industry in Saudi Arabia has demonstrated a resolute desire to not only incorporate but enhance their e-health services. In spite of the evident challenges and roadblocks to progress, the medical community remains dedicated to advancing healthcare practices and technology to serve the populace more efficiently. In this way, they aspire to surmount the impediments standing in the way of an optimal health delivery system.

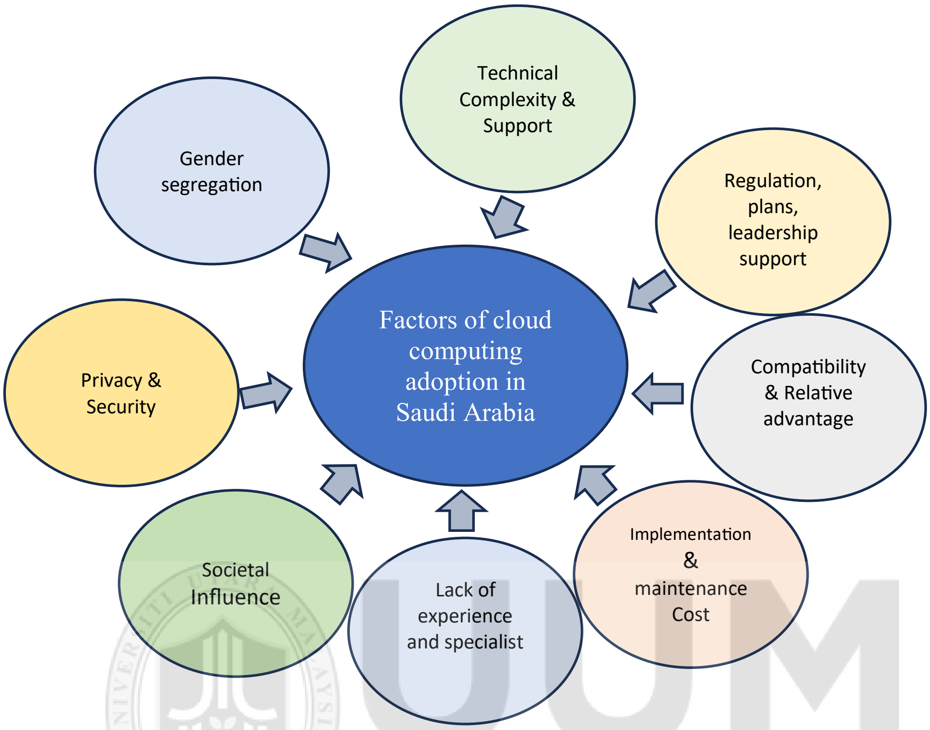


Figure 2.1.
Cloud Computing Adoption Factors in Saudi Arabia
Sources: Author 2025

2.2.4.2 Review Implementation of E-Health in other Neighboring Countries

The traditional paper- based medical record is rapidly being replaced by modern health information technologies (HITs) to better manage patient information (B. Alanazi et al., 2020). can assist health- care providers in generating, storing and retrieving vital patient information, ranging from medical histories to lab diagnostics, for the provision of high-quality care at different levels (B. Alanazi et al., 2020). Services have brought about a tremendous change in the administration of health systems worldwide. Health systems have benefited from automating many tasks that were once done manually, moving from paper to paperless services and digitizing so that records are now interconnected for a more efficient and uniform system (Abdelhay-Altamimi, 2014).

Saudi Ministry of Health (MOH) having the majority of facilities in the health sector has been working on connecting hospitals to each other through a national plan for an service, since some hospitals have computerized systems while others do not. Even among those hospitals that do have computerized health information systems, the systems come from different vendors and are not integrated, creating a complex set of difficulties for the implementation of a nationwide system (Alsulame et al., 2016).

Improvement of healthcare is indeed a major component of Vision 2030 which calls for enhancing access to care, improving the value of the care provided, and strengthening preventive measures for the health status of residents (Al-Shorbaji et al., 2018). Saudi Arabia currently has a national health care system in which governmental agencies provide 78.9% of total health services.

Thus, the e-health has emerged as an important tool for enhancing efficiency in healthcare processes, facilitating information sharing between healthcare providers themselves and between healthcare providers and their patients, and improving the quality of care as well as patient safety. Due to these perceived benefits of e-health in health service provision, the systems are increasingly adopted in various healthcare settings across the world. The countries in the Gulf Cooperation Council (GCC), namely Saudi Arabia, Kuwait, Oman, Qatar, United Arab Emirates (UAE) and Bahrain have also increased their investments in various forms of HITs to improve efficiency and delivery of healthcare services in hospitals and primary care centres (Khoja et al., 2017). For example:

United Arab Emirates (UAE)

IT usage in the healthcare centres of the UAE dates back to the 1990s. Also, the IT center at the MOH was established to facilitate the creation of mechanized information systems in healthcare centers, in 1993. Up to year 2008, both single and different HISs were implemented in the country's hospitals. The UAE launched a health information system (HIS), known as Wareed in 2011 to link electronic medical records in all public hospitals and clinics across Dubai and the Northern Emirates to improve efficiency in the public healthcare system (Moghaddasi et al., 2018).

By the end of 2010, Oman had implemented the national repository of E-HEALTHs (Moghaddasi et al., 2018) while Saudi Arabia committed $1.1 billion between 2008 and 2011 for the development of E-health programme and implementation of various health information tools, including E-HEALTHs to improve health and care services as part of its E-health strategy in Saudi Vision 2030 (Noor, 2019). According to Global Digital Health Monitor (GDHM) UAE has reached the highest maturity rating (Phase 5) in the WHO, placing it among the world leaders in digital health (Global Digital Health Monitor, 2023). In Dubai specifically, electronic medical records (EMRs) are implemented in 100% in public hospitals and in 75% of private clinics (Pablos, 2024).

Bahrain

The process of mechanization for hospitals in Bahrain was started in the 1980s, when various approaches about Hospital Information System (HIS) were adopted. The results of these approaches led to the formation of a committee in 1989 to implement the Health Information System Project, and the hospital information system as the core of this project. After a contract in 1990, the first phase of the system, which included a module of PAS (Patient Administration System), was installed in the country's hospitals in 1992. Launched in 1993, the second phase contained other modules including radiology, pathology, pharmacy, physician orders and communications, and continued its activities up to 2000 (Moghaddasi et al., 2018)

Oman

The first use of IT (Information Technology) in the state of Oman refers to Royal Hospital in 1986. Along with the importance of IT in healthcare centers, after the formation of the IT unit, a team consisting of clinicians, executive officers and IT personnel was formed to decide about the use of IT in healthcare centers, aiming to support the healthcare services was one of the most crucial decisions of the team. In 1998, the first in-house developed HIS (Al-Shifa system) was implemented in Nizwa hospital. Since 1998, the process of mechanization of new centers was considered as one of the paramount strategies of the MOH. Therefore, by 1998, all healthcare centers, including hospitals in the country onwards, were all mechanized.

Due to the emphasis of the World Health Organization on health information systems planning, the strategy of the country has been changed to e-health since 2004. In this strategy (e-health), Al- Shifa hospital information system was on the basis of all the programs of the Ministry of Health. Hence, this system was implemented in all hospitals and health centres. In the second phase, all HIS systems were to become interconnected by the end of 2007 with a middleware called e-referral engine. In phase III (final), the national repository of electronic health records was created by the end of 2010 (Elhadi et al., 2007).

Cloud computing in Saudi Arabian e-health has significant implications for both patient outcomes and clinical efficiency by providing a secure infrastructure. By migrating to cloud-based systems, healthcare providers can store and manage vast amounts of patient data, including electronic health records (EHRs) and medical images, securely and in a centralized location. This enables healthcare professionals to access comprehensive patient histories and information from any location, facilitating more informed and timely clinical decision-making.

Moreover, cloud computing supports telemedicine, allowing patients in remote or rural areas to access specialist care and receive virtual consultations, which directly improves access to care and patient outcomes across the Saudi Arabia. The adoption of cloud computing also enhances clinical efficiency by improving collaboration and streamlining workflows. Cloud-based platforms, facilitate real-time data sharing and interoperability, allowing for better coordination among doctors, labs, and pharmacies. This reduces administrative burdens, minimizes duplicate tests, and decreases the risk of human errors associated with manual data entry.

2.2.4.3 Gulf-wide Strategic Healthcare Digitization Projects

Regarding the Middle East region, several e-health initiatives have been incorporated in some of its countries, including Saudi Arabia, Jordan, Turkey, Israel, Qatar, Kuwait, United Arab Emi- rates, Oman, Iran, Bahrain and Iraq (Alanezi, 2021). In developing countries, cloud activities are focused on the large economies like China and India. However, in the Arab countries, Gulf Arab countries are taking quick steps toward cloud computing. Arab countries also are getting much attention from leading companies in cloud computing as DELL company announced offering cloud services to companies in the Middle East and Saudi Arabia (Karim & Rampersad, 2017).

According to the Information Society Report – ITU (2015), and based on the ITU ICT Development Index "The ICT Development Index (IDI) is a composite index that combines 11 indicators into one benchmark measure that can be used to monitor and compare developments in information and communication technology (ICT) between countries and over time.” The sixteen Arab countries included are ranked from 27 to150 out of 162 classified countries.

In 2017 a project by MENA Cloud Alliance developed a Cloud Competitiveness Index 2017 (CCI, 2017) view of the cloud status, now and for a continuous basis. This measure evaluates the affordability of the cloud computing ecosystem for the six Gulf Cooperation Council countries: UAE, Qatar, Bahrain, Kuwait, Oman & KSA. The report has indicated that the most cloud-competitive economies were (UAE and Qatar) respectively.

Qatar has achieved near-universal adoption of EHRs, with 96% of healthcare facilities using them as of 2023 (Oxford Business Group, 2024). Public sector rollout of the Clinical Information System (CIS) was completed across all Hamad Medical Corporation hospitals in 2016, and PHCC facilities also operate CIS (Hamad Medical Corporation, 2016; Primary Health Care Corporation, 2018)..

Doha, Dubai & Kuwait City are rated within top 50 most talent -competitive cities in the world (32nd, 36th, and 43rd respectively). Regarding to Saudi Arabia, it is mentioned in the report that Saudi Arabia‟s Communications and information technology Commission (“CITC”) has recently invited public suggestions coming back to its proposed guideline of cloud computing (Aldossary, 2019).

2.2.5 Saudi Telehealth regulatory frameworks

The Saudi Arabian government has announced several initiatives in addition to the Vision 2030 plan to encourage innovation and entrepreneurship in the healthcare industry. Several efforts under the 2016-launched National Transformation Program are geared toward improving healthcare, including creating a national health information exchange and promoting telemedicine and e-health services (Alharbi, 2023). These programs lay the groundwork for the country's healthcare providers to implement e-hospitals in order to facilitate the success of a primary healthcare center-based integrated delivery model (Alharbi et al., 2021).

The National Health Information Center (NHIC) aims to provide quality, knowledge and integrated services to the Saudi health system assuring to meet the standards of global best practices. NHIC supports the privacy and confidentiality of health information by providing standards and regulations and best practices in the field of digital health (NHIC, 2023). The key regulatory requirements & implications for health cloud computing deployment is the data protection. Health data is treated as a sensitive category under the Public Data Protection Law (PDPL) and requires stronger safeguards and specific processing conditions (NHIC, 2023). Telehealth practices must adhere to Saudi Arabia's health information exchange policy, ensuring data security and patient privacy.

Saudi Arabia's telehealth application guidelines emphasize patient safety, data privacy, and the establishment of a valid provider-patient relationship before providing telemedicine services. These guidelines, issued by the NHIC, cover various aspects, including technical requirements, clinical service continuity, and insurance coverage.

Under the requirement of telehealth, according to the NHIC (2023) the information and communications technology used for telehealth should be fit for the clinical purpose of the consultation, specifically;

i. The equipment is reliable and works well over the locally available network and Bandwidth.

ii. The equipment is compatible with equipment used by the patient-end health worker.

iii. The equipment and network secured, and privacy and confidentiality during the consultation can be ensured.

iv. The equipment is of a high enough quality to facilitate good communication between all participants and accurate transfer of clinical information.

v. Exchange of data shall be governed by the same overarching guidelines on privacy, security and accurate representation of truth e.g. high-quality imagery of diagnostic studies, body parts, etc. Hence, cloud platforms used for tele-consultation must support these requirements.

E-hospitals allow patients to access healthcare services from their own homes, using smartphones or other digital devices. These platforms enable patients to book appointments, consult with doctors, and receive medical advice. This can help alleviate the strain on healthcare facilities, especially in urban areas where overcrowding is common. Furthermore, this technology empowers healthcare administrators to find solutions to issues related to the shortage of qualified doctors, especially in rural regions (Almazroi & Shen, 2019). It improves access to healthcare professionals, reducing referrals and minimizing travel costs for patients. Another

Another sign that Saudi Arabia is ready to adopt e-hospitals is the country's widespread use of smartphones and other mobile devices. With 99% of internet users and 79.3% of social media users in 2023, it is clear that Saudi Arabia has made the digital transition for various reasons, including communication, entertainment, and work. This high rate of mobile phone ownership lays the groundwork for adopting e-hospitals, which can be accessed via mobile devices and offer patients remote access to healthcare services (Al-Anezi, 2022). Healthcare provider readiness is key to successful e-hospitals implementation. Therefore, this study aims to identify the current readiness of healthcare providers to adopt e- hospital technologies, determine the factors in influencing this adoption and describe the perceived facilitators and barriers about working at e-hospitals.

2.2.6 Telehealth Data Management

Health data management in general is the process of developing and executing plans, policies, initiatives, and practices to enable entities to manage and govern their data (NHIC, 2023). Hence, telehealth data management in particular means having a data-operating system in place that serves as the foundation for getting data controlled under a discrete authority (regardless of the database structure, whether centralized, decentralized, or hybrid) (NHIC, 2023). This is to ensure the confidentiality, integrity and availability of such data used for telehealth purposes and that, first, this data is available a timely manner for authorized HCP and used in across any organization (e.g. hospital or clinic) participating or willing to participate in telehealth services.

2.2.7 Types of e-Health Services

2.2.7.1. Telemedicine and Cloud Adoption Drivers

Telemedicine depends heavily on real-time communication and data exchange, making cloud computing particularly valuable for enabling remote consultations and diagnostics. Cloud infrastructure provides scalability and remote access, which are crucial for handling large volumes of video, imaging, and patient monitoring data (Butpheng et al., 2020). However, telemedicine is also more sensitive to latency, bandwidth, and security issues compared to other e-health applications. Studies indicate that the adoption of telemedicine through cloud platforms is strongly influenced by the availability of robust infrastructure and facilitating conditions, as disruptions in connectivity can compromise patient outcomes (W. M. G. Alshammari et al., 2021; Patterson et al., 2021). Consequently, performance expectancy and facilitating conditions are dominant adoption drivers in the telemedicine context.

2.2.7.2. Electronic Health Records (EHRs) and Cloud Adoption Drivers

For **electronic health records** systems, the critical adoption drivers center on data security, privacy, and regulatory compliance. Cloud computing offers healthcare organizations a cost-effective way to store, share, and retrieve patient records across different facilities while supporting interoperability (Ben-Assuli, 2015). However, the sensitivity of patient data makes regulations and policies such as HIPAA and GDPR key factors influencing cloud adoption in **electronic health records** contexts (Alsulame et al., 2016; Sulaiman et al., 2018). Unlike telemedicine, where real-time communication is central, EHR adoption relies more heavily on the perception that cloud providers can safeguard data integrity, ensure long-term storage reliability, and facilitate seamless data sharing across organizational boundaries. Thus, security, privacy, and regulatory frameworks carry more weight as adoption drivers for EHR cloud systems.

2.2.7.3. Mobile Health (mHealth) and Cloud Adoption Drivers

MHealth applications, such as mobile apps for self-monitoring, health tracking, and patient engagement, respond differently to cloud adoption drivers because they are often end-user oriented. For patients, effort expectancy the ease of use and convenience of mobile platforms is a strong predictor of adoption (Dwivedi et al., 2016). Social influence also plays a prominent role, as patients are more likely to adopt mHealth solutions recommended by peers, physicians, or community health workers (Hoque et al., 2017). Unlike electronic health systems, which rely on organizational compliance, or telemedicine, which requires strong infrastructure, mHealth adoption is more dependent on user perceptions of usefulness, convenience, and accessibility (B. Alanazi et al., 2020). Therefore, relative advantage and social influence are especially critical for mHealth adoption, reflecting its patient-centered orientation.

2.2.7.4. Comparative Perspective across E-Health Services

Overall, the influence of cloud adoption drivers varies across e-health service types because of their distinct objectives and user groups. Telemedicine adoption is driven primarily by performance expectancy and facilitating conditions due to its reliance on real-time communication (Bergman et al., 2021; Golinelli et al., 2020). Electronic health system systems are more heavily shaped by security, privacy, and regulatory compliance because they involve sensitive, long-term patient data. mHealth, on the other hand, responds most strongly to ease of use, social influence, and perceived usefulness, given its direct engagement with patients (Alonso et al., 2021). Despite these differences, much of the current literature still treats cloud adoption in healthcare as a uniform process (W. M. G. Alshammari et al., 2021; Hamdan et al., 2023). A more nuanced understanding that differentiates between service types would allow policymakers and healthcare providers to design targeted strategies that address the unique adoption drivers of each e-health service.

2.3 **Factors Affecting the Adoption of E-Health Cloud Computing**

2.3.1 Relative Advantage

A core determinant of cloud computing adoption is its perceived benefits over traditional healthcare systems. Cloud-based e-health offers real-time data availability, precise data management, and reduced reliance on paperwork, allowing professionals to focus more on patient care (Alharbi et al., 2016; Sivan & Zukarnain, 2021). These systems enhance the quality of health services by providing accurate patient records that support better-informed decision-making (Ishak et al., 2021). This will significantly improve the operational efficiency.

E-health automation reduces manual data entry errors and streamlines workflows (França et al., 2022). Cloud-based systems also cut costs by phasing out paper-based methods, lowering IT maintenance expenses, and reducing downtime (Noor, 2019). Cloud technologies facilitate secure communication, data sharing, and the use of analytical tools to improve coordination among healthcare teams (Chang et al., 2021; Adler-Milstein et al., 2021).

Relative advantages from user perspective are captured under performance expectancy, which reflects the belief that adopting e-health cloud-based or mobile health (mHealth) services improves healthcare performance and outcomes (Dwivedi et al., 2016;

Hoque et al., 2017). Studies consistently revealed that performance expectancy strongly affect decision to adoption cloud computing (Wu et al., 2011; Rofiah et al., 2022)

Performance expectancy in the context of mHealth refers to the extent to which individuals believe that using mobile health services will enhance their personal performance and health management (Dwivedi et al., 2016). Users are more motivated to adopt new technologies when they perceive them as offering significant advantages in accomplishing daily tasks (Rofiah et al., 2022). Prior studies consistently report that performance expectancy exerts a strong positive influence on users' behavioral intention to adopt innovative technologies. Wu et al. (2011) found a clear positive relationship between performance expectancy and the intention to adopt mHealth services, while Wang et al. (2006) highlighted performance expectancy as a critical determinant in mHealth adoption. Similarly, Hoque et al., (2017) confirmed that performance expectancy is among the most significant predictors influencing users' BI to use mHealth solutions.

2.3.2 Technical Complexity

Despite these benefits, adoption is hindered by technical complexities. Implementing cloud solutions requires specialized expertise, robust IT infrastructure, and significant resource allocation for integration and staff training (Ishak et al., 2021). Healthcare facilities without sufficient expertise face challenges in system adaptability, data security, and scalability (Abdullah et al., 1997; Meri et al., 2019). Complexity also influences organizational decision-making, as institutions must balance the benefits against costs, training demands, and potential privacy concerns (Faloye et al., 2021). Furthermore, complexity is context-dependent —

institutions with pre-existing IT capacity experience fewer barriers compared to those starting from scratch (Chang et al., 2021).

From the user side, these challenges link to effort expectancy, which relates to the perceived ease of use of new systems. Users are more likely to adopt cloud or mHealth platforms if they are intuitive, convenient, and require minimal learning effort (Dwivedi et al., 2016; Alalwan et al., 2018). High usability and low complexity positively influence behavioral intention (Sun et al., 2013; Zhang et al., 2017).

Effort expectancy refers to the degree of ease connected with using a new system (Sun et al., 2013). Within the broader context of mHealth, it is described as the level of convenience tied to remotely and independently using the system (Dwivedi et al., 2016). Generally, users are more inclined toward adopting technologies that are straightforward, convenient, and require minimal effort to learn and operate (Alalwan et al., 2018; Dwivedi et al., 2016). Wu et al. (2016) further examined how users' profiles, the number of interactions, and the effort required can shape their intention to adopt mHealth services. Overall, Effort expectancy has been identified as a critical factor directly influencing users' behavioral intention to engage with mHealth systems (Sun et al., 2013; Zhang et al., 2017).

2.3.2 Security and Privacy

Security and privacy remain critical barriers in cloud adoption for healthcare. Sensitive patient data managed by third-party providers raises concerns about unauthorized access, compliance with varying international regulations, and data sovereignty (Chenthara et al., 2019; Chomutare et al., 2021). Security encompasses data protection, disaster recovery, and business continuity (Katzan, 2010), while privacy focuses on safeguarding patients' rights and confidentiality (Ryan & Loeffler, 2010).

Recent advances such as encryption, blockchain integration, and stronger identity management systems help mitigate these risks by enhancing secure access and data sharing (Azzez & Van der Vyver, 2019; Sivan & Zukarnain, 2021). Nonetheless, security and privacy concerns continue to shape both organizational strategies and patient trust in cloud-based healthcare solutions.

Security is concerned with the safety of user's data (Smith, 2009). Security in cloud computing is not just about authenticity, authorization, and accountability, but is more concerned with data protection, disaster recovery, and business continuity (Katzan, 2010). Privacy is concerned with clear definition and protection of user's rights to their data. Privacy and confidentiality concerns are raised in cloud computing because service providers have access to all the data of the SMEs and they can intentionally or unintentionally use it for the unauthorized purpose (Ryan and Loeffler, 2010).

Social influence refers to the extent to which an individual perceives that significant others believe he or she should adopt a new system (Zhang et al., 2017). Dwivedi et al. (2016) describe it in the mHealth context as the degree to which individuals feel encouraged by others to use mobile health services instead of traditional healthcare practices. Prior research has shown that SI plays a notable role in shaping perceptions of both usefulness and ease of use regarding mHealth technologies (Chen & Lin, 2018). Similarly, Sun et al. (2013) highlighted the strong effect of SI on users' behavioral intention to adopt mHealth services. Based on these insights, the following hypothesis is proposed.

2.3.4 Regulations and Policies

Adoption is also strongly influenced by regulatory environments. Healthcare organizations must comply with strict data protection laws, such as HIPAA in the United States and GDPR in

Europe, which set standards for security, consent, and patient privacy (Nahai, 2019). However, the lack of standardized, health-specific cloud regulations in some regions remains a barrier (Kaur et al., 2019).

Supportive regulatory frameworks enhance adoption by fostering trust among patients, providers, and stakeholders (Chenthara et al., 2019). Governmental investments in clear legal frameworks, interoperability standards, and supportive technology adoption policies are therefore critical to ensure safe, secure, and effective cloud integration (Nahai, 2019).

Generally, the existing literature underscores the fundamental role of regulations and policies in facilitating the adoption of e-health cloud computing. Without sufficient legal frameworks and health-specific security policies, the incorporation of e-health via cloud computing might face challenges. To circumvent these, healthcare organizations must stay updated with applicable laws and establish secure IT infrastructures. By diligently analyzing relevant laws and implementing secure IT systems, healthcare organizations can ensure patient data's privacy and security while reaping the advantages of integrating e-health technology into cloud computing.

Facilitating conditions are defined as the degree to which an individual believes that adequate organizational and technical resources are available to support the use of a new system (Venkatesh et al., 2003). (Williams et al., 2015) found that facilitating conditions positively affect the actual intention to use health information technologies. Similarly, Boontarig et al. (2012) reported that facilitating conditions have a significant positive impact on both behavioral intention and actual usage of smartphones for healthcare purposes. Dwivedi et al. (2016) further emphasized FC as one of the dominant factors influencing consumers' behavioral intention to adopt mHealth services. Based on this, the following hypothesis is proposed.

Table 2.1
Matrix Content Analysis

Citation	Relative Advantage	Security and Privacy	Technical Complexity	Regulations and Policies
(Alkurdi, 2022).	X	X	X	X
(Meri et al., 2019).		X	X	
(Calegari & Fettermann, 2022)		X	X	X
(Zhu et al., 2015)				X
(Chang et al., 2021)		X		
(Alharbi et al., 2016)	X	X	X	X
(Sivan & Zukarnain, 2021)		X		X
(Chenthara et al., 2019)		X		
(Azeez & Van der Vyver, 2019)		X		X
(Sikandar et al., 2021)		X		X
(Butpheng et al., 2020)		X		
(Faloye et al., 2021)		X		X
(Henaku et al., 2022)			X	
(Idoga et al., 2018)		X		
(Sadoughi et al., 2020)		X	X	
(Rofiah et al., 2022)	X			

2.3.5 Gender Segregation

Several studies in various fields have revealed that revealed gender segregation to have influences on performance. For instance, previous studies revealed that gender diversity have positive influence on performance; there are studies also that report a negative relationship or no relationship at all (Andrieș et al., 2017; Andries & Capraru, 2013). Riquelme and Rios, (2010) studied the moderating effect of Gender in the adoption of mobile banking. (Presbitero et al., 2014) also investigated that gender-based discrimination in credit markets. Gender difference is also studied in entrepreneurship and financial inclusion (Saviano et al., 2017).

Gender is also measure as mediator variable by Tan et al., (2025) while investigation the mediating effect of digital financial inclusion on gender differences in digital financial literacy and financial well-being : Evidence from Malaysian households. Furthermore, Almarazroi et al., (2019) investigated gender effect on cloud computing services adoption by university students: Case study of Saudi Arabia.

Saudi Arabia has been undergoing significant social reforms, particularly related to women's rights and the adoption of cloud computing. While gender segregation in public spaces was once a common practice, recent policies have aimed to relax these restrictions, particularly in restaurants and public events. Concurrently, Saudi Arabia is actively promoting cloud computing adoption through its "Cloud First Policy". The increased adoption of cloud computing could potentially empower women by creating new job opportunities and facilitating access to information and services. However, there may also be challenges related to digital literacy and access in certain segments of the population.

Under vision 2030, led by Crown Prince Mohammed bin Salman, aims to modernize the kingdom socially and economically, which includes significant easing of gender segregation laws: Women in the Workforce: One of the major goals is to increase female participation in the labor force from 22% to over 30%, which was already surpassed by 2021. Gender-mixed workplaces are now permitted in many sectors, including retail, finance, hospitality, and government offices.

2.4 Types of Cloud Computing Services

2.4.1 Cloud Computing Platform as Services

Technological advancements such as cloud computing have amplified the pace of change. Cloud computing promises many benefits, including scalability, reliability, flexibility in managing data, software applications, and infrastructure needs (Vellela et al., 2023). One distinctive advantage of this technology is its ability to deliver platform services at scale. This enables developers to develop and deploy high quality applications without worrying about underlying infrastructure management.

Cloud computing platforms as services refer to a suite of tools ranging from libraries and infographics important for building and utilizing exciting applications (Wang & Li, 2016). These platforms feature abstraction layers that enable application development without concerns about background hardware or software infrastructure support. Platform services also provide automatic provisioning/deprovisioning tools based on application requirements, making it versatile for scalable apps that need scaling up or down easily.

Its multi-language programming capabilities add significant versatility to its functionality offerings. Cloud computing has many app deployment and creation advantages, as it enables developers to focus more on innovation rather than thinking about infrastructure management (Siddiqui et al., 2019). Platforms such as these are amazingly scalable - operating nearly in tandem with business needs while significantly slicing costs related to utilizing apps. However, using these services have some disadvantages; one of which being the inability to customize the underlying infrastructure properly considering its subject to third party control – ultimately compromising app uniqueness (Vellela et al., 2023). Contemporary mobile apps built for data communication must meet elevated security requirements.

2.4.2 Cloud Computing Infrastructure as Service

IaaS (Infrastructure as a Service) is now generally adopted by businesses globally utilizing this virtualized network resource allocation system that comprises computing power, storage capacity & network access (Mohammed & Zeebaree, 2021). The easy-to-navigate system offers scalability at will - making it a game-changer in business technology enhancing organizational operational expenditures positively by reducing risks. The most effective way to manage the entire lifecycle of existing IT systems is to scale resources up and down effectively using IaaS (Suliman & Madinah, 2021). Virtualization technology empowers businesses to allocate computing resources based on their needs, leading to optimum hardware utilization levels and more flexible IT operations.

AWS, Google Cloud, Microsoft Azure & IBM Cloud provide IaaS services uniquely designed with features/benefits like AWS's reliable and robustness in its cloud infrastructure management (Borge & Poonia, 2020). Google Cloud does an outstanding job of scaling computing/storage/network capacity while competing favorably in pricing by offering scalability without compromising the quality-of-service level agreements.

Microsoft Azure's enterprise-class level brings scalable features at a cost to enable prompt VM deployment within minutes for businesses looking to maximize size reduction with sizing capacity-reducing optimization features cloud storage offerings with flexibility and exceptional capabilities. To meet the demands of large-scale customers, Microsoft has designed Azure Virtual Machines that are highly robust and scalable while still maintaining flexibility.

IBM Cloud has developed a secure cloud infrastructure that emphasizes productivity needed for successful operations especially when dealing with major jobs (Borge & Poonia, 2020). IBM Cloud's SoftLayer Infrastructure as a Service demonstrates an impressive speed since it allows organizations to deploy servers, storage resources & networking resources almost instantly through automation.

2.4.3 Cloud Computing Software as Services (SaaS)

SaaS shows a pattern shift in software conveyance, as the service provider hosts the software on their cloud infrastructure and allows end users to access it by web browser (Panda & Chakravarty, 2021). With the elimination of the need for installation, management, and licensing responsibilities, cloud users can seamlessly operate software while entrusting the cloud service provider with data and infrastructure control. Organizations that adopt the SaaS model benefit from significant operational cost reduction due to a lack of upfront investment requirements. Further, this innovative delivery model enables enterprises to divest from managing IT services, allowing them to concentrate on core business objectives while relying on the cloud service provider to handle the maintenance, upgrades, backups, and security tasks. Such transformative benefits suggest that SaaS adoption is critical to business continuity in an increasingly digital world (Ferreira et al., 2019).

SaaS has the abilities to considerably decrease the period of time and struggle needed to obtain cloud computing services. Raghavan and Nargundkar (2020) emphasize the many processes that SaaS eradicates, such as administrative approvals for hardware and software procurement and technical development, deployment, and testing. Still, security concerns have a main challenge for several businesses thinking about adopting SaaS. Ferreira et al. (2019) mentioned that these concerns include data location, access, segregation, and integrity.

Despite this, the SaaS model provides clear advantages when it comes to the cost. In contrast to other cloud computing models such as PaaS and IaaS, SaaS offers less and direct pricing schemes, whereby the cloud consumer pays per month and/or per user (Panda & Chakravarty, 2021). Furthermore, some SaaS services offer limited free storage to their customers, followed by additional payment only when additional storage space is required.

The utilization of cloud computing models for business operations, particularly IaaS and PaaS, is highly dependent on cost allocation, where cloud consumers are charged for every unit of resources consumed. However, compared to IaaS and PaaS, adopting SaaS offers a lower entry barrier for businesses with less sophisticated IT infrastructure. Nonetheless, the deployment of SaaS solutions still requires the establishment of adequate security policies and procedures. Identifying and protecting classified data, employee access to such data, and SLAs pertaining to the security measures used for data protection are among the issues that need to be addressed.

Adopting a SaaS solution requires cautiously taking into account and dealing with these security and policy concerns. The challenges included in integrating SaaS applications with cloud based or on premise applications have been a issue if interest due to the deficit of a standardised Application Programming Interface (API) (Raghavan & Nargundkar, 2020). This has presented a main obstacle to the successful functioning of these applications. However, researchers have found solutions to subdue these challenges.

Organizations deciding to adopt SaaS or other cloud computing solutions must recognized the Service Level Agreements (SLAs) that they must accept and monitor (Panda & Chakravarty, 2021). This knowledge will enable them to establish best practices and optimally utilise cloud computing solutions. By implementing these measures, organizations can realise the numerous benefits of cloud computing. Therefore, organizations must invest in developing appropriate strategies to optimise their utilization of SaaS and cloud-based applications.

Table 2.2
Summary of differences between cloud service types

	Control of resources	**Responsibility for Security**	**Cost**	**Level of IT skills**
SaaS	User control over their own data, but	Limited options for user security, like	Low initial costs as long as managing	Needs minimum IT expertise

	no control over sources	access management	services doesn't need hiring IT personnel	
PaaS	Data and application control by the user	Limited data and application security for cloud users	No initial outlay; developers are included in operating costs.	Strong IT abilities are required because PaaS is developer-focused.
IaaS	complete user authority over all resources—aside from physical	User accountability for system security, including application and operating system	Hiring managers and developers are some of the up-front expenditures associated with buying virtual machines (VMs) and running them.	Because IaaS entails managing OS, virtual machines, and networks, it requires advanced IT expertise.

2.5 Theoretical Background

There are many theories used in technology adoption studies. According to Nedev, (2014) the most-used adoption frameworks or theories appear to be the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Diffusion Of Innovation (DOI) theory and the Technology-Organization-Environment (TOE) framework. These models aimed to determine the factors that influence user adoption and usage behavior within organizations (Tadesse, 2014). In general, theories may consider different layers of analysis, usually the user at "micro-level", the organization in a "meso-level" or the market/innovation at the "macro-level". Given the healthcare organizations are the focus of this study, the attention of this study will be at organizational level of ICT innovation adoption process (Tadesse, 2014).

2.5.1 Theory of Reasoned Action (TRA)

On the basis of the focus of the Health Belief Model (HBM) on individual perceptions, the Theory of Reasoned Action (TRA) was formulated, also focusing on the attitude toward the intended outcome behavior but adding measures of subjective norm, that is, the perception of the behavior in question by those whose opinion is valued by the individual (Fishbein & Ajzen, 1977).

The TRA, developed by Fishbein and Ajzen, (1977), proposes that an individual's behavior is determined by their behavioral intention, which in turn is influenced by attitude toward the behavior whether the person sees the behavior as beneficial or harmful and subjective norms perceived social pressure to perform or not perform the behavior, influenced by important referents (e.g., peers, superiors, institutions) (Sahoo et al., 2023).

The adoption of cloud computing can be derive by attitude toward the behavior whether to adopt or no not. For instance, the adoption of e-health cloud computing. For healthcare professionals, administrators, and IT staff, attitude is shaped by Perceived benefits like better patient data access, improved decision-making, reduced paperwork, scalability, and integration with telemedicine. Perceived risks such as data security/privacy concerns, cost implications, learning curve, dependency on internet connectivity, and Past experience that is if previous ICT adoption went smoothly, attitude is more positive; if past systems were slow or unreliable, skepticism rises (Alam et al., 2020).

Furthermore, based on the preposition of TRA adoption of cloud computing In healthcare can be derive by, subjective norms are powerful because adoption decisions often require consensus. These include Institutional influence like Ministry of Health directives, hospital board policies, or NGO recommendations. Peer influence for instance, if neighboring hospitals or respected colleagues are adopting e-Health clouds, there's perceived pressure to keep up, and Patient expectations such as increasing demand for online access to medical records or teleconsultations (Gu et al., 2021; Sahoo et al., 2023).

TRA is applicable for predicting attitude toward the use of a teleconsultation system in neurology. Perceived control over one's own health was added to the theory later on, developing the Theory of Planned Behavior (TPB) (Ajzen, 1991). The TPB is applicable to the use of fitness apps (Herrmann & Kim, 2017). TRA and TPB constructs were used by Davis to explain acceptance of technology as a precondition for its use. The Technology Acceptance Model (TAM), along with several additions (Harst et al., 2019).

2.5.2 Technology Acceptance Model (TAM)

Among the various theoretical models, Technology Acceptance Model (TAM) is commonly accepted model for understanding IT usage and adoption processes. It explains much of the difference in users' behavioral intention related to IT usage and adoption across a wide variety of contexts (Hong et al., 2006). It predicts a user's acceptance of information technology and its usage on the job (Au and Zafar, 2008) and explains the determinants of user acceptance of a wide range of end-user computing technologies (Davis, 1986).

TAM seeks to explain the relationship between technological acceptance, adoption and subsequently, behavioral intention to use it (Autry et al., 2010). It poises the perceived ease of use (PEOU) and perceived usefulness (PU) as primary determinants of system use (Chen and Tan, 2004; Au and Zafar, 2008).

2.5.3 Task-Technology Fit (TTF) Theory

The TTF adoption model Developed by Goodhue & Thompson (1995) suggests that the user will adopt a new technology if it is good enough to execute the daily task efficiently (Oliveira et al., 2014). Since Technology is more likely to be adopted and used effectively if it fits the tasks that users need to perform. Hence, the adoption to a new information system (cloud computing) will depend greatly on the users' daily tasks. This model explains adoption using four constructs task characteristics, technology characteristics, task technology fit, and use.

The task characteristics and technology characteristics determine the task technology fit which leads to the adoption and use of the information system (Lee et al., 2007). TTF has been used in several studies (Santini et al., 2019). Dishaw and Strong, (1999) used an integrated TTF model with TAM to explain the relationship between software use and user performance. Lee et al., (2007) use a modified TTF model to explore the factors affecting the adoption of mCommerce in the insurance industry. Klopping and Mckinney, (2004) studied e-commerce adoption using a hybrid model comb- ing TTF and TAM.

TTF is relevant for e-health cloud adoption research in various ways. For instance, beyond perception: Unlike TAM or TRA, TTF focuses not just on perceptions (usefulness, ease) but actual functional alignment. Also, the performance linkage is another unique assumption of TTF theory; It directly links technology-task alignment to performance, making it ideal for healthcare studies where patient safety is a non-negotiable metric. In addition there its design feedback: Findings can guide cloud system vendors to tailor solutions for healthcare-specific workflows.

2.5.4 Technological-Organizational-Environmental (TOE) Framework

TOE framework was developed by Tornatzky and Fleischer (1990) to examine organizational level adoption of various IS/IT products and services. It has emerged as one of the common theoretical perspective on IT adoption (Ibrahim et al., 2025). TOE Inclusion of technological, organisational and environmental variables has made it more advantageous over other adoption models in studying technology adoption, technology use and value creation from technology innovation (Kruger & Steyn, 2024; Marfo et al., 2023).

TOE provides a holistic picture for user adoption of technology, foreseeing challenges, its implementation, its impact on value chain activities, the post-adoption diffusion among firms, factors influencing business innovation-adoption decisions and to develop better organisational capabilities using the technology (Amini & Javid, 2023). Several studies have used this model to analyze IT adoption by firms. The framework identified three context groups: technological, organizational and environmental, that may influence the process of cloud computing adoption at the organizational level.

Several studies have used this model to analyze IT adoption by firms. The framework identified three context groups: technological, organizational and environmental, that may influence the process of technological innovation adoption at the firm level.

The first context is the technological context that refers to internal and external technologies applicable to the firm. In this context, both equipment and processes may indicate technology. Essentially, it is believed that the fit between the existing technologies set in a firm and the intended technology innovation will be one of the determinants in the decision to adopt technology innovation (Salleh et al., 2015).

As Lynn et al., (2018) revealed that TOE framework identifies three features that influence cloud computing adoption: technological context which includes both internal and external technologies used by the firm (relative advantage, perceived complexity, and perceived compatibility), organizational context refers to descriptive characteristics of the organization, including firm size and scope, complexity of firm managerial structure, and quality and degree of its human resources (top management support, firm size, and technology readiness), and environmental context refers to the firm industry and its dealings with trading partners, competitors and government (competitive and trading partner pressures) (Lynn et al., 2018). The TOE framework serves as an important theoretical perspective for studying contextual factors (Tornatzky and Fleischer, 1990).

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

Over the years, there has been an increased use of systems related to Information and Communication Technology (ICT), such as cloud computing and e-health systems. The extensive adoption of these new technologies requires a practical theoretical approach to understanding its processes. One such model is the Unified Theory of Acceptance and Use of Technology (UTAUT), which is often applied to technology acceptance studies in various sectors (Tamilmani et al., 2021).

UTAUT formulation is based on eight research models, namely, technology acceptance model, theory of reasoned action, hybrid model TAM–TPB, motivational model, theory of planned behaviour, model of PC utilization, innovation diffusion theory and social cognitive theory. Detailed analysis of these eight models revealed that performance expectancy, social influence, effort expectancy and facilitating condition had significant influence on user intention to adopt technology (Rahi et al., 2019; Venkatesh et al., 2003a) .

Thus, the UTAUT framework identifies four critical components that influence adopting technology. These include effort expectancy; performance expectancy; facilitating conditions and social influence are included in UTAUT studies to identify the factors for the motivation of users using information technology (Apfel & Herbes, 2021). The first three are direct determinants of usage intention and behaviour, and the fourth is a direct determinant of user behaviour. Performance expectation refers to an individual's belief that adopting cutting-edge technologies will enhance their ability to meet specific goals or perform better (Apfel & Herbes, 2021).

Effort expectation highlights the user-friendliness aspect of a designated ICT system. Social influence underscores how opinions and beliefs influence ICT adoption. Finally, facilitating conditions reflect whether practical support such as training programs or technical assistance is readily available for users navigating newly adopted digital systems (Apfel & Herbes, 2021).

Undoubtedly one of UTAUT's standout features is its comprehensive nature which enables it to illuminate multiple potential motivators behind moves towards increased digital technology incorporation in personality contexts at once while also accounting for big picture factors like wider societal trends- offering versatility and multiple approaches available for users when evaluating specific advancements most useful (Ahmed et al., 2020). The UTAUT framework's adaptability comes in handy as researchers can easily customize it according to their research problem area or context.

However, while UTAUT is a useful resource, it has several limitations. For example, its application assumes equal access to technology for all users but lacks accommodation in cases where this is not practicable in some situations. Additionally, although individual decision-making processes receive detailed attention from UTAUT guidelines systematically assessing environmental impacts alongside organizational dynamics regarding technological acceptance, they remain unexplored.

Nonetheless, understanding how cloud computing or e-health systems get adopted or utilized benefits tremendously from using the UTAUT model as an analytical tool when implemented properly. It facilitates recognition of key elements influencing technology uptake within individuals' daily practice routines (Tamilmani et al., 2021). The authors revealed that this helps policy makers determine ideal corrective measures if need be or tools for encouraging positive user attainment milestones. Therefore, these technology outputs can catalyze improvements in patient care quality, improving overall health status performance results.

2.5.5.1 Development of Unified Theory of Acceptance and Use of Technology

In 2003, Venkatesh and his research team conducted a review of eight theories regarding technology acceptance. These theories included the Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM), a combined model of TAM and TPB (C-TAM-TPB), the Model of PC Utilization (MPCU), the Innovation Diffusion Theory (IDT), the Motivational Model (MM), and the Social Cognitive Theory (SCT). Following their review, they introduced a new theory called the Unified Theory of Acceptance and Use of Technology (UTAUT). This new theory integrated the unique aspects of each of the previously mentioned theories and models to create a comprehensive framework.

According to Qingfei, Shaobo, and Gang (2008), there are two primary concerns with acceptance theories. First, although each theory employs different terminologies for their constructs, they fundamentally refer to the same concepts. Second, due to the intricate nature of behavior research and the limitations of the researchers, no single theory encompasses all behavioral factors. In other words, each theory has its own limitations and does not complement the others. Table 2.3 (Momani, 2020) provides a summary of the major strengths and weaknesses of the most significant technology acceptance theories, along with information about their development.

Table 2.3
Summary of the technology acceptance theories

Theory	Developer and year	Field of development	Strength	Weaknesses
TRA	Ajzen and Fishbein, 1980	Social Psychology	It is one of the most essential theories of human behavior, crafted to explain nearly any type of human behavior.	It is broad and consistent, yet it does not account for other variables that influence behavioral intention, such as fear, threat, mood, or prior experience.
TPB	Ajzen, 1985	Social	It has been effectively applied to	It proposes that behaviors are

		Psychology	understanding individual acceptance and usage of a wide variety of technologies.	predetermined and does not consider other variables that influence behavioral intention.
DTPB	Taylor and Todd, 1995	Social Psychology	It is enhanced by incorporating certain factors from the IDT model, making it more relevant for managers in influencing adoption and usage.	It is similar to TPB, as it breaks down the constructs of TPB and still maintains that behaviors are pre-planned.
TAM	Davis, 1986	IT Field	It is a robust model for technology applications, replacing TRA's attitude toward behavior with two measures: perceived usefulness and perceived ease of use. However, it is less general than TRA and TPB.	It excludes TRA's subjective norms and does not offer feedback on factors such as integration, flexibility, completeness of information, and information currency. Additionally, it does not clarify how expectancies influence behavior.
TAM2	Venkatesh and Davis, 2000	IT Field	It accounts for perceived usefulness and perceived ease of use through social influence and includes subjective norms. It also explains changes in acceptance over time as users become more experienced with the technology.	As an extension of TAM, it does not specify how expectancies influence behavior and cannot predict user behavior within a cultural context.
C-TAMTPB	Taylor and Todd, 1995	IT Field	It merges the TPB model from social psychology with TAM from the IT field to enhance the application of TPB in technology acceptance.	The constructs of TAM are not fully represented, and the aspect of behavioral planning is not addressed. Additionally, it still does not consider fear or threat related to use.
MPCU	Triandis, 1979	IT Field	It is well-suited for predicting individual acceptance of various technologies and is effective in understanding and explaining usage behavior with a voluntary basis.	The complexity factor influences computer and technology usage, indirectly affecting perceived short-term consequences.
IDT	Rogers, 1983	Social Science	It possesses the capability to analyze any type of innovations and can elucidate and forecast the factors influencing the adoption rates of innovations.	It is broad in scope. It does not specify how attitudes influence decisions to accept or reject, nor does it detail how innovation factors affect decisions.
MM	Deci and Ryan, 1985	Social Psychology	It finds extensive applications in studies of motivation, learning, and healthcare. It can also be applied to comprehend the adoption and utilization of new technologies.	It requires the inclusion of several factors to become more suitable for studying technology usage.

2.5.5.2 Key constructs of Unified Theory of Acceptance and Use of Technology

Performance expectancy is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003). Performance expectancy is based on the constructs from Technology Acceptance Model (TAM), TAM2, Combined TAM and the Theory of Planned Behaviour (CTAMTPB), Motivational Model (MM), the model of PC utilisation (MPCU), Innovation Diffusion Theory (IDT) and Social Cognitive Theory (SCT) (i.e. perceived usefulness, extrinsic motivation, job-fit, relative advantage and outcome expectations). It is the strongest predictor of use intention and is significant in both voluntary and mandatory settings (Zhou, Lu & Wang, 2010; Venkatesh, Thong & Xu, 2016).

According to Martins et al., (2014), performance expectancy in technology context is the degree where an individual believes that using technology will help him/her to attain gains in performing tasks. Similarly, Alalwan and Williams, (2014) postulated that performance expectancy is considered as a term of utility that is encountered during the use of technology. Several researchers have provided evidence of significant influence of performance expectancy on user behavioural intention to adopt new technology in various field (Martins et al., 2014; Oliveira et al., 2014, 2016; Sok Foon & Chan Yin Fah, 2011).

Effort expectancy is defined as "the degree of ease associated with the use of the system" (Venkatesh et al., 2003). Effort Expectancy is constructed from perceived ease of use and complexity driven from TAM, MPCU, IDT, which share a similarity in definitions and scales. The effect of the construct becomes non-significant after extended usage of technology (Gupta, Dasgupta & Gupta, 2008; Chauhan & Jaiswal, 2016).

Furthermore, Venkatesh et al., (2012) defined EE as "the degree of ease associated with the use of an innovative technology". It essentially assesses how consumers understand

and apply new technologies (Andreas, 2012). Recent research also suggests that users' expectation of effort affects their decision to embrace an innovative product (Baishya & Samalia, 2020; Martins et al., 2014; Oh et al., 2009). Thus, when user feels that new technology is easy to use and does not require much effort, they would have high chances to adopt it. Since e-health consultation is an IT-based service, it is reasonable to assume that patients would choose to use it if they believe it takes less effort.

Social Influence is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003). Social influence is similar to the subjective norms, social factors and image constructs used in TRA, TAM2, TPB, CTAMTPB, MPCU, IDT in the way that they denote that the behaviour of people is adjusted to the perception of others about them.

Social influence is described as "the degree to which a person believes important, others believe he or she should apply the new method" (Venkatesh et al., 2012). People in developing countries live in joint families and rely on one another in various socio-economic situations (Ray et al., 2019). As a result, their usage of e-health consultation services in this situation will not only be observed by their close friends and family, but it will also inspire them to utilize them in the future (Ray et al., 2019). As a result, it is vital to look into the relationship between Social influence and cloud computing adoption in health sector.

The effect of social influence is significant when the use of technology is mandated (Venkatesh et al., 2003). In the mandatory context, individuals might use technology due to compliance requirement, but not personal preferences (Venkatesh & Davis, 2000). This might explain the inconsistent effect that the construct demonstrated across further studies validating the model (Zhou, Lu & Wang, 2010; Chauhan & Jaiswal, 2016).

Facilitating conditions is defined as "the degree to which an individual believes that an organisation's and technical infrastructure exists to support the use of the system" (Venkatesh et al., 2003). It also refers to the technological and organizational support and services accessible to a customer to perform a behavior (Venkatesh et al.,2012). This concept is comparable to theory of planned behaviour's perception of behavioural control. The facilitating conditions construct is formed from compatibility, perceived behavioural control and facilitating conditions constructs drawn from TPB, CTAMTPB, MPCU and IDT. Facilitating conditions have a direct positive effect on intention to use, but after initial use, the effect becomes nonsignificant. Therefore, the model proposes that facilitating conditions have a direct significant effect on use behaviour (Venkatesh et al., 2003).

Furthermore, the ambient factors that support or restrict technology adoption are expressed in enabling circumstances. Practical usage of e-health consultation services is contingent on the availability of suitable information and communication technology (ICT) infrastructure, as it requires constant contact between remote physicians and patients (Al-Mahdi et al.,2015). Given that previous study has demonstrated that facilitating conditions is necessary for advancing any breakthrough technology, hence the link between FC and adoption of cloud computing I the health sector should be investigated.

2.5.5.3 The relation of UTAUT constructs with other theories constructs

Based on the relationship between UTAUT and other theories, each construct within UTAUT shares characteristics with constructs from other theories within the same context. For example, performance expectancy corresponds to the usefulness of technology, similar to perceived usefulness in the Technology Acceptance Model (TAM) and job-fit in the Model of PC Utilization (MPCU). Likewise, effort expectancy parallels perceived ease-of-use in

TAM and complexity in MPCU. Table 2.3 illustrates the UTAUT constructs, their related constructs from other theories reflecting the same concepts, and the original theory for each construct. This information, collected, classified, and summarized by the researcher, is based on the work of Venkatesh et al. (2003).

The comparison among these theories indicates that performance expectancy and its related constructs have strong predictive power across all theories, making it the most significant predictor of behavioral intention. It remained significant across three measurement times in both voluntary and mandatory usage contexts. Similarly, the effort expectancy construct and its related constructs significantly affected behavioral intention in both usage settings, particularly during the post-training phase. Social influence showed varied effects; it was insignificant in voluntary contexts but significant in mandatory contexts, especially for users with low experience or when rewards or punishments were involved. Furthermore it was revealed that Social influence, and trust might be at the same time inhibiting and promoting factors for customers' adoption of new technology (Chaouali et al., 2016). Facilitating conditions and their related constructs showed a significant impact on behavioral intention during the initial training phase but this effect diminished in the second training phase (one month post-implementation) as individuals' experience levels increased (Venkatesh et al., 2003).

Table 2.4
Relation of UTAUT constructs with other theories constructs

UTAUT Constructs	Related Constructs	Theories
Performance expectancy	• Job-fit • Extrinsic motivation • Relative advantage • Perceived usefulness	• MPCU • MM • IDT • TAM and C-TAM-TPB

	• Outcome expectations	• SCT
Effort expectancy	• Complexity • Perceived ease of use • Ease of use	• MPCU • TAM • IDT
Social influence	• Subjective norm • Social factors • Image	• TRA, TPB, and C-TAM-TPB • MPCU • IDT
Facilitating conditions	• Perceived behavioral control • Facilitating conditions • Compatibility	• TPB and C-TAM-TPB • MPCU • IDT

2.5.5.4 Applications and Practical Implications of Unified Theory of Acceptance and Use of Technology

The UTAUT model have been examined in various geographical contexts to assess the influence of culture on technology adoption and to confirm the generalizability of the theory's principles (Gupta, Dasgupta, & Gupta, 2008; Im, Hong, & Kang, 2011; Venkatesh, Thong, & Xu, 2012). Most studies found that UTAUT constructs remained significant across different cultures. For instance, a comparative study of technology acceptance in the USA and China revealed that the model has a strong explanatory power in both regions. However, the model explained more variance in behavioral intention when fewer moderators were included (Venkatesh, Thong, & Xu, 2012).

In a research conducted in Korea and the USA, while the relationship strengths varied slightly, the significance remained consistent across both samples (Im, Hong, & Kang, 2011). Similar outcomes were seen in cross-cultural tests of the UTAUT model between individualistic and collectivistic nations, where the model proved effective in both cultural settings, though the strength of the relationships differed. This indicates that culture strongly moderates the model's pathways (Udo, Bagchi, & Maity, 2016).

AbuShanab and Pearson (2007) utilized the UTAUT model to explore the key factors influencing Internet banking adoption in Jordan. They assessed the model's applicability to Internet banking technologies by distributing a survey questionnaire to 940 customers across three Jordanian banks. Using ANOVA tests, the study revealed that performance expectancy, effort expectancy, and social influence significantly impact behavioral intention. These factors effectively predicted the intention to adopt Internet banking. Additionally, the researchers discovered that gender moderates the relationship between these constructs and behavioral intention.

Al Mashagba and Nassar (2012) also applied the UTAUT model to study Internet banking adoption in Jordan, specifically in the context of mobile banking. They enhanced the model by incorporating additional factors such as security, design issues, and reliability as determinants of behavioral intention. The study included education level as the sole moderator. They found that effort expectancy did not significantly affect behavioral intention. Using PLS path modeling and the Varimax procedure, the researchers discovered that both the level of experience and education influenced the relationship between performance expectancy and behavioral intention, as well as the relationship between facilitating conditions and usage behavior.

The UTAUT models have been utilized to investigate technology acceptance across various sectors, including healthcare (Chang et al., 2007), e-government (Gupta, Dasgupta, & Gupta, 2008; Chan et al., 2010), mobile internet (Venkatesh, Thong, & Xu, 2012; Thong et al., 2011), enterprise systems (Chauhan & Jaiswal, 2016; Ling Keong et al., 2012), and mobile banking and apps (Zhou, Lu, & Wang, 2010; Mütterlein, Kunz, & Baier, 2019). These applications have consistently shown that behavioral intention strongly depends on perceived performance and perceived ease of use. For instance, the technology acceptance framework was applied to study the adoption of pharmacokinetics-based clinical decision support systems, revealing that all constructs significantly influenced intention except for facilitating conditions, which only affected actual usage (Chang et al., 2007).

In the context of e-government, a study on employees in a state organization in a developing country found that all UTAUT variables, moderated by gender, significantly influenced adoption, with performance and effort expectancy having the strongest impacts (Gupta, Dasgupta, & Gupta, 2008). When examining ERP software training acceptance, three out of four predictors of use intention were significant.

Effort expectancy, performance expectancy, and facilitating conditions influenced employees' intention to adopt training tools, while social influence did not. This was likely due to the instrumental nature of ERP software and its dependence on utility factors, which overshadowed the role of social influence in users' decisions (Chauhan & Jaiswal, 2016). Finally, the UTAUT model has several practical applications. It can be employed to predict the expected acceptance rate of a product, allowing companies to maintain adequate stock levels to meet consumer demand. Additionally, insights derived from the model can help practitioners design products that are more user-oriented (Venkatesh, Thong, & Xu, 2012).

2.5.5.5 Limitations of Unified Theory of Acceptance and Use of Technology

Researchers integrating eight competing theories into UTAUT overlooked the adoption process's communication stages before technology adoption. This omission underscores the necessity of merging the adoption decision process with UTAUT to grasp the full spectrum of factors influencing acceptance. Moreover, UTAUT's focus on user perspectives limits its applicability in organizational contexts, which involve more complex adoption dynamics than individual settings (Kiwanuka, 2015). Integrating UTAUT with other theories could provide a more holistic understanding of technology adoption processes across various contexts.

2.5.6 Diffusion of Innovations Theory

The Diffusion of Innovations Theory holds a vital position as a framework used widely in discerning how innovative methods are adopted across industries including healthcare (Sartipi, 2020). DOI is concerned with how new ideas are adopted within organisations over time and how they change the organisation. DOI adoption is affected by five influences: relative advantage, trialability, complexity, compatibility and observability. One of the advantages of DOI theory is that it identifies factors which can be used to examine the success or failure of adopting new technology in an organisational context.

Relative advantage is the first factor of DOI which examines whether the new technology could add value when compared to the existing system. Previous studies considered these factors to be purely technological aspects. For instance, Alshamaileh (2013), while other studies argued that these factors could be approached from different perspectives (Lin & Chen, 2013). Observability aspects about such technologies which impact its uptake and integration process must align accordingly; these five elements are paramount. Relative advantage refers to how the new technology is viewed versus its predecessor. In e-health systems and cloud computing, users view these technologies as superior to traditional healthcare methods by increasing efficiency while safeguarding patient data (Benhabib et al., 2021). Compatibility indicates how much technical tools align with the values and experiences of their users (Alharbi et al., 2016). For effective integration, e-health system designs require adapting into existing healthcare processes without straining users otherwise such a tech may suffer slow or non-existent adoption.

Complexity signifies how hard it seems to adopt a new technology being perceived as problematic in understanding or using it initially as confusing elements are factored in (Alkurdi, 2022). Hence, user-friendly interfaces and workflows that exhibit common-sense sorting traits with simplicity at every stage of engagement should be the outcome. Healthcare providers chiefly operate within patient care settings rather than dealing with technical complexities; therefore, this element carries significance. Trialability involves evaluating an innovation before committing fully to assess its impact thoroughly and make informed decisions accordingly (Sartipi, 2020).

Before introducing any technological innovation into their facilities however small; health-care providers must also consider testing cloud-based medical records system benefits alongside demerits. In healthcare technology adoption, observability refers to how apparent its benefits are for others (Sartipi, 2020). For e-health systems, patients and providers will see their usefulness through accessing medical records or coordinating care more effectively through real-time data exchange.

To help guide the understanding of how new technologies in healthcare get adopted successfully requires a framework like Diffusion of Innovations Theory. This theory emphasises five main factors: identifying significant advantages against current systems; confirming compatibility between user experiences/values; ensuring usability; ability for a test run prior full integration; making visible positive effects on patients' outcomes. Applying these principles will increase chances of cloud computing integration within e-health health-care settings.

2.5.6.1. Limitation of Diffusion of Innovation Theory

Diffusion of Innovation Theory has several limitations. First, its supporting evidence, such as adopter categories, largely comes from fields outside of public health and was not originally tailored for the adoption of new health behaviors or innovations. Second, it does not encourage a participatory approach in adopting public health programs, potentially limiting community engagement. Third, the theory is more effective in explaining the adoption of new behaviors rather than efforts to cease or prevent existing behaviors. Finally, it overlooks individual factors like resources and social support that are crucial for successfully adopting new behaviors or innovations in health contexts. (Boston University School of Public Health, 2022)

2.5.6.2. Rational behind the Selection of UTAUT, DOI in the Study

UTAUT incorporated the perceived attributes of innovation by incorporating elements such as perceived advantage in performance expectancy, friability in performance expectancy, observability in performance expectancy, complexity in effort expectancy, and compatibility in social influence from the Diffusion of Innovation theory. Although the constructs influencing technology acceptance are crucial, the procedural aspect they traverse is equally essential for the success of information systems projects.

Despite claiming to incorporate the Diffusion of Innovation theory into UTAUT, the researchers neglected to consider the Innovation Diffusion Process, which encompasses the communication stages technology undergoes before adoption. The stages of Diffusion of Innovation were omitted when integrating eight competing theories of technology acceptance into UTAUT. Therefore, there is a need to amalgamate the Innovation Decision Process with

UTAUT to gain a more comprehensive understanding of the acceptance process and the constructs influencing innovation adoption.

UTAUT is more relevant to users than organizations, making it more suitable for comprehending studies primarily influenced by human factors. On the other hand, the Diffusion of Innovation theory is better suited for the organizational context and has found applications in various fields, including agriculture, sociology, and information systems. Researchers highlighted that adoption in an organizational context is more intricate than at an individual level (Kiwanuka, 2015).

DOI is one of the first theories developed to observe technology adoption (Rogers, 2007). DOI is defined as "a theory of why, how and at what rate new ideas, process innovation and technology spread through a society, an organization or a country" (Cua, 2012). DOI consists of two aspects, diffusion and innovation. Diffusion is a special type of communication concerned with the spread of messages that are perceived as new ideal (Rogers, 2007). Thus, the process in which a new idea or innovation is spread through certain channels among the members of a social system over time can be describe as diffusion (Rogers, 2007), while innovation is an idea, object or practice perceived as new by society, individual, government or other unit of adoption (Rogers, 2007). Rogers identified five stages of innovation adoption: knowledge, persuasion, decision, implementation and confirmation. In this process a decision-making unit goes from gaining the necessary knowledge for innovation, attitudinal building toward the new idea, adopting or rejecting the decision toward the innovation, implementing it and finally confirming the decision.

Various studies have used the DOI theory to support investigation into the adoption of new technologies at both the individual and organisational levels (Martins et al., 2014; Rahimli, 2013). Technology adoption theory plays an important role in investigations of the adoption of technology in different contexts such as health (de Grood et al., 2016), RFID (Ramanathan et al., 2014), e-enterprises (Ramdani et al., 2013), and e-business (Lin & Lin, 2008). In addition, several studies used technology adoption theories to investigate the adoption of cloud computing (Alshamaileh, 2013).

The study's conceptual model, therefore, is built upon UTAUT, as a primary theory, and supported by DOI. Also, UTAUT is chosen to be the primary theory as it covers many aspects of individual's perceptions. Based on this argumentation the conceptual model of the study is built upon UTAUT and DOI.

In conclusion, Inclusion of DOI theory alongside UTAUT is valuable because DOI provides a broader perspective on how innovations spread within social and cultural contexts, which is especially relevant in Saudi Arabia's healthcare sector. While UTAUT focuses on individual perceptions such as performance expectancy, effort expectancy, social influence, and facilitating conditions, DOI emphasizes attributes of the innovation itself relative advantage, complexity, security and regulations that influence adoption at both organizational and societal levels. In the Saudi context, where healthcare institutions operate under distinct cultural and regulatory structures,

DOI helps explain how perceived complexity with cultural norms (including gender-based service delivery) and relative advantage over existing practices shape adoption decisions.

Moreover, DOI theory is particularly useful when analyzing gender segregation as a moderating factor in cloud computing adoption. Gender norms in Saudi Arabia influence work practices, access to technology, and communication patterns between male and female professionals. DOI's focus on social systems and communication channels provides a framework to understand how gendered structures affect the speed and pattern of diffusion of cloud-based e-health solutions. By integrating DOI with UTAUT, researchers can capture both individual behavioral drivers and systemic sociocultural factors, offering a more holistic understanding of cloud computing adoption in a gender-segregated healthcare environment.

2.6 Summary

This chapter highlights the issues about the adoption of cloud computing technology. A number of relevant studies were identified which address the use of cloud computing technology in health organization. The gap has been founded and revealed that there are no empirical researches on the use of cloud computing in Saudi Arabia's healthcare industry. Therefore, this chapter provided a thorough foundation on all aspects of adopting cloud computing and removed any confusion regarding the research problem. Also, the chapter reviewed the relevant previous studies in the literature to understand all the factors that could affect the adoption of cloud computing. Finally, the theoretical background supported technology acceptance are explained.

CHAPTER THREE
Methodology

3.1 Introduction

The study will use a quantitative technique in order to establish an E-Health Cloud Computing Adoption Framework, particularly in Saudi Arabia. A planned methodology has been established to achieve this objective, encompassing various fundamental stages to obtain insightful and relevant data.

The chapter outlines the various components of empirical research utilized within the context of this thesis. First of all, provides the crucial aspect of selecting the research method that aligns with the research objective is elucidated, with an in-depth introduction to the principles of empirical research, and the quantitative research methodologies that are implemented throughout this research. Moreover, the design that informs the methodology utilized throughout the research process also discussed in this chapter.

Then the means by which the data is collected is expounded and the research sample, or population, in detailed presented. Following this, we provide an in-depth analysis of the data collected, Moreover, an overview of the E-health model development is covered, followed by the ethical aspects related to the study are discussed. Lastly, concludes this chapter with a summarized discussion.

3.2 Choosing a Research Method

Empirical research, as a scientific method, is heavily rooted in observations and measured phenomena rather than just theoretical speculations, serving to enhance our knowledge and comprehension of our surroundings. Papa et al. (2020) state that this approach provides a complete and exhaustive view of reality, backed by first hand experiences and observations, granting an intricate understanding of the research topic. Moreover, this research methodology endorses rigorous experimentation and uses multiple analysis methods and viewpoints, a notion supported by Mittal et al. (2017).

Smite et al. (2008) highlight the dearth of empirical studies in this field, reflecting the relative immaturity of the E-Health cloud computing industry. As pointed out by Lethbridge et al. (2005), empirical research provides several benefits, including: 1) identifying needs for developing new E-Health cloud computing methods; 2) providing crucial perspectives for improving the real-world application of E-Health cloud computing; and 3) generating new theories or hypotheses that can be subjected to systematic experimental testing. Such an approach can be very beneficial in advancing this important area.

This research uses a quantitative research methods for data collection and analysis (Niazi, 2004). The description of the research design described in Section 3.3, involves the collection of data, through a questionnaire survey in order to perform statistical analyses.

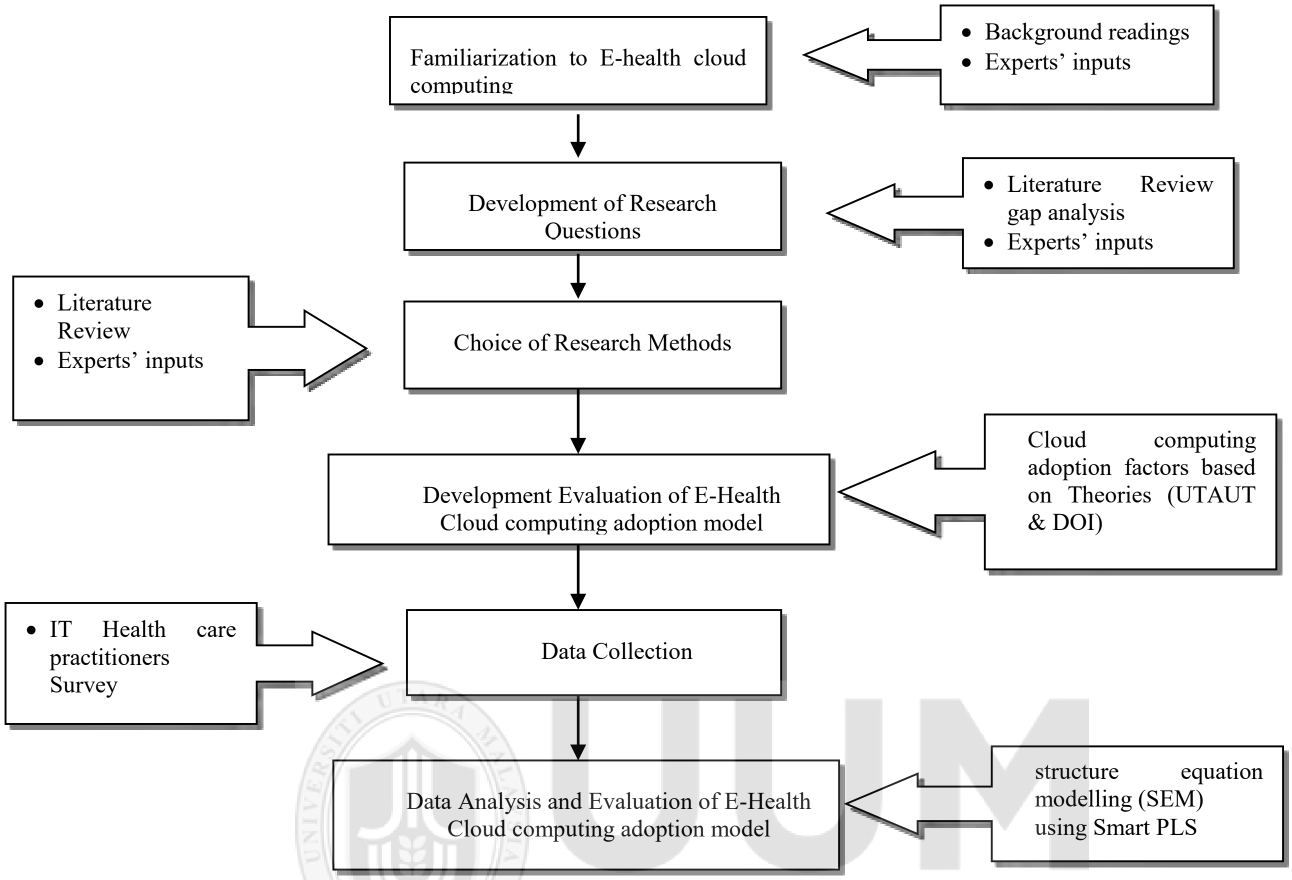


Figure 3.1
Research Procedures
Source: Author 2025

3.3 Research Design

The research design is a master plan or an outline that specifies the procedures and methods for gathering and analysing the needed information to arrive at a solution (Sekaran & Bougie, 2009b; Zikmund et al., 2010, 2013). This study adopts a quantitative approach to determine the factors influencing E-Health Cloud Computing Adoption in Saudi Arabia.

The research is divided into several cardinal stages, including data collection, data analysis, and the framework's eventual design and evaluation. The first phase will be a content analysis of all-encompassing review of existing literature on cloud computing and its adoption within the E-Health sector.

3.4 E-health model Development

This section discusses the conceptual model development based on the UTAUT & DOI and the factors derived from the literature review. This model will effectively integrate all relevant factors identified throughout the extensive literature review, to form a structured representation of the specific elements essential for cloud computing adoption in the E-Health sector of Saudi Arabia. The model is meant to serve as an indispensable tool, providing crucial guidance to key decision-makers, and driving policies related to adoption of e-health cloud computing. Author ensures the framework's completeness, validity, and practicality within the Saudi Arabian context. By seamlessly integrating all relevant findings and aspects, this proposed model seeks to offer an organized and effective solution to assist and guide individuals, organizations, and policymakers in making well-informed decisions. As a result, this new E-Health Cloud Computing Adoption model will make cloud computing adoption smoother and more streamlined and effectively address the specific challenges facing Saudi Arabia.

The process of developing a cloud computing adoption model based on the UTAUT theory as primary theory begins by categorizing key factors under the UTAUT framework to understand their influence on the adoption of E-Health Cloud Computing (Dash & Sahoo, 2022b). This involves aligning the operational definitions of UTAUT constructs that discuss in chapter two with the specific factors identified in the context of E-Health Cloud Computing taking in consideration the Relation of UTAUT constructs with other theories constructs as explained in table 2.4 and the operational definitions of cloud computing adoption factors as explained in table 3.3

Performance Expectancy: This construct is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003). For E-Health Cloud Computing, the Relative Advantage is a critical factor. It affirms the advantages and their effects upon deployment, such as improved access to patient records, enhanced data management, and increased efficiency in healthcare delivery. These benefits directly contribute to the users' expectations of performance enhancement, making relative advantage a core component of performance expectancy in the model (Alharbi et al. 2016)

Effort Expectancy: is defined as "the degree of ease associated with the use of the system" (Venkatesh et al., 2003), this construct includes Technical Complexity. Technical complexity refers to the advanced technical understanding and proficiency required for effective execution and administration (Ishak et al., 2021). High complexity may deter users due to perceived difficulty, while low complexity encourages adoption.

Social Influence: Is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003). This construct considers the expected influence of others on the user's decision to start and continue using the technology. Regulations and Policies are critical, as they govern the use of technology, ensuring access, and data management advantages (Kaur et al. (2019). This factor shape the social environment and normative pressures, impacting user adoption behaviors.

Facilitating Conditions: is defined as "the degree to which an individual believes that an organisation's and technical infrastructure exists to support the use of the system" (Venkatesh et al., 2003), this construct includes Security and Privacy. Security and privacy measures are vital to protect data from unauthorized access and ensure user trust (Sivan & Zukarnain, 2021).

To develop a comprehensive cloud computing adoption model, it is beneficial to amalgamate the Innovation Decision Process with UTAUT. This combined approach provides a more holistic view of the adoption process, accounting for both individual perceptions as covered by UTAUT and the stages of organizational decision-making and implementation as detailed by DOI.

In developing the model, each factor is carefully analyzed to understand its impact on the adoption process. Survey with healthcare providers and IT professionals will be conducted to gather data on perceptions and experiences related to these factors. Statistical analysis methods Structural Equation Modeling (SEM), will be employed to validate the relationships between UTAUT constructs and the adoption factors, ensuring a robust and comprehensive model. This model aims to provide actionable insights for stakeholders in the healthcare sector, guiding the strategic implementation of E-Health Cloud Computing to maximize adoption and utilization.

At the organizational level, diffusion of innovation theory (DOI) has been widely applied in the previous studies to understanding how innovations are adopted and diffused (Mahler & Roger, 1999). However, the limitation of this theory is that it does not include the environmental context. According to Low, et al. (2011), environmental factors are imperative to adoption of cloud computing in the organization. Abdollahzadehgan, et al. (2013) have added that the model for cloud computing diffusion requires a theoretical model to take into consideration the weaknesses and defects in the diffusion and adoption of technological innovation which results from the explicit (Sulaiman & Magaireah, 2014)

DOI explains how new technologies spread across a population. In e-health cloud computing, the theory also highlights perceptions of the innovation itself that influence adoption. More importantly, DOI offers a clear view of the organizational decision-making process, describing how adoption progresses through sequential stages — knowledge, persuasion, decision, implementation, and confirmation. It explains how organizations move through these phases when adopting new technologies(Adlung et al., 2025).

UTAUT focuses on user behavior and intention in adopting technology (Dash & Sahoo, 2022a). The theory explains how users' perceptions, social context, and infrastructure drive adoption. It also examines human and organizational factors with key construct such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating Conditions (FC) (Dash & Sahoo, 2022a). From the above it reveals UTAUT is user adoption determinants (human/organizational side) (Sahoo et al., 2023).

Hence, both theories complement each other, they create a robust conceptual framework for analyzing cloud e-health adoption in developing and emerging markets like Saudi Arabia.

Based on the literature, the researchers proposed that each factor identified by UTAUT model plays a different role in contributing to the adoption of technology. Consequently, this study developed a model that will be empirically tested to explain the relationship (if any) between factors necessary for influencing the adoption of technology and adoption of cloud computing in the health sector. Based on the literature review, a model for the proposed theoretical framework was developed to identify the effect of UTAUT factors necessary for accepting technology on adoption of e-health cloud computing in the sector as shown in Figure 3.2.

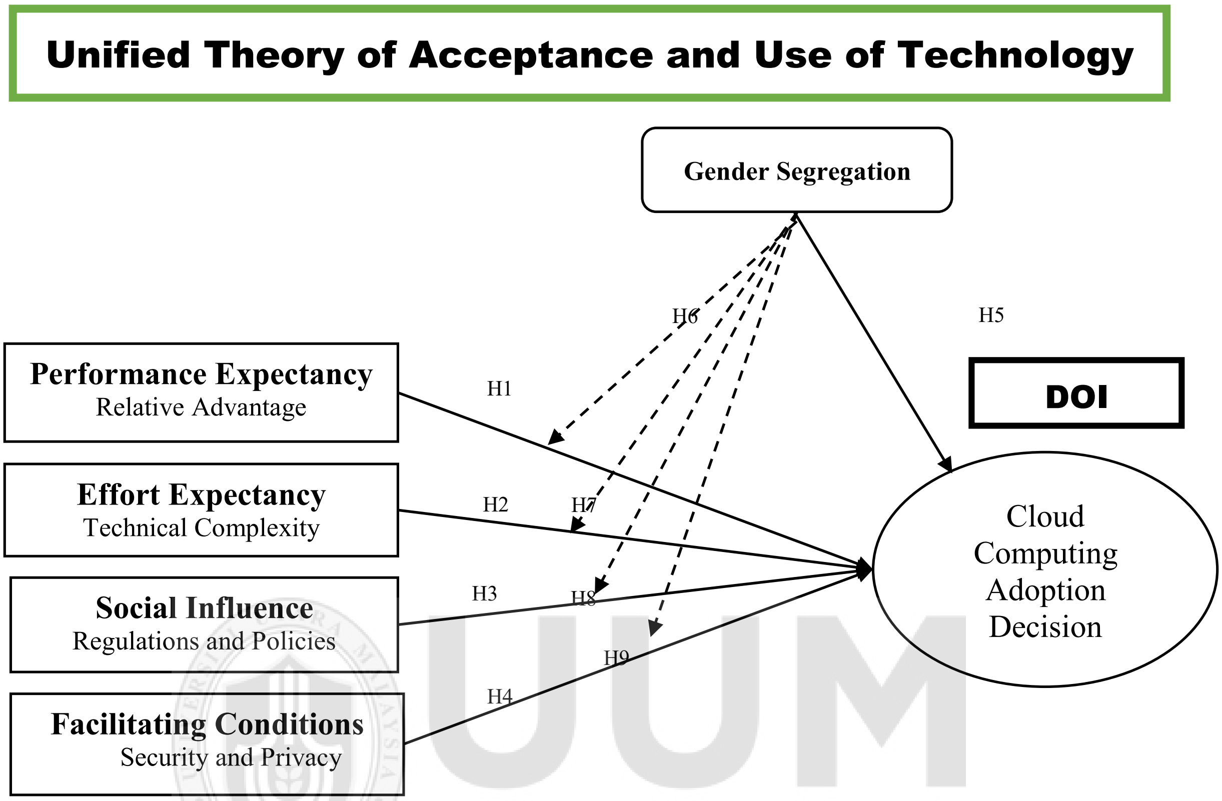


Figure 3.2
Conceptual Mode
Source: Author 2025

Figure 3.2 above depicts the relationships between performance expectancy, effort expectancy, social influence and facilitating conditions factors. They were hypothesised to have a significant impact on the dependent variable (Cloud Computing Adoption) and Gender segregation moderates the impact on these factors and cloud computing adoption decision. Thus, this study enriches the existing literature by filling the gap in the factors that influence cloud computing adoption in health care setting in Saudi Arabia. The models will be fully validated through a more extensive data collection process across health care setting in Saudi Arabia.

3.4.1 Hypothesis Development

Based on this research framework, Nine (9) hypotheses have been developed to test the model factors as variables: performance expectancy (relative advantage); effort expectancy (technical complexity); social influence (regulation and policies); and facilitating conditions (security, and privacy) See Tables 3.1 The following set of hypotheses is derived from the research questions.

3.4.1.1. Performance Expectancy

Performance expectancy is hypothesized to have a positive effect on the adoption of cloud computing in the Saudi Arabian health sector. This relationship is grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), where performance expectancy is defined as the degree to which an individual believes that using a new system will help them attain gains in job performance (Venkatesh et al., 2003). In the context of Saudi Arabia's healthcare system, this is one of the factors that influence the adoption of cloud computing. It is perceived to enhance efficiency and effectiveness in patient care through improved access to electronic health records, better collaboration among medical professionals, and advanced data analytics capabilities.

Previous research, such as that by Alshammari et al., (2021) and Alharbi (2017), indicates that the perceived benefits and usefulness of cloud technologies are critical drivers of their adoption by Saudi healthcare organizations. This relative advantage of implementing cloud computing services can bring many benefits to users, such as improved speed of communications, efficient inter-company coordination, and patient's communications, time savings, and reduced administrative costs (Tawfik et al., 2023). Previous studies revealed that relative advantage was shown to be a strong predictor of intention to use IT (Abdelwahed et al., 2024; Almazroi & Shen, 2019; A. Chowdhury, 2021). Therefore, organizations that recognize significant advantages from cloud computing are expected to adopt the technology more readily.

Hence this study proposes Hypothesis (H1): Performance expectancy has a positive effect on the adoption of cloud computing in the Saudi Arabian health sector.

3.4.1.2. Effort Expectancy

This hypothesis is based on the Unified Theory of Acceptance and Use of Technology (UTAUT), which defines effort expectancy as the degree of ease associated with using a new technology (Venkatesh et al., 2003b). In the context of Saudi Arabia's health sector, this refers to the perceived simplicity of a cloud computing system which includes the ease of learning, the nature of its interface, and the effort required for adoption and maintenance. Studies on technology adoption have revealed low perceived effort expectancy as one of the strong predictor of a positive behavioural intention to use and adopt a system (Alnassar & Baashirah, 2024).

High levels of complexity can create resistance to adoption, especially in healthcare environments that require seamless operation and minimal downtime (B. Alanazi et al., 2020; Jung et al., 2022). Hence, the more complex the technology is perceived to be, the lower the likelihood of its adoption. Hospitals and clinics often rely on legacy systems. Integrating these existing systems with new cloud infrastructure can be a complex and resource-intensive process Alshammari et al., 2021). The successful adoption of cloud computing requires a workforce with specialized skills in cloud management, data security, and system migration. A shortage of such skilled IT professionals can hinder adoption (Nasser et al., 2024).

Research on technology adoption in the Middle East and specifically Saudi Arabia supports this hypothesis. Studies by Alzahrani (2017) and Alshammari (2017) found that the perceived technical difficulty and complexity of cloud solutions were among the major factors influencing the adoption of cloud computing negatively in the country.

From the above this study proposes Hypothesis (H2): Effort expectancy has a negative effect on the adoption of cloud computing in the Saudi Arabian health sector.

3.4.1.3. Social Influence

This hypothesis, derived from the Unified Theory of Acceptance and Use of Technology (UTAUT), postulates that an individual's decision to use a new technology is significantly shaped by the opinions and behavior of those around them (Venkatesh et al., 2003b). In the Saudi Arabian health sector, this means that the adoption of cloud computing is positively influenced by the actions and recommendations of influential peers, families, leaders, and regulatory bodies. When a leading hospital, a prominent medical university, or the Ministry of Health adopts and publicly endorses cloud technology, it creates a social norm that encourages other healthcare organizations to follow suit. Research from Alnassar and Baashirah (2024) revealed that social influence is a significant determinant of the behavioral intention to use cloud computing, while other studies have highlighted the role of government policy and competitive pressure as external factors that create a supportive social environment for cloud adoption (Karim & Rampersad, 2017).

Regulations for data protection, patient privacy laws, and healthcare standards, plays a critical role in technology adoption in health sector (Alasiri & Mohammed, 2022; Sulaiman & Magaireah, 2014). In Saudi Arabia, where healthcare policies emphasize compliance with strict legal frameworks, adherence to regulatory requirements can significantly encourage adoption (Derendinger & Frank, 2023; Jiang et al., 2017). In determining factors influencing cloud computing adoption, facility in- charges and health records were considered to give both a technical and non-technical perspective on security (Ogwel, 2020). Previous research revealed that service quality was looked at in terms of security, privacy of data and timeliness and the results of the studies revealed security and privacy had a statistically significant effect on health service delivery as a result of cloud computing adoption (ezedin Abdela Mohammed, 2019; Ogwel, 2020).

Therefore, regulatory compliance is assumed to have effect on the adoption of cloud computing in the Saudi Arabian health sector. Hence there is need for government bodies, such as the Saudi Ministry of Health to establish clear and supportive regulations. These regulations often provide a clear framework for data security, privacy, and governance, which directly addresses one of the primary concerns for healthcare providers regarding cloud adoption (Alzahrani, 2017). A well-defined regulatory environment can therefore reduce perceived risks and uncertainties, making the adoption of cloud computing a more attractive for hospitals and clinics. This positive effect is supported by research showing that robust regulatory guidance acts as a key enabler for technology adoption within the healthcare sector (Alshammari, 2017).

This study proposes Hypothesis (H3): Social influence has a positive effect on the adoption of cloud computing in the Saudi Arabian health sector.

3.4.1.4. Facilitating Conditions

This hypothesis is based on the Unified Theory of Acceptance and Use of Technology (UTAUT), which defines facilitating conditions as the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of a system. Also, it refers to the availability of infrastructure, technical support, and resources required for the adoption of cloud technology (Venkatesh et al., 2003b). In the context of the Saudi Arabian health sector, this includes the availability of necessary technological infrastructure, adequate financial resources, and the presence of trained technical personnel to implement and manage cloud solutions. When these conditions are perceived as favorable, they directly influence adoption of cloud computing.

Previous research such as Alharbi (2017) and Alshammari (2017) revealed that factors like security, availability of skilled employees, organizational support, and sufficient financial resources are critical in influencing a positive decision to adopt new technologies. Security concerns involve perceptions of data confidentiality, integrity, and protection against cyber threats. In healthcare, where sensitive patient information is involved, security assurances are crucial (Hamdan et al., 2023).

In this study facilitating conditions is hypothesized to have a positive effect on the adoption of cloud computing within the Saudi Arabian health sector. This hypothesis argues that the factors like robust security measures offered by professional cloud service providers are perceived as one of the factors influencing the technology adoption (Alanezi, 2021). This perceived advantage of a more secure and resilient system directly addresses compliance requirements and helps to safeguard sensitive patient data, ultimately reducing organizational risk and making the adoption of cloud technology a more attractive and strategically sound decision (Alshammari, 2017; Alzahrani, 2017).

Therefore, this study proposes Hypothesis (H4): Facilitating conditions have a positive effect on the adoption of cloud computing in the Saudi Arabian health sector.

3.4.1.5. Gender Segregation

Gender segregation is a unique cultural factor in Saudi Arabia that may influence decision-making processes and access to technology training or implementation. Gender segregation can significantly influence technology adoption decisions, particularly in sensitive sectors such as healthcare. Previous research suggests that when occupational roles and decision-making power are unequally distributed between genders, the likelihood of adopting innovative solutions (cloud computing) will be affected negatively (Venkatesh et al., 2012; Alryalat et al., 2021). In the context of e-health cloud computing, high levels of gender segregation may limit collaborative decision-making and slow the acceptance of new technologies (Tarhini et al., 2016). Thus, it is hypothesized that increased gender segregation will negatively affect the decision to adopt e-health cloud computing.

Hypothesis (H5): There is a negative relationship between gender segregation and the decision to adopt cloud computing in Saudi Arabian health sector.

3.4.1.6. Moderating effect of Gender Segregation on Performance Expectancy

Performance expectancy relates to the belief that cloud computing will enhance productivity, service quality, and operational efficiency (Adebo et al., 2025). When healthcare professionals anticipate performance gains, adoption becomes more likely (Alnassar & Baashirah, 2024).

This hypothesis suggests that the perception of performance benefits from cloud computing will not be uniform across genders in the Saudi Arabian health sector, due to gender-segregated work environments. This means the positive effect of performance expectancy on adoption is likely to be stronger for one gender over the other. Hence, gender segregation may affect this perception, potentially amplifying or reducing its influence. For example, a male surgeon might perceive the primary performance benefit as being the ability to access and analyze large-scale medical data for research, while a female physician might perceive the benefit as improved, real-time access to patient health records for immediate diagnostic purposes. This is consistent with studies that show how socio-cultural factors and organizational context can significantly influence technology acceptance and adoption (Alshammari, 2017). Hence, this study hypothesis that:

Hypothesis (H6): performance expectancy has a positive significant effect on the adoption of e-health cloud computing, and this relationship is moderated by gender segregation.

3.4.1.7. Moderating effect of Gender Segregation on Effort Expectancy

Effort expectancy is the perceived ease of using cloud systems. A user-friendly interface and minimal training requirements are expected to increase the likelihood of adoption e-health cloud computing (Alnassar & Baashirah, 2024). This hypothesis suggests that the perception of ease of use (effort expectancy) and its effect on cloud computing adoption will differ between male and female healthcare professionals due to gender-segregated work environments. This difference in perception could be influenced by varying levels of digital literacy and access to technology training based on gender. For example, if men are more likely to hold IT-intensive roles, they may perceive cloud solutions as easier to learn and use, mitigating the negative effect of complexity on adoption. Conversely, women in roles with less technological exposure might view the same system as more difficult and complex, strengthening the negative relationship between effort expectancy and their intention to adopt e-health cloud computing. However, gender segregation may influence access to resources and training, moderating the relationship between effort expectancy and adoption (Alshammari, 2017).

Hypothesis (H7): Effort expectancy has a negative effect on the adoption of e-health cloud computing, and this relationship is moderated by gender segregation.

3.4.1.8. Moderating effect of Gender Segregation on Social Influence

Social influence reflects the extent to which peers, supervisors, or industry stakeholders encourage cloud adoption (Uddin et al., 2024). In a collectivist culture like Saudi Arabia, social approval significantly shapes technology decisions. This hypothesis suggests that the influence of peer pressure and the opinions of key stakeholders on the adoption of cloud computing will vary between male and female healthcare professionals due to gender-segregated work environments. Within the Saudi Arabian context, social and professional networks are often gender-specific. This means that male professionals may be influenced by the technology adoption decisions of their male colleagues and superiors, while female professionals may be influenced by a different, or parallel, network of female peers and mentors (Alam et al., 2020). As a result, the positive effect of social influence on adoption is not a universal force but is instead moderated by gender, which shapes an individual's exposure to and perception of social norms regarding technology use (Alam et al., 2020). This is consistent with models like UTAUT, which recognize that social factors can significantly impact an individual's behavioral intention to use a new system (Alnassar & Baashirah, 2024). Hence, gender segregation may moderate this effect by influencing social interactions and communication networks.

This study propose Hypothesis (H8): Social influence has a positive effect on the adoption of e-health cloud computing, and this relationship is moderated by gender segregation.

3.4.1.9. Moderating effect of Gender Segregation on Facilitating Conditions

Facilitating conditions include security and privacy facilities such as infrastructure, technical support, and organizational resources (Venkatesh et al., 2003b). Adequate support enhances adoption, but gender segregation may determine who can access such resources, thus moderating the relationship between facilitating conditions and adoption. This hypothesis suggests that the presence of facilitating conditions such as adequate technical infrastructure, financial support, and skilled personnel will have a different effect on the adoption of cloud computing for male and female professionals (Alam et al., 2020).

It is believable that men and women, due to their distinct roles and access to resources, may experience these conditions differently. For example, men in senior IT or management positions may have direct control over budgetary decisions and technical infrastructure, making the presence of these conditions a strong, positive motivator for adoption. Conversely, women in administrative or clinical roles may feel that a lack of trained IT support or insufficient technical resources is a greater barrier, thereby weakening the positive effect of facilitating conditions on their individual adoption decisions. This is supported by studies that highlight how organizational and environmental factors, which can be influenced by gender, are critical to understanding technology adoption in the region (Alam et al., 2020; Alnassar & Baashirah, 2024; Gu et al., 2021).

Hypothesis (H9): Facilitating conditions have a positive effect on the adoption of e-health cloud computing, and this relationship is moderated by gender segregation.

Table 3.1
List of Research Hypothesis Development

Hypothesis Number	Hypothesis Development
H1	There is a positive relationship between performance expectancy and the decision to adopt e-health cloud computing in the Saudi Arabian health sector.
H2	There is a negative relationship between effort expectancy and the decision to adopt e-health cloud computing in the Saudi Arabian health sector.
H3	There is a positive relationship between social influence and the decision to adopt e-health cloud computing in the Saudi Arabian health sector
H4	There is a positive relationship between facilitating condition and the decision to adopt e-health cloud computing in the Saudi Arabian health sector
H5	There is a negative relationship between gender segregation and the decision to adopt cloud computing in Saudi Arabian health sector.
H6	Gender segregation moderates the relationship between positive effect of performance expectancy and the decision to adopt e-health cloud computing in the Saudi Arabian health sector
H7	Gender segregation moderates the relationship between negative effect of effort expectancy and the decision to adopt e-health cloud computing in the Saudi Arabian health sector
H8	Gender segregation moderates the relationship between positive effect of social influence the decision to adopt e-health cloud computing in the Saudi Arabian health sector
H9	Gender segregation moderates the relationship between positive effect of facilitating condition the decision to adopt e-health cloud computing in the Saudi Arabian health sector.

Table 3.2
Details of Research Hypotheses

Hypothesis Number	Variables	Variables classification	Dependent Variable
H1	**Performance Expectancy** *Relative Advantage*	Independent Variables (IV)	Cloud Computing Adoption
H2	**Effort Expectancy** *Technical Complexity*	Independent Variables (IV)	Cloud Computing Adoption
H3	**Social Influence** *Regulations and Policies*	Independent Variables (IV)	Cloud Computing Adoption
H4	**Facilitating Condition** *Security and Privacy*	Independent Variables (IV)	Cloud Computing Adoption
H5	**Gender Segregation**	Independent Variables (IV)	Cloud Computing Adoption

Table 3.3
Details of Research Hypotheses (Moderating)

Hypothesis Number	**Moderating Variable**	Independent Variables (IV)	**Dependent Variable**
H6	Gender Segregation	**Performance Expectancy** *Relative Advantage*	Cloud Computing Adoption
H7	Gender Segregation	**Effort Expectancy** *Technical Complexity*	Cloud Computing Adoption
H8	Gender Segregation	**Social Influence** *Regulations and Policies*	Cloud Computing Adoption
H9	Gender Segregation	**Facilitating Condition** *Security and Privacy*	Cloud Computing Adoption

3.4.2 Operational Definitions

The conceptual model includes the four UTAUT context and nine variables as. The model contains independent; moderating and dependent variables as presented in Table 3.4 and the definitions are explained.

Table 3.4
Definition of Operational Variables

Factor Name	**Definition**
Performance Expectancy	Is the degree to which using a technology will provide benefits to consumers in performing certain activities (Brown & Venkatesh, 2005)
Relative Advantage	Affirm advantages and their effects upon deployment (Alharbi et al. 2016)
Effort Expectancy	Is the degree of ease associated with consumers‘ use of technology (Brown & Venkatesh, 2005)
Technical Complexity	Advanced technical understanding and proficiency required for the effective execution and administration of these technologies (Ishak et al., 2021).
Social Influence,	Is the extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology (Brown & Venkatesh, 2005)
Regulation and Policies	Policy to regulate the utilization of technology to promising access, and data management advantages (Kaur et al. (2019)
Facilitating Condition	Refer to consumers‘ perceptions of the resources and support available to perform a behaviour (Brown & Venkatesh, 2005)
Security and Privacy	Criteria to safeguard data from unauthorized access, meddling, or corruption (Sivan & Zukarnain, 2021).
Gender Segregation	It refer to the work environment in Saudi Arabia health care setting
E-Health Cloud Computing	Refers to integrating cloud computing technologies and digital health services to support efficient management, access, and use

	of patient-centric healthcare data (Chang et al., 2021).

3.4.3 Questionnaire Development

In the pursuit of gaining valuable insights into the status and factors related to cloud computing software as services adoption in the E-Health sector of Saudi Arabia and considering the objectives of the research and available resources, the researcher decided to use a survey research method to understand cloud computing adoption factors in the E-Health sector of Saudi Arabia.

A survey research method is considered suitable for gathering self-reported quantitative and qualitative data from a large number of respondents (parry et al,. 2021). A survey can use one or a combination of several data gathering techniques such as interviews, self-administered questionnaires and others. Researcher decided to use a questionnaire as a data collection instrument due to several factors such as collecting data from diverse range of respondents and available resources. A questionnaire was developed based on existing literature.

The survey instrument was designed based on constructs validated in prior research (and which showed good Cronbach alpha values) , standardized and revised to the context of this study (Creswell, 2014). The survey questions were prepared in English considering the nature of respondent and their level of education; the medium of communication is the English language. To avoid misinterpretations by respondents, a lot of time and effort were devoted to selection of words in the questionnaire design.

It is important to make the questionnaire conducive for the respondents. Respondents are more likely to give accurate answers if the questions are phrased in a simple, appropriate, relevant and neutral manner. This position is supported by Creswell (2014) who argued that the questionnaire format, general appearance, and physical arrangement of items must be able to attract respondents, thereby ensuring the success of the study.

For this study, a structured questionnaire was utilized for data collection from the targeted respondents consistent with Alharbi et al. (2016); Alkurdi (2022); Almazroi et al. (2019); Almazroi and Shen (2019); Brown and Venkatesh (2005); Collins et al. (2021); Meri et al. (2019). The survey questionnaire comprised of two parts. Part 1 included questions regarding the respondent's demographic information such as gender, age, highest qualification, and department. Part 2 was made up of several sections which consisted of questions to measure Relative Advantage, Complexity, regulatory and policy, security and privacy, Gender Segregation, and cloud computing adoption. Table 3.5 shows details of the questionnaire.

The items on the questionnaire are adapted from the previous literature and was based on UTAUT main constructs. In order to gain the tacit knowledge on factors open ended questions were also included in the questionnaire to find any other factors from the identified ones. The questionnaire was also designed to elicit each respondent's importance on each factor.

The Unified Theory of Acceptance and Use of Technology (UTAUT) identify four core predictors of behavioural intention and use: Performance Expectancy (Relative advantage), Effort Expectancy (Technical complexity), Social Influence (Regulation and Policies), and Facilitating Conditions (Security and Privacy); and it proposes demographic moderators (age, gender, experience) and voluntariness of use (Venkatesh et al., 2003a). UTAUT has strong explanatory power in organisational and consumer IT adoption research and has been widely applied and extended to cloud computing contexts (Venkatesh et al., 2003b).

Applied to cloud computing, Performance expectancy maps to perceived benefits of cloud services (relative advantage), Effort expectancy maps to perceived ease or complexity of using cloud platforms, Social Influence captures influence from peers/leadership via regulation and policies to adopt cloud, and Facilitating Conditions captures security and privacy) and organisational readiness that enable actual use. UTAUT extensions for cloud adoption commonly add Perceived Security because cloud services' reliance on third-party providers makes trust/privacy central to uptake.

UTAUT recognizes moderator (gender segregation and voluntariness) but treats culture implicitly (Venkatesh & Davis, 2000). In national or organisational contexts with strong cultural signals, national culture and socio-religious norms systematically shape how users interpret Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions (Li et al., 2013).

. Saudi Arabia's cultural profile high power distance, collectivism (low individualism), strong uncertainty avoidance tendencies, pronounced religiosity and gender role norms means cultural values will likely alter the strength and sometimes the direction of UTAUT relationships in measurable ways (studies of ICT and e-government adoption in Saudi Arabia show culture and religion materially affect acceptance) (Al-Anezi, 2022; Alanazi et al., 2016). Therefore a well-justified extension of UTAUT for Saudi cloud adoption replaces or supplements the generic demographic moderators with theoretically relevant cultural moderators. Empirically, Saudi studies find religiosity, social norms and organizational culture affect willingness to adopt new IT; other Saudi cloud/IT studies explicitly extend UTAUT by adding socio-cultural variables and report improved explanatory power when culture is modelled (e.g., trust-UTAUT extensions and Saudi public sector studies) (Almazroi & Shen, 2019; Rahman & Al-Borie, 2020).

The survey items for this study are adapted from previous studies. For instance items for relative performance are adapted from (Alam et al., 2020; Gu et al., 2021), effort expectancy (A. Chowdhury, 2021; Gu et al., 2021), social influence (Alam et al., 2020;

Hoque et al., 2017), facilitating condition (Garavand et al., 2022; Uddin et al., 2024) and gender segregation (Almazroi et al., 2019; Zhang et al., 2014)

Tables 3.5 summarize the instrument used for all variables included within the study's proposed as the main variables that could influence cloud computing adoption in Saudi Arabia Health Care setting.

Table 3.5
Measurement Items for Factors

Variable	Items
Performance Expectancy (Relative Advantage)	1. Cloud computing technology helps you to access data in real-time. 2. Cloud computing technology helps you to improve accuracy and reduce errors. 3. Cloud computing technology help in increases business productivity. 4. Cloud computing technology help in enhance the quality of service for patients.
Effort Expectancy (Technical Complexity)	1. The implementation of cloud computing technology involves complexities in usage. 2. The technical skills that you need for using cloud computing technology can be challenging. 3. Cloud computing technology will require a number of specialized technical staff in your organization to manage it. 4. The technical staff may face technical challenges in the implementation of cloud computing technology.
Societal Influence (Regulation and Policies)	1. You believe there is a significant deficiency in regulations concerning cloud computing technology. 2. The well-established rules and policies in your organization lead to adopt Cloud Computing technology in a proper way. 3. Regulatory concerns prevent your organization from adopting cloud computing technology. 4. Your organization is facing pressure from certain government agencies to adopt cloud computing technology.
Facilitating Condition (Security and Privacy)	1. Your organization is concern about security issues for information within the realm of cloud computing technology. 2. Your organization is concern about privacy issues for information within the realm of cloud computing technology. 3. Our organization is worried about the idea of cloud providers misusing the data for commercial purposes. 4. Concerns about security and privacy play a role in shaping your organization's level of cloud computing technology.
Cloud Computing Adoption	1. E-Health Management in your organization invests resources in cloud

	computing technology. 2. Your organization activities require the use of cloud computing technology. 3. Your organization functional areas require the use of cloud computing technology.
Gender segregation	1. In your organization females cannot work in male workplaces 2. 2.In your organization separates males and females as much as possible 3. Gender segregation affects the perceived benefits of adopting cloud computing technology in your organization. 4. Gender segregation affects how perceive the technical complexity of adopting cloud computing technology in your organization

In order to safeguard the confidentiality of the data and privacy of the participants, a statement of the ethical principles that the research team would follow was sent to the participants. Participants were also assured that their data would not be accessible to anyone except the research team. Moreover, the researcher explicitly made it clear to the participants that the research team would not share the data with anyone in a way that could reveal any participant's organization or identity.

The study acknowledges that the input from E-Health specialists is crucial, given that they have significant influence over the sector and can contribute significantly towards a better understanding of the issues concerning cloud computing adoption.

The following section describes the content validity process." The questionnaire was reviewed and validated through three main steps after which are content validity, face validity, and pilot study. At each stage, the questionnaire was revised and modify. The detail of each step is as follows;

3.4.3.1 Content and Face Validity:

Before using the questionnaire for the real data collection, it is suggested to examine its suitability (Sekaran & Bougie, 2010). Content validity was tested to confirm that the statements utilized to measure the variables are deemed suitable, aligned and match to the idea they planned to measure. This type of validity can be done by a group of experts who scan and examine the questionnaire and ensure whether the statements convey the intended concept accurately and whether their language is comprehensible and Straightforward (Sekaran & Bougie, 2010). Seasoned Instructors in Saudi Arabia were contacted to evaluate the questionnaire and to provide response on its language, clarity and comprehensive layout.

Sekaran and Bougie (2016) suggest many types of validity test for deciding the accuracy of testing: face and content validity. Salkind (2010) mentioned the extent to which a test or measurement instrument appears, on the surface, to measure what it is intended to measure. The questionnaire was examined and validated by 4 researchers and field experts, as shown in Table 3.6 (see Appendix B for researchers CVs)

Table 3.6
Content and Face Validity Result

Reviewer ID	**Qualification / Expertise**	**Feedback**	**Correction / Action Taken (Final Survey Items)**
A.K	PhD in Computer Science – Specialist in information systems and software development.	Questionnaire measures intended constructs, but some statements need linguistic modification; delete items not related to their dimensions.	- Reviewed all items for language clarity. - Deleted unrelated items to ensure alignment with each construct. - Example: Original gender segregation item (*"…affected by gender segregation job place"*) was rephrased to: *"Gender segregation impacts your concerns about the security and privacy of adopting cloud computing technology."*
N.Z	PhD in [Management/Health Sciences]* (specializes in research methods and healthcare systems).	Requested adding clear terminological definitions in the questionnaire; place hypotheses/questions upfront; modify/add/delete items with weighting for each study field; conduct pilot study to establish	- Added terminological definitions at the start of the questionnaire. - Placed main hypotheses and research questions before the measurement items. - Modified items (added, deleted, reworded) with

Reviewer ID	Qualification / Expertise	Feedback	Correction / Action Taken (Final Survey Items)
		construct validity.	weighting per study field. - Conducted pilot study to confirm internal construct validity.
M.G	PhD in Computer Science – Expert in cloud computing and IT management.	Suggested reducing number of independent variables; noted linguistic errors; some items misaligned with their fields.	- Reduced and streamlined independent variables. - Corrected grammar and rephrased unclear items. - Example: Original security/privacy item (*"...depends on the security and privacy..."*) was revised to: *"Concerns about security and privacy play a role in shaping your organization's level of cloud computing technology."*
I.M	PhD in Computer Science & Engineering – Associate Professor, extensive research in cloud computing, AI, and e-health .	Confirmed all items are clear and understandable.	- No corrections required. - Final survey version maintained as provided.

3.5 Data Collection

Data collection methods significantly influence the data analysis process; therefore, the data collection methods need to be carefully chosen. The researcher has used a questionnaire survey for data collection. These methods are chosen because they are well-matched for the nature and type of data that this research analyses.

To initiate data collection, the questionnaire will be distributed to IT health care personnel and policymakers to get back their viable feedback about the factors effecting the cloud computing adoption in context of Saudi Arabia health care setting, and evaluate the proposed model.

3.6 Population and Sampling

3.6.1 Target population

Since the goal of this research was to understand the factors that have a positive or negative impact on adopting cloud computing and base on it build the cloud computing model, researcher needed to collect data from IT practitioners, top management, and policymakers involved in E-Health cloud computing activities across the Saudi Arabia governmental, private and other military or educational hospitals. The inquiry on the construction of an E-Health Cloud Computing Adoption model in Saudi Arabia scrutinizes the assemblage of individuals intricately associated with the E-Health sector of the region. The target population here are all professionals in the Saudi Arabian E-Health sector. According to the statistics of the ministry of Health, the total numbers of the employees in Ministry of Health are 580,000 workers comprises of (499 hospitals across the Kingdom. The total health workforce comprised 113,300 physicians, 25,970 dentists, and 213,110 nurses from both the public and private sectors. In addition, there were 36,810 pharmacists, 153,688 allied health professionals, and 4,997 midwives. These figures highlight the significant size and diversity of the healthcare workforce in Saudi Arabia during 2023) (Healthcare Establishments and Workforce Statistics 2023).

3.6.2 Sampling Technique

The selection of participants for the study on cloud computing adoption within the Saudi Arabian E-Health sector necessitates a deliberate approach to sampling. With an array of stakeholders within the sector. In this study The Multi-stage sampling steps taken in this research according to (Zikmund et al., 2012) are: Stage 1 facilities were within each stratum to select public/private and hospital size. Stage 2 Departments/units were selected for participation in the survey. In this regard IT department were selected to participate in the research because of their knowledge in cloud computing. Stage 3 respondents were selected within the IT departments.

Hence, the stratified method and convenience sampling techniques were employed to select individuals with prior exposure to or interest in Cloud computing in Saudi Arabia. Convenience sampling method was used to distribute the survey instrument with judgment sampling in some aspect (Creswell, 2014a); convenience sampling facilitated a diverse range of perspectives in the sample by engaging individuals who were willing and able to participate in the study. Convenience sampling strategy is rapid, economical and easy to contact various respondents and widely accepted in IS research (Alam et al., 2020).

The sampling methods adopted in distribution of questionnaires to the respondent is convenience sampling technique. The convenience sampling technique will be employed to access individuals that are easily available and reachable within the E-Health sector in Saudi Arabia (Parker et al., 2019). By employing this method, efficient data collection will be attained, while logistical challenges will be reduced. Therefore, this method is highly preferred as it assures a representative sample and enhances the validity of the findings.

3.6.3 Sample Size

The appropriate sample size for this research will be determined through the tenets of saturation (Van Deun et al., 2009). Before starting any statistical analysis of the data, it is necessary to make sure that the sample size is good and sufficient to estimate and study the phenomenon. This step will be prepared in two ways:

The first is by determining the minimum size of a sample drawn from the study population of a certain size and at a certain degree of confidence to estimate a certain statistical constant such as the arithmetic mean, standard deviation, or per centage.

The second trend is the statistical adequacy test, which indicates the validity of the sample in representing the data after it was collected through the questionnaire.

In this research, the minimum sample size n that must be drawn with repetition has been calculated from this population in order to estimate the average of the opinions of developing the E-Health Cloud Computing Adoption model in Saudi Arabia at 95% confidence interval, i.e. the standard score is Z = 1.96. The appropriate significance level of this type of study (P-value) is 5%, and it will be used for all statistical tests in this research. The standard deviation of the average opinions in the community is estimated as σ =1 according to previous studies in this (Alharbi, 2016), and that the real difference between the average opinions in the sample and the average of the opinions in the community does not exceed d=0.2. According to the Probability Sampling Equation (Levy,2013) to:

$$n = \frac{N * Z^2 * \sigma^2}{(N-1) * d^2 + Z^2 * \sigma^2}$$

$$= \frac{580000 * (1.96)^2 * (1)^2}{(580000-1) * (0.2)^2 + (1.96)^2 * (1)^2} \approx 96\, Workers$$

However, to enhance the robustness and reliability of our findings, the research aims to collect data from at least 381 participants. This is in accordance with Krejcie and Morgan (1970) table.

This larger sample size will help ensure that our results are more representative and reduce the margin of error further. Data collection will continue until redundancy is attained, meaning that additional data will no longer provide new insights or significantly alter the results. This approach guarantees comprehensive coverage and the accuracy of our conclusions regarding the E-Health Cloud Computing Adoption model in Saudi Arabia. (Van Deun et al., 2009).

The number of participants selected will be contingent on the thoroughness and multifaceted nature of the data gathered; ascertaining that it adequately addresses the research queries and yields an all-inclusive comprehension of the factors that impact the implementation of cloud computing within the E-Health sector in Saudi Arabia. To this end, the depth and scope of the information collected will determine the sample size that will provide insightful, informative, and reliable results (Saunders et al., 2018). As such, it is crucial that the sampling methodology implemented for this research captures the essence of the E-Health landscape in Saudi Arabia to guarantee that all-encompassing information is gathered, and the results are a valid reflection of the prevailing climate within the sector.

To ensure the quantitative component of the study generates reliable and generalizable findings, the researcher will administer a questionnaire to a representative sample of individuals from the target population in Saudi Arabia's E-Health sector. The sample will include a diverse group of stakeholders to provide comprehensive insights. The inclusion criteria for participation are:

1. **E-Health practitioners:**

- Actively involved in the implementation and management of e-health services.

- Employed in departments such as telemedicine, electronic medical records (EMR) management, and digital health services.

2. **IT professionals:**

- Specializing in IT infrastructure, cloud computing, and cybersecurity within the healthcare sector.
- Working in departments such as IT support, cybersecurity, and cloud infrastructure management.

3. **Top-management and Policymakers in e-health:**

- Senior executives and decision-makers responsible for strategic planning and the adoption of new technologies.
- Positions may include Chief Information Officers (CIOs), Chief Technology Officers (CTOs), and Directors of E-Health Programs.

Exclusion criteria are as follows:

1. **Individuals without direct involvement in e-health services:**
   - Those who do not actively participate in the e-health sector will not be included.
2. **Non-professionals:**
   - Laypersons or individuals lacking professional expertise in e-health, IT, management, or policy-making related to e-health will be excluded.
3. **Participants from unrelated sectors:**

- Stakeholders from sectors outside healthcare and e-health will not be considered for this study.

By adhering to these criteria, we ensure that our sample is composed of relevant stakeholders who can provide valuable and informed opinions on the adoption of cloud computing in e-health.

3.7 Data analysis

Data analysis is the process of changing the data into meaningful Intuition and statistical inference. It consists of data screening, i.e. inputting missing data, detection of outliers, normalisation of the data, reliability, and construct and content validity. The data screening is performed to ensure that the data is suitable for drawing inferences. The hypotheses are tested using correlation and regression techniques as statistical analysis methods. In this section, the data analysis will be explained to show how the relationships between cloud computing factors and the moderating variable on cloud computing adoption were tested. SmartPLS is used, for five major techniques: descriptive statistics, factor and reliability analysis, correlation analysis and regression analysis. The research hypotheses are tested by structure equation modelling (SEM) using the software application SmartPls. SEM is considered as the best second-generation multivariate method that meets this purpose (Kline, 2011). It has two major functions: measurement (i.e what are the things to be measured, how should they be measured and how are the reliability and validity conditions met); and explaining the relationship among the variables which are complex and unobserved (Hair et al., 2010). SEM is deemed the most appropriate method for testing the conceptual model and hypotheses in this study

3.7.1 Statistical reliability and pilot study

Pilot study can be a process by which a researcher will use responses from a few respondents who had evaluated and completed the instrument to makes changes to an instrument (Creswell, 2012). The aim of pilot Study is to address problems that would increase measurement error if not resolved (Blair & Conrad, 2011). Hence, a pilot study enhances the review on the survey questionnaire with respect to a technicality, interpretation of questions, and ambiguity avoidance (Memon et al., 2017).

Kumar et al., (2013) asserted that the purpose of piloting a questionnaire is to ensure whether: (i) the respondents have clearly understood all the questions, (ii) the wording of the questions is correct, (iii) the sequence of questions is correct, (iv) additional questions are needed, or some questions should be eliminated and, (v) the instructions are clear and adequate. All developed scales, or items, whether adapted or adopted, should be piloted to confirm whether the questions work accurately in a new setting with the new respondents.

Face and content validity was carried out by the researcher before the pilot study for all the measures by assessing the suitability of the items in representing the operational definition of each variable. Face validity refers to the extent to which items that are projected to measure a concept actually measure such concept on its face, while content validity is the extent to which measures integrate adequate items that completely represent such concept. This involved meeting and discussing with a number of respondents and experts in order to pass judgment on the validity of the selected items to measure the construct (Sekaran & Bougie, 2010).

Therefore, this research has undergone face validity by referring to academic members and industrial practitioners. Academicians commented more on the sentence structure, suitability of the construct, and to what extent the concept is measured. This study took consideration suggestions proposed by four academicians in developing research instrument. The instrument/questionnaire covered so many issues that aim to examine the moderating effects of gender segregation on the relationship between the identified factors and cloud computing adoption in the Saudi Arabian healthcare sector.

Furthermore, the practitioners have provided feedback with respect to the suitability of the concept from the industry perspective. The content validity of the items was also assessed by referring to previous studies. The researcher identified items that were designed to measure each of the hypothesized constructs or variables based on the works of prominent scholars, such as Alharbi et al., (2016); Alkurdi, (2022); Ishak et al., (2021) (Meri et al. 2019); Kaur et al. (2019); (Sivan & Zukarnain, 2021).Therefore, a total of 23 items were used in the questionnaire in examining all the five variables illustrated in the model of the study.

To ensure a good instrument and that the selected instrumentations were well-suited to the context of the study, clarity of questions were utmost importance to ensure an understanding of the questions. A Pilot was then performed in two steps. In the first step, sampling technique was conducted with 50 staff of Saudi Arabian healthcare sector and it was carried out the by researcher to guarantee a higher per centage of response rate. The process takes five months for data collection and analysis.

The second step dealt with the analysis of Cronbach's alpha and Composite Reliability [often referred to as Internal Consistency (IC) statistic to validate the internal reliability consistency for each of the selected instrumentations (J. F. Hair et al., 2013; Zikmund et al., 2013). Traditionally, coefficient alpha (α) is calculated to check for internal consistency reliability of the measures (Memon & Ting, 2017). This enabled the researcher to predict potential issues during the full-scale research.

Validating the instrument is important because it refers to the degree by which the instrument is measuring what it is supposed to measure and not something else, whereas reliability measures the extent to which an instrument is error free, and hence consistent and stable across time (Sekaran & Bougie, 2009a).

Following Johanson and Brooks, (2009) a total of 50 questionnaires were distributed for the pilot survey. However, only 44 completed questionnaires were returned this represent a response rate of 88%. It should be noted that these 50 staff of Saudi Arabian healthcare sector were not included in the actual study. A PLS-path modelling using Smart PLS 3.0 M3 software (Hair et al., 2014) was employed to ascertain the internal consistency reliability and discriminant validity of the constructs used in the pilot study.

3.16.1 Reliability Testing

Reliability testing guarantees the survey instrument produces similar results across repeated measures either with a similar population or within the same population. A reliable survey is generalizable and therefore expected to reproduce similar results (Tell, 2013). There are different types of reliability tests; the most widely used technique in many types of research is internal consistency reliability (Heale & Twycross, 2015).

The cronbach‘s alpha and composite reliability coefficient test was carried out to measure the internal consistency reliability. The conditions for assessing the reliability of the instruments were Cronbach’s alpha and composite reliability for its internal consistency of the scales using reliability coefficients (Gliem & Gliem, 2003; J. F. Hair et al., 2013). In determining the reliability of the research instrument, a sample questionnaire for Cronbach’s alpha and composite reliability test was administered to measure the reliability of the underlying dimensions of the instrument. Avkiran and Ringle, (2018) provided the recommended limit of Cronbach's alpha to be ≥0.60.

Other methods such as Average Variance Extracted (AVE) and composite reliability coefficient were also used to test the reliability of the instrument. Fornell and Larcker, (1981) suggested that the rule of thumb for the AVE score should be 0.5 or more. The authors further stated that adequate discriminant validity will be achieved if the square root of the AVE is greater than the correlations among latent constructs. Meanwhile, Bagozzi and Yi, (2012; Hair et al., (2011) suggested that the composite reliability coefficient threshold should be at least 0.70 or more.

Table 3.7 below presents the AVE and composite reliability coefficients of the latent constructs for the Pilot. As shown in Table 3.7, the Cronbach's Alpha coefficient is within the range of 0.630 to 0.946 all exceeded the rule of thumb of 0.60 (Avkiran & Ringle, 2018). Also, the composite reliability coefficient of each latent construct were found to be within the range of 0.755to 0.955, exceeding the minimum threshold of 0.70 which also confirmed the adequate internal consistency reliability of the construct used in the pilot study Bagozzi and Yi, (1988); Hair et al., 2011). The table also shows that the values of the AVE were between the ranges of 0.501 and 0.717, suggesting acceptable values.

Table 3.7
Pilot Testing: Reliability and Validity of Constructs (n=44) Latent variables No. of Indicators

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Clod Comp	0.802	0.883	0.717
Gender	0.946	0.955	0.682
Regulations	0.630	0.785	0.553
Relative Adv.	0.817	0.867	0.687
Security	0.631	0.759	0.519
Technical Complexity	0.644	0.755	0.523

Table 3.7 compares the correlations among the latent constructs with the square root of AVE to test for discriminant validity. The square root of the AVE (values in boldface) was compared with the correlation among the latent constructs. The table shows that the square root of the AVEs was all higher than the correlations among latent constructs, demonstrating adequate discriminant validity (Fornell & Larcker, 1981).

Table 3.8
Fornell-Larcker Criterion

	Cloud Comp	Gender	Regulation	Relative	Security	Technical Compl
Clod Comp	**0.847**					
Gender	-0.366	**0.826**				
Regulation	0.185	0.260	**0.744**			
Relative Adv.	0.109	0.114	0.585	**0.829**		
Security and Policies	0.159	0.098	0.262	0.086	**0.721**	
Technical Complexity	0.340	0.064	0.412	0.470	0.256	**0.723**

Note: Values in **boldface** represent the square root of the average variance extracted while the other values represent the correlations.

3.8 Ethical Consideration

Throughout the sampling process, the researcher will be cognizant of ethical concerns and take the necessary precautions to ensure the participants' welfare. The paramount ethical principle of informed consent governs the study and is sought from each participant to enable them to make an informed decision before being involved in the research. The researcher will apprise the participants of the research's aim, procedures, potential risks, and benefits, and allow them ample time to ask any relevant questions or clarify issues they deem essential. This approach accords the participants with an active role in the study and ensures their autonomous decision-making power. Data privacy and confidentiality are sacrosanct in the study, and the team adopts stringent measures to protect them. Personal information is excluded and substituted with unique identifiers to obfuscate the participants' identities during data collection and analysis. This approach is vital in protecting the participants' dignity, which is a cardinal principle in research ethics. Another critical ethical issue is the right to withdraw, which is sacrosanct in the research study. Participants reserve the right to exit the research study at any point without facing any penalties or consequences. This provision reassures the participants that they are free to participate and can make autonomous decisions without coercion. Generally, the research team recognizes the ethical underpinnings of the study and adopts rigorous ethical standards to protect the participants. The team considers ethical issues of informed consent, privacy, confidentiality, and the right to withdraw throughout the research process. Therefore, upholding ethical principles in research safeguards participants' welfare, autonomy, and dignity and underscores the fundamental tenets of research ethics.

3.9 Limitations of the Study

The study employs a cross-sectional design, which limits the ability to establish causality between variables. This methodological approach observes variables without influencing them and only captures a snapshot in time, making it difficult to infer causal relationships (Thomas, 2023; Hunziker & Blankenagel, 2021). Additionally, the data collection relies on self-reported surveys, which can introduce bias and inaccuracies due to subjective perceptions and recall issues. The availability of comprehensive and up-to-date data on cloud computing adoption in healthcare facilities may be limited, leading to potential gaps in the analysis (Thomas, 2023). The relatively small sample size impacts the statistical power and generalizability of the study results. However, increasing the sample size to 300 participants could mitigate these limitations, enhancing the robustness and generalizability of the findings (Hunziker & Blankenagel, 2021).

3.10 Summary

This chapter is devoted to presenting the research methodology, design and data collection that will be employed in developing an E-Health Cloud Computing Adoption model in Saudi Arabia. A quantitative method approach, will be used, this approach aims to capture a nuanced and complete understanding of the phenomenon under study. The research design will incorporate various stages that will enable us to collect the relevant and insightful data that is necessary to develop this model. The study aims to utilize questionnaire survey to acquire insights from IT practitioners, E-Health professionals and E-Health experts in Saudi Arabia, focusing on validating the model and factors related to cloud computing adoption and its current usage in the E-Health industry.

CHAPTER FOUR
Results

4.1 Introduction

The main objective of this chapter is to provide empirical results from analysis of PLS-SEM path modeling. It presents the research findings of the study based on the data collected from Saudi Arabian Health sector. Results include discussions on the initial preliminary data analysis, such as description of the profile of the respondents, preliminary data screening and cleaning, the response rate, process of checking and replacing missing values, outlier's treatment, and running of descriptive statistics. Subsequently, the main data analysis started with a measurement model analysis or goodness of measures through construct validity and internal consistency reliability analysis. Furthermore, results of hypotheses testing and structural models are presented, namely, significance of the path coefficients, level of the *R*-squared values, effect size, and predictive relevance of the model. Finally, the results of the complementary PLS-SEM analysis which examines the moderating effects of gender on the structural model are discussed.

4.2 Response Rate

The response rate of the survey is an important concern in a study because it ensures the questionnaires collected are valid for data analysis (Hair et al., 2010). Table 4.1 shows that for this study, 381 questionnaires were distributed to respondents. Of these, 320 questionnaires were retrieved (83.99%) which was far above the expected rate of response. This was a result of the researcher‘s persistence through several phone calls, reminders, and visits to the respondents (as suggested by Traina, MacLean, Park, & Kahn, 2005) and a series of follow-up through short message service (SMS) for completion of each questionnaire. Of the 320 collected questionnaires, only 305 were found to be useful for further analysis which accounted for 83.06% valid response rate. Twenty-three questionnaires were excluded from the analysis due as they were either not duly completed or were considered as outliers.

Table 4.1
Response Rate of the Questionnaires

Response	**Frequency**	**Per centage (%)**
No. of distributed questionnaires	381	100
Completed and returned questionnaires	320	83.99
Unusable questionnaires:	16	4.37
Incompleteness and non-eligibility	07	2.19
Univariate and multivariate outliers	9	2.46
Returned and usable questionnaires	304	83.06

Scholars have suggested a minimal level for response rate, for example, Sekaran and Bougie (2009) suggested a response rate of 30 per cent as acceptable for surveys. However, other researchers had proposed other minimal level, causing an inconsistency across the literature concerning acceptable response rate. Babbie (2008) suggested 50 per cent as the minimal level, Groves et al. (2004) suggested 60 per cent while De-Vaus (2002) argued for 80 per cent. Hence, the response rate of this study is adequate for further analysis. More importantly, the tool of analysis for the current study, which is PLS, requires a minimum of only 30 responses (Chin, 1998b); thus a total of 304 responses for this study is adequate for analysis. Also, the 83.06% response rate is above the range of common response rate of between 40% - 50% in social science study in Nigeria (Osuagwu, 2001).

4.3 Profile of the respondents

Table 4.2 shows that of the total 304 respondents, 194 are male (63.8%) and 110 are female (36.2%). This shows that a majority of the respondents, made up of male officers from Saudi Arabian health sector. This gender disparity reflects the socio-cultural practice in Saudi

Arabia. On their personal experience usig cloud computing in health sector, 131 of the officers (43.1%) indicated that they are satisfied with cloud computing.

The remaining 57 respondents (18.8%) have rate their cloud computing as very good and 42 respondents (13.8%) have indicated fair/poor performance of cloud computing from their experience while 45 respondents (14.8) rated it as poor. The responses from the respondents are quite impressive and attest to the caliber of staff respondents to this study. The respondents also indicated they are familiar with and have a high level of knowledge of the subjects on which they were responding to.

Table 4.2 also shows that 44 participants (14.5%) are from the ministry of health. Private institutions participants of this study are 96 (31.6%) while others are 165 participants (53.9%). This clearly shows that the study has reached its target respondents. A majority of the respondents (121 respondents, 41.8%) have between 2-5 years of work experience in the health sector, 61 respondents (20.1%) have more than 6 Years of working experience while the remaining of the respondents 116 (38.2%) are having not more than 2 years of working experience. This revealed that the respondents are educated enough to respond to the study effectively.

Table: 4.2
Demographics of the Respondents

Demographics	**Frequency**	**Per centage (%)**
Gender		
Male	194	63.8
Female	110	36.2
Personal experience using cloud computing		
Absent/Poor	45	14.8
Fair	42	13.8
Satisfactory	131	43.1
Very good	57	18.8
Excellent	29	9.5
Institution		
Ministry of Health	44	14.5
Private Health Care	96	31.5
Others	164	53.9
Work Experience		
Less Than 2 Years	116	38.2
2 -5 years	127	41.8
6 years and above	61	20.1

4.4 Test of Non-Response Bias

Previous studies have established that the non-respondents occasionally differ systematically from the respondents both in demographics, perceptions, attitudes, and behaviors, in which any or all of which might affect the results of the study. Non-response bias is a common mistake that a researcher expects to make while estimating sample characteristics because some group of respondents may be underrepresented as a result of non-response.

The issue of non-response bias arises when there is a difference in the answers between respondents and non-respondents (Lambert & Harrington, 1990). Non-response bias can affect the results of the study and generalizations of results to the population. Therefore, in a multivariate analysis there is a need to conduct a non- esponse bias test to detect if it exists before moving on to the main analysis.

With a possibility of the existence of a non-response bias, a time-trend extrapolation method was followed in this this research (Armstrong & Overton, 1977) by comparing the early and late respondents. As shown in Table 4.3 respondents were divided into early and late response groups with regards to the ten study variables (i.e., Compatibility, Cost, Cultural Soc, Gender, Infrastructure, Regulation, Relative, Security, Technical Exp and Cloud Computing Adoption).

Questionnaires received within the first two months were classified as early responses while those received after two months were classified as late responses. The table shows that, generally, standard deviation and mean for the early responses and late responses are distinctly diverse.

In addition, an independent samples *t*-test was conducted for all the variables under study to examine if there is any difference between the two groups. As shown in Table 4.3, the results of independent samples *t*-test revealed that the equal variance significance values for each of the variables were greater than the 0.05 significance level of Levene's test for equality of variances. Field (2013) and Pallant (2010) suggested that non-response bias should be considered if the significant value for Levene's test is larger than 0.04. Hence, this study indicated that the assumption of equal variances between early and late respondents had not been violated.

Table 4.3:
Group Descriptive Statistics for Early and Late Respondents

	Non-Response Bias	N	Mean	Std. Deviation	Std. Error Mean	Levene's Test for Equality of Variances F	Sig.
Rel_Adv	Early Response	288	3.8194	.61653	.03633	.097	.756
	Late Response	14	3.2429	.58272	.15574		
Technical Complexity	Early Response	288	3.6649	.54793	.03229	.496	.482
	Late Response	14	3.0000	.44936	.12010		
Reg & Sec	Early Response	288	3.6722	.54542	.03214	.899	.344
	Late Response	14	2.9143	.43475	.11619		
Security & Privacy	Early Response	288	3.7274	.52583	.03098	2.472	.117
	Late Response	14	3.0714	.34570	.09239		
Gend	Early Response	288	2.5325	.78157	.04605	3.621	.058
	Late Response	14	1.7143	.48742	.13027		
Cloud_Comp	Early Response	288	3.2137	.57568	.03392	.379	.538
	Late Response	14	2.4180	.51247	.13696		

4.5 Descriptive Statistics of the Variables

Descriptive analysis was used to examine the variables to obtain their minimum, maximum, mean and standard deviation values. The questionnaire employed is a 5-point Likert scale to measure the study variables, with 1.09 depicting the minimum value while 5 depicts the maximum value. Table 4.4 shows the values of the minimum, maximum, mean, and standard deviation for each variable.

The obtained mean values of the constructs were as follows: ‘Rel_Adv had the highest mean value (mean = 3.80; standard deviation = 0.63), followed by Sec. &_Priv’ (mean = 3.70, standard deviation = 0.53), 3.64, Tech Complexity (mean = 3.64, standard deviation = 0.56), ‘Regulation’ (mean = 3.64, standard deviation = 0.56). ‘Cloud comp’ (mean = 3.12, standard deviation = 0.60), ‘Gender’ (mean = 2.50, standard deviation = 0.79). The construct with the smallest mean value was ‘Gender’ (mean = 2.50, standard deviation = 0. 79). The variables were measured on a 5-point Likert scale.

Table 4.4
Mean and Standard Deviation of the Variables

Variable	N	Minimum	Maximum	Mean	Std. Deviation
Rel_Advantage	304	2.40	5.00	3.8007	.63152
Tech_Complexity	304	2.25	5.00	3.6382	.56162
Regulations & Policy	304	2.00	5.00	3.6355	.56199
Sec & Privacy	304	2.25	5.00	3.6974	.53479
Gender Seg	304	1.09	4.45	2.5027	.79483
Cloud_Com	304	1.52	5.00	3.1804	.59616
Valid N (listwise)	304				

4.6 Preliminary Analysis

To address the research questions and objectives of the study through statistical analysis, some preliminary analyses were needed to be performed first (Pallant, 2007). Nonetheless, to carry out such preliminary analyses, the data should be coded and keyed into a particular data file of a researcher choice, depending on the requirements of the study. In this study, SPSS v23 was used for coding the data, screening, and preliminary analysis.

4.6.1 Missing Value Analysis

Missing value is one of the most pervasive problems in data analysis, its seriousness depends on the pattern of missing data, how much is missing, and why it is missing (Tabachnick & Fidell, 2007). It is statistically imperative to check for missing values before conducting multivariate analysis because some statistical packages (e.g., SmartPLS) will not function even with a single data missing. Furthermore, vital information would be missed as a result of overlooking cases with missing values, which consequently minimizes the statistical power and increases standard errors (Dong & Peng, 2013).

The indication of a missing data is when a respondent intentionally or otherwise failed to write a response on one or more questions, thus making the collected data not appropriate for subsequent analysis (Hair et al., 2010). In view of the serious effect of missing data, a precautionary step was taken by the researcher to prevent the problem from the point of data collection to decrease their occurrence. This was achieved when upon receipt of the questionnaire from the respondents; an immediate check was carried out on each questionnaire from beginning to end to ensure that all questions were properly answered.

Although no acceptable per centage of missing values in a data set exit in the literature for making a valid statistical inference, it was argued that a missing rate of 5% or less is non-significant (Schafer & Olsen, 1998; Tabachnick & Fidell, 2007). To treat for missing values it was suggested that mean substitution could be used and is the easiest way of replacing missing values and is time effective if the total per centage of missing data is 5% or less (Tabachnick & Fidell, 2007). Therefore missing values were treated and replaced with the mean variable option using SPSS SMEANS. Checking and replacement of missing data was essential in running PLS-SEM which is very sensitive to missing data. However, in this study no missing data were noticed. Hence data is valid for making statistical inference.

4.6.2 Assessment of Outliers

Apart from missing data, another important step of data screening is the assessment and treatment of outliers, which are the extreme case scores that may likely have a substantial negative impact on the outcomes. Outliers are extreme scores or values of data sets with uncommonly low or high values that may have significant effects on the analysis and results of the study (Hair et al., 2010). To ensure further data screening, treatment and assessment of both univariate and multivariate outliers were conducted. The presence of outliers in a regression-based analysis data set, can seriously mislead the estimates of regression coefficients and lead to unreliable results (Verardi & Croux, 2008). Outliers can be univariate or multivariate.

Thus, the presences of univariate outliers can be detected using either standardized variable values (z-score) or by using frequency distribution tables such as histograms, box plots, or normal probability plots. This study used standardized variable values (z-scores) threshold of ±3.29 as recommended by Tabachnick and Fidell (2007) to detect outliers. A total of nine univariate cases of outliers were identified using standardized variable values (z-score). In particular, the nine cases were items with code numbers 157, 171, 216, 230, 260, 262, 268, 269, and 289 as shown in Table 4.5. The univariate outliers were subsequently deleted from the dataset because they could affect the accuracy of the data analysis technique.

Table 4.5:
Univariate Outliers Identified Based on Standardized Values

Respondents ID	Item cases with standardized values exceeding ± 3.29
157	-3.56894
171	-3.56894
216	-3.51621
231	-3.06635
260	-3.56894
262	-3.63683
268	-3.39287
269	-3.42247
289	-3.56894

In addition, the Mahalanobis distance (D2) was also tested to locate the presence of multivariate outliers. Tabachnick and Fidell (2007) defined Mahalanobis distance (D2) as the distance of a case from the centroid of the remaining cases, that is the point created at the intersection of the means of all the variables. Hence, a linear regression in SPSS v23 was used to calculate Mahalanobis D2, followed by the computation of a value for chi-square. Given that 23 items were used, 57 represent the degrees of freedom in the chi-square table with $p < 0.001$, so the criterion is 95.71 (Tabachnick & Fidell, 2007).

This means that any item case with a Mahalanobis D2 value of 95.71 or above (i.e., for the 23 items) at 0.001 degrees of freedom should be removed. However, no single case of a multivariate outlier was recorded. Thus, the remaining 304 responses were thus considered for further multivariate analysis.

4.6.3 Normality Test

Normality is one of the most important concepts in multivariate analysis (Hair et al., 2010; Tabachnick & Fidell, 2007). Normality deals with the nature of data distribution for an individual construct and its association with a normal distribution (Tabachnick & Fidell, 2007). Assessing for normality and factors affecting the shape of the distribution before tests of hypotheses are carried out can help researchers draw more accurate conclusions and assist in diagnosing potential problems that can affect the results of the statistical analysis and assumptions underlying the hypotheses (Cruz, 2007).

Previous researchers Reinartz et al., (2009) and Wetzels et al., (2009) had traditionally assumed that PLS-SEM provides accurate model estimations in situations with extremely non-normal distributions. However, this assumption has been criticized by (Hair, Sarstedt, Pieper, et al., (2012) who suggested that researchers should perform a normality test on the data. Highly skewed or kurtosis can inflate the bootstrapped standard error estimation (Chatterjee & Hadi, 2006; Chernick, 2011), which in turn, will underestimate the statistical significance of the path coefficients (Hair, Sarstedt, Ringle, et al., 2012).

Therefore, this study employed multivariate normality test to evaluate data distribution using kurtosis and skewness (Hair et al., 2010). The range of acceptable values of the skewness and kurtosis is < 2 and < 7, respectively (Tabachnick & Fidell, 2007).

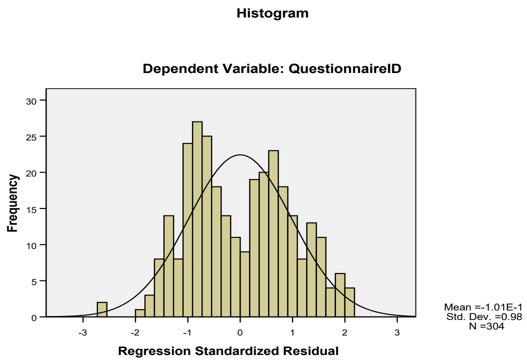
Table 4.6 shows the results for tests of skewness and kurtosis where the values of skewness were found to be between -0.67 to 1.34 which is below 2, while the values of kurtosis were between -0.08 to 4.14 which is below 7.

Table 4.6
Results of Test of Skewness and Kurtosis

	N	Minimum	Maximum		Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Std. Error	Statistic	Std. Error
Rel_Advantage	304	2.00	5.00	.03622	.63152	-.099	.140	-.421	.279
Tech_Complexity	304	2.00	5.00	.03221	.56162	-.146	.140	-.246	.279
Regulation & Policy	304	2.00	5.00	.03223	.56199	-.669	.140	.402	.279
Security &_Privacy	304	2.00	5.00	.03067	.53479	-.469	.140	.008	.279
Gender	304	2.00	5.00	.04559	.79483	.373	.140	-.679	.279
Cloud_Com	304	2.00	5.00	.03419	.59616	.407	.140	.616	.279
Valid N (listwise)	304								

However, Field, (2009) noted that a large sample may inflate the value of the skewness and kurtosis statistics caused by decreases in standard errors. Therefore, it is more important to look at the shape of the distribution graphically rather than looking at the values of skewness and kurtosis. Against this background, this study also employed a histogram and normal probability plots to check for normality of data (Tabachnick & Fidell, 2007).

Figure 4.1 and Figure 4.2 show the histogram and normal distribution of the data for this study, respectively. Both Figure 4.1 and 4.2 shows that data collected confirmed to a normal distribution curve indicating that multivariate normality assumptions had not been violated in the present study.



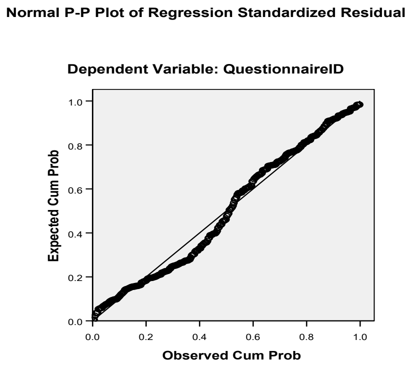


Figure 4.1
Histogram
Source: Author computation 2025

Figure 4.2
Normal probability plots
Source: Author computation 2025

4.6.4 Multicollinearity

Multicollinearity refers to a situation where two or more exogenous latent constructs are extremely correlated. Multicollinearity occurs when the independent variables are highly correlated to each other (Hair et al., 2010; Tabachnick & Fidell, 2007). The presence of multicollinearity among the exogenous latent constructs can substantively alter the estimates of regression coefficients and their statistical significance tests (Samprit Chatterjee & Hadi, 2006). Specifically, multicollinearity increases the standard errors of the coefficients, which in turn make the coefficients statistically insignificant (Tabachnick & Fidell, 2007). As recommended by Chatterjee and Yilmaz, (1992); Peng and Lai, (2012) the process of detecting multicollinearity can be carried out by several techniques, namely, correlation matrix, and VIF and tolerance.

Thus, this study examined the correlations of the exogenous latent constructs. Table 4.7 shows the correlation matrix of all exogenous latent constructs used in the study and found that the correlation coefficients values were between the range of -0.040 to 0.692. According to Hair et al. (2010), a correlation coefficient above 0.90 indicates multicollinearity between exogenous latent constructs. Thus, multicollinearity was not present in the data collected.

Table 4.7
Correlation Matrix of the Exogenous Latent Variables

	1	2	5	7	9	10
Rel_Adv	1					
Tech_Adv	.676(**)	1				
Regulation & Policies	.589(**)	.578(**)	1			
Security & Privacy	.652(**)	.609(**)	.670(**)	1		
Gender Seg	-.040	.045	.024	.100(*)	1	
Cloud_Com	.264(**)	.268(**)	.190(**)	.268(**)	.582(**)	1

** Correlation is significant at the 0.01 level (1-tailed).
* Correlation is significant at the 0.05 level (1-tailed).

Following the analysis of the correlation matrix for all the exogenous latent variables, this study also conducted a second analysis to test for the presence of multicollinearity through variance inflation factors (VIF) and tolerance values. Hair et al., (2011) suggested a threshold value of VIF to be less than 5, and the tolerance value greater than 0.20.

Table 4.8 shows the VIF and tolerance values for this study's exogenous latent constructs. The table shows that the independent variables under study did not have a multicollinearity problem because the tolerance values which were between the range of 0.801 and 0.876 are greater than 0.20. In addition, the VIF values were within the range of 1.141 to 1.249 are less than 5) which is acceptable (Hair et al., 2011). Hence, it was concluded that multicollinearity was not an issue in this study.

Table 4.8
Tolerance and Variance Inflation Factors (VIF)

	Collinearity Statistics	
	Tolerance	**VIF**
(Constant)		
Relative Advantage	0.367	2.723
Technical complexity	0.434	2.306
Regulation & Policies	0.363	2.754
Security & Privacy	0.326	3.071
Gender	0.584	1.712

Cloud_Com	0.557	1.796

4.6.5 Common Method Variance Test

Common method variance also known as common method bias (CMB) represents one of the most frequently cited concerns among social science researchers (Podsakoff et al., 2003) and information systems (IS) (Malhotra et al., 2006). According to (Podsakoff et al., 2003), CMB refers to the variance that is perpetually attributable to the measurement procedure rather than to the actual constructs the measures represent.

CMB is important due to its potential of bias when estimating the relationship among the theoretical constructs of the research (Podsakoff et al., 2003). However, there is general agreement that CMB is a major concern for researchers using self-report surveys (Lindell & Whitney, 2001). Hence, since the endogenous variables were collected at the same time and using the same instrument as the exogenous variables, the research tested common method bias to establish that such bias did not distort the data we collected. Several procedural remedies were adopted in this study to minimize the effects of CMB (Viswanathana, & Kayandeb, 2012).

Firstly, to reduce evaluation fear, for instance, respondents were given full freedom of choice and expression assuring that their responses will be kept confidential and will be used for study purposes only. Also, the respondents were duly informed that there is no wrong or right answer to the items in the questionnaire. Respondents were free to choose whether to participate or not in the study (there was autonomy). The researcher distributed and collected the survey questionnaires without asking for the respondents' identification or any other form of personal data at any stage of the data collection process as suggested by Schwepker and Schultz, (2013).

Second, scale items were improved by the removal of ambiguous items so as to reduce CMB. This was achieved by avoiding unclear concepts in the questionnaire. The length of questionnaire was reduced (Singhapakdi et al., 2013). To further improve scale items, all questions in the survey were concise, specific, and written in simple language.

Finally, this study examined CMB by applying Harman's single factor test as suggested by Alwin et al., (2017) where all items in the study were subjected to a principal components factor analysis. Table 4.9 show the outcome of the factor analysis yielded five factors, explaining a total variance of 56.16%. The first factor only explained 17.83% of the variance which suggested that CMB does not exist in the present study since it was less than 50% (R. Kumar, 2011). All analyses carried out showed that CMB is not a serious problem in this study.

Table 4.9
Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	15.544	31.722	31.722	15.544	31.722	31.722	8.736	17.828	17.828
2	8.919	18.202	49.924	8.919	18.202	49.924	8.190	16.714	34.542
3	2.093	4.272	54.196	2.093	4.272	54.196	4.176	8.522	43.063
4	1.813	3.699	57.895	1.813	3.699	57.895	3.312	6.759	49.822
5	1.448	2.956	60.851	1.448	2.956	60.851	3.105	6.338	56.160
6	1.394	2.846	63.696	1.394	2.846	63.696	2.642	5.392	61.552
7	1.124	2.294	65.990	1.124	2.294	65.990	1.643	3.353	64.905
8	1.071	2.186	68.176	1.071	2.186	68.176	1.603	3.271	68.176
9	.982	2.004	70.180						
10	.954	1.946	72.126						
11	.884	1.805	73.931						
12	.808	1.649	75.580						
13	.773	1.577	77.156						
14	.713	1.455	78.612						
15	.638	1.301	79.913						
16	.611	1.246	81.159						
17	.590	1.204	82.363						
18	.568	1.159	83.522						
19	.552	1.127	84.649						
20	.488	.996	85.645						
21	.474	.967	86.612						
22	.465	.949	87.561						
23	.428	.873	88.434						

Extraction Method: Principal Component Analysis.

4.7 Evaluation of PLS-SEM Result

After data was checked and screened, the next step was to assess the outer model and inner model (Asyraf & Afthanorhan, 2013; Henseler et al., 2011). PLS-SEM was used in this study to evaluate the outer model (measurement model) which is also called the outer model's validity and reliability (Ramayah et al., 2011). Once the measurement model is assessed and found to be valid and reliable, the structural model (i.e., theoretical model) was then assessed (Chin, 1998b). The two-step approach for of PLS analyses is summarized (Henseler et al., 2011) and shown in Figure 4.3.

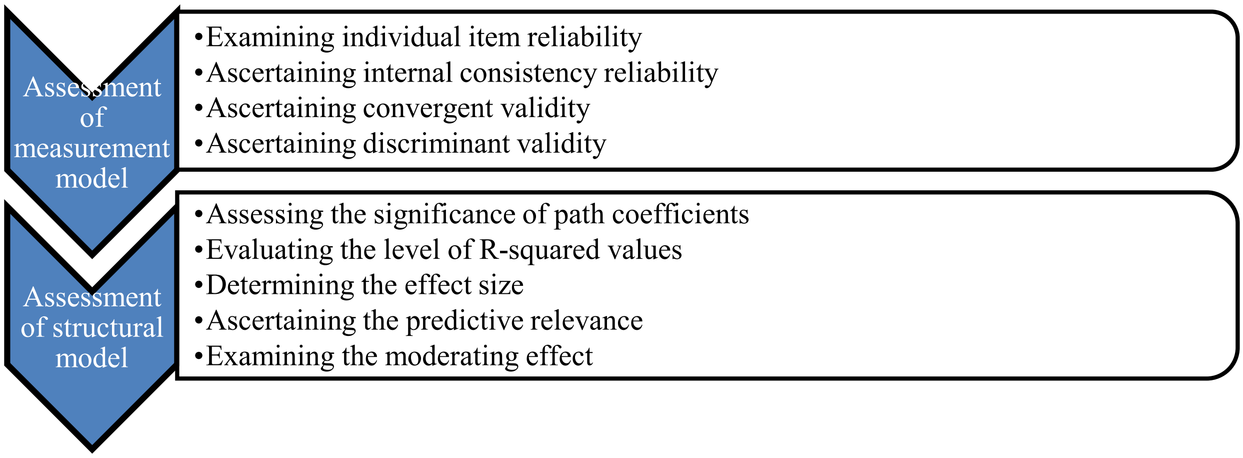


Figure 4.3
A Two-Step Process of PLS Path Model Assessment
Sources: Henseler et al. (2009)

Before conducting PLS-SEM analysis, there was a need to configure the model in a way that it will be clearly understood. To do this, indicators were clarified to establish which indicators are formative if any, and which are reflective. It is essential to note that model configuration is vital because approach in testing reflective measurement model is quite different from approaches used in testing formative measurement model (Lowry & Gaskin, 2014). In this study, all the indicators of latent variables are reflective.

Specifically, the latent (unobserved) variables and the indicator (observed) variables in this study are reflective rather than formative. A reflective measurement model is a type of measurement model in which the direction of arrows is from the latent variable to the assigned indicators, indicating that, the latent construct causes the measurement of the indicator variables.

4.7.1 Assessment of Measurement Model

To evaluate the measurement model, previous literature had suggested an examination of the average variance extracted (AVE), composite reliability (CR), and indicator loadings to measure convergent validity (CV). CV evaluates whether or not the items represent one and the same underlying construct. Firstly, loadings of the indicators were conducted to ensure that they were above the threshold of 0.4 (Avkiran & Ringle, 2018), AVE ≥ 0.5 is preferred (Avkiran & Ringle, 2018), and CR ≥ 0.7. As shown in Table 4.12 and Table 4.13 all the values were above the recommended value points, thus ensuring achievement of CV.

The measurement model in Figure 4.4 determines the individual item measures reliability, internal consistency, convergent validity and discriminant validity in measuring the construct (Hair et al., 2014). The first stage in PLS-SEM analysis is the evaluation of the outer model (measurement model). The outer model deals with the measurement of the component, which confirms that the survey items measure the constructs they were designed to measure, thus ensuring that they are reliable and valid.

Two main criteria in PLS-SEM, to assess reliability and validity, were used to evaluate the outer model (Hair et al., 2014). The structural results of the relationship among constructs (inner model) depend on the validity and reliability of the measures. In addition, the measurement model can be evaluated by examining: (i) internal consistency reliability, indicator reliability and individual item reliability using Cronbach's alpha and composite reliability, (ii) convergent validity of the measures assessed by calculating the average variance extracted of the indicators associated with individual constructs (Mackenzie et al., 2011), and (iii) discriminant validity using Fornell-Larcker criterion and the indicator’s outer loadings, and the heterotrait-monotrait ratio of correlations ($HTMT_{0.90}$) which has become a primary criterion for assessing discriminant (Avkiran & Ringle, 2018). Figure 4.4 shows the measurement model of this study.

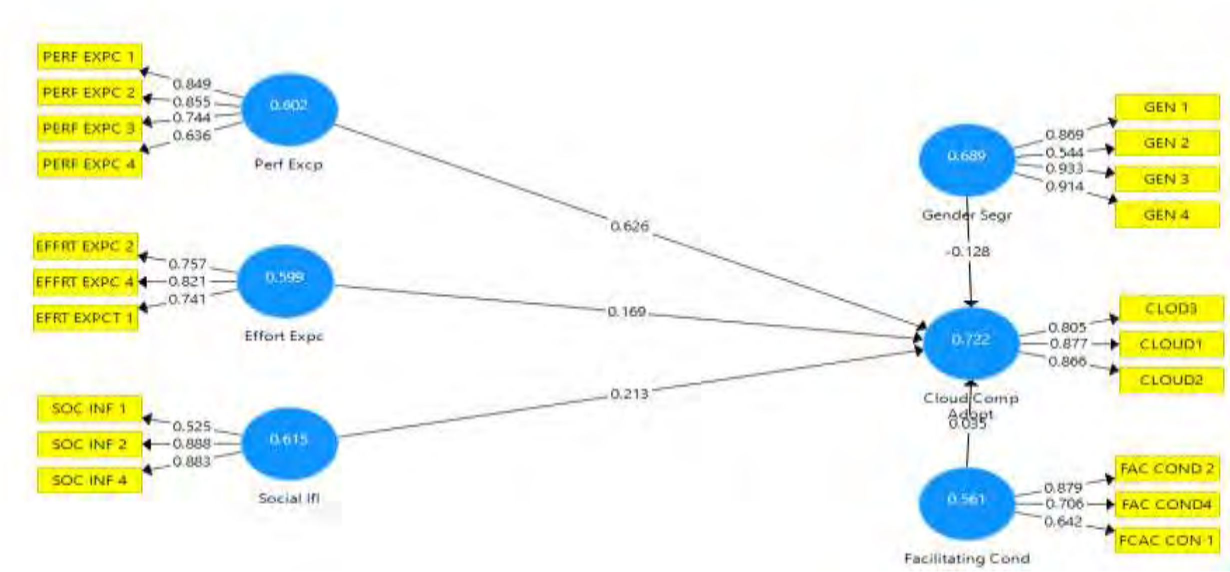


Figure 4.4
PLS-SEM Algorithm (Measurement Model)
Source: Author 2025

Table 4.10
Outer Loadings

Construct	Item	Loading
Cloud Computing	**Cloud 1**	**0.805**
	Cloud 2	**0.877**
	Cloud 3	**0.866**
Effort Expectancy	**Effrt expc 2**	**0.757**
	Effrt expc 4	**0.821**
	Efrt expct 1	**0.741**
Facilitating Condition	**Fac cond 2**	**0.879**
	Fac cond4	**0.706**
	Fcac con 1	**0.642**
Gender Segregation	**Gen 1**	**0.869**
	Gen 2	**0.544**
	Gen 3	**0.933**
	Gen 4	**0.914**
Performance Expectancy	**Perf expc 1**	**0.849**
	Perf expc 2	**0.855**
	Perf expc 3	**0.744**
	Perf expc 4	**0.636**
	Soc inf 1	**0.525**
Social Influence	**Soc inf 2**	**0.888**
	Soc inf 4	**0.883**

This study evaluates individual items reliability based on their respective outer loadings as shown in table 4.10 and a threshold value ≥ 0.40 (see table 4.11) (Hulland, 1999; Hair et al., 2014). Hence, indicators with weaker outer loadings Less than 0.40 deleted. Of the total of 23 items, three items were deleted (Effrt expc 3, Fac cond 3, Soc inf 3). Thus, 20 items were retained for analysis as their loadings were in the range of between 0.525 to 0.933. Figure 4.4 and Table 4.10 show the items and their respective loadings.

3.6.3.1 Internal Consistency Reliability

Internal consistency measures the consistency of results between items of the same test. It measures whether the proposed items measuring the construct are producing similar scores (Hair et al., 2013). In this study, internal consistency reliability was assessed by examining Cronbach's alpha coefficient and composite reliability (CR), where Cronbach's alpha > 0.6 is acceptable (Nunnally and Bernstein, 1994) while CR coefficient ≥ 0.60 or greater is acceptable (Hair et al., 2014; Henseler, Hubona, & Ray, 2016; Peterson & Kim, 2013). Nonetheless, the CR coefficient is considered to be a better indicator of the unidimensionality of a block than Cronbach's alpha (Chin, 1998b). It allows for an evaluation of the construct's internal consistency (Avkiran & Ringle, 2018).

Table 4.11 shows that Cronbach's alpha coefficients were in the range of 0.644 to 0.833 which were above 0.60 as suggested by Ramayah et al. (2011). Likewise, the coefficients of the CR were in the range of 0.790 to 0.895 indicating the reliability of the measurement model. These reliabilities measures provided evidence of unidimensionality and showed that the constructs were suitable for further analysis (Hattie, 1985). The values of Cronbach's alpha and CR were within the recommended threshold value of 0.60 and above suggesting that the measurements were reliable.

Table 4.11
Cronbach's Alpha and Composite Reliability Values

	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Cloud Comp Adopt	0.807	0.808	0.886	0.722
Effort Expc	0.739	0.833	0.817	0.599
Facilitating Cond	0.641	0.761	0.790	0.561
Gender Segr	0.833	0.859	0.895	0.689
Perf Excp	0.777	0.799	0.857	0.602
Social Ifl	0.655	0.708	0.820	0.615

4.7.1.2 Convergent Validity

Convergent validity is the extent to which measures of the same constructs are related to each other (Henseler et al., 2011). In other word it shows the extent of correlation among the measures of the same construct (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014). With regards to identifying an element of convergence in the measurements of the construct, average variance extracted (AVE) is used with a threshold value $\geq$ 0.50 (Hair et al., 2010; Henseler et al., 2009). An AVE of 0.50 means that the constructs account for 50% of the variance in its indicators, which is considered adequate (Hair et al., 2014). In other words, the latent construct explains half of the variance of its indicators and indicates adequate convergent validity (Hair et al., 2014).

Table 4.12
Average Variance Extracted Values (AVE)

Variables	AVE
Cloud Comp Adopt	0.722
Effort Expc	0.599
Facilitating Cond	0.561
Gender Segr	0.689
Perf Excp	0.602
Social Ifl	0.615

The results in Table 4.12 and Figure 4.4 show that AVE values were in the range 0.561 to 0.722. Thus, the AVE values of all the constructs exceeded the minimum threshold value of 0.50 (Hair, Sarstedt, Ringle, & Mena, 2012; Henseler et al., 2009). The results demonstrate adequate convergent validity and unidimensionality. Convergent validity was therefore satisfied (Vinzi et al., 2010). Estimations of the hierarchical measurement models were then conducted.

4.7.1.3 Discriminant Validity

Similarly, this study assessed discriminant validity using average variance extracted (AVE) (Fornell-Lacker Criterion), cross loadings, and Heterotrait-Monotrait (HTMT) to measure the extent to which one construct is actually different from another construct. Convergent validity can be measured by calculating the AVE in the indicators that is accounted for by the focal construct (Mackenzie et al., 2011). Discriminant validity is established when the value of the square root of AVE of each construct is higher than the construct's highest correlation with any other latent construct (Hair et al., 2014; Henseler et al., 2009).

Hence, discriminant validity was evaluated in this study by comparing the square root of the AVE for each construct with the highest correlation of the latent construct in the matrix. Table 4.13 presents the assessment of the Fornell-Larcker criterion with the square root of the AVE (in boldface). The square root of AVE when compared with the correlations was higher than the correlations of any other constructs. Therefore, these results showed that the required level of the discriminant validity on the variables of this study has been achieved (Hair et al., 2013; Henseler et al., 2009).

Table 4.13:
Discriminant Validity (Fornell-Lacker Criterion) (n=304)

	1	**2**	**3**	**4**	**5**	**6**
Cloud Comp Adopt	**0.850**					
Effort Expc	0.524	**0.774**				
Facilitating Cond	0.214	0.222	**0.749**			
Gender Segr	0.229	0.236	0.087	**0.830**		

Perf Excp	0.740	0.522	0.202	0.203	**0.776**	
Social Ifl	0.274	0.233	0.121	0.874	0.206	**0.784**

Note: Entries shown in boldface represent the square root of the average variance extracted (Measurement Model)

Moreover, as stated previously, discriminant validity can be achieved by comparing the cross-loadings with indicator items loadings (Chin, 1998). To establish satisfactory discriminant validity, Chin (1998) recommended that cross-loadings should be less than all the indicator items loadings. Table 4.14 below shows a comparison of the indicator items loadings with indicators. It revealed that cross-loadings is lower than all indicator items loadings, thus, recommend acceptable discriminant validity for further analysis. Therefore, in this study, all the criteria for attaining discriminant validity were achieved.

Table 4.14
Discriminant Validity (Cross Loadings) (n=304)

	Cloud Comp Adopt	**Effort Expc**	**Facilitating Cond**	**Gender Segr**	**Perf Excp**	**Social Ifl**
Cloud3	**0.805**	0.420	0.191	0.204	0.702	0.237
Cloud1	**0.877**	0.429	0.144	0.188	0.616	0.242
Cloud2	**0.866**	0.487	0.210	0.188	0.549	0.216
Effrt expc 2	0.251	**0.757**	0.216	0.189	0.254	0.174
Effrt expc 4	0.559	**0.821**	0.152	0.187	0.556	0.195
Efrt expct 1	0.238	**0.741**	0.184	0.178	0.237	0.166
Fac cond 2	0.221	0.188	**0.879**	0.057	0.181	0.096
Fac cond4	0.130	0.127	**0.706**	0.130	0.121	0.144
Fcac con 1	0.084	0.207	**0.642**	0.002	0.153	0.013
Gen 1	0.162	0.202	0.054	**0.869**	0.200	0.745
Gen 2	0.167	0.146	0.094	**0.544**	0.092	0.488
Gen 3	0.183	0.196	0.043	**0.933**	0.202	0.815
Gen 4	0.228	0.225	0.092	**0.914**	0.173	0.802
Perf expc 1	0.547	0.560	0.161	0.180	**0.849**	0.141
Perf expc 2	0.536	0.489	0.146	0.141	**0.855**	0.108
Perf expc 3	0.716	0.323	0.162	0.189	**0.744**	0.226
Perf expc 4	0.417	0.238	0.156	0.096	**0.636**	0.140
Soc inf 1	0.168	0.085	0.142	0.354	0.113	**0.525**
Soc inf 2	0.226	0.214	0.088	0.734	0.142	**0.888**
Soc inf 4	0.241	0.225	0.070	0.886	0.218	**0.883**

Though the Fornell-Larcker criterion was well-known for over 30 years ago, essentially there is no systematic examination of its effectiveness for assessing discriminant validity, a problem which was first noted by Rönkkö and Evermann (2013). Thus, Henseler, Ringle, and Sarstedt (2015) proposed heterotrait-monotrait (HTMT) ratio of correlation as another measure for discriminant validity. The authors showed that HTMT is able to achieve higher sensitivity rates (97% to 99%) as compared to Fornell-Lacker criterion (20.82%) and cross-loadings criterion (0.00%). The HTMT criterion is defined as the mean value of the indicator correlations across constructs (i.e., the heterotrait-hetero method correlations) relative to the (geometric) mean of the average correlations of indicators measuring the same construct (Sarstedt et al., 2017). HTMT values close to 1 indicates a lack of discriminant validity. Based on previous research, Henseler et al. (2015) suggested a threshold value of 0.90. HTMT (HTMT$_{0.90}$) value exceeding 0.90 suggests a lack of discriminant validity.

Table 4.15 shows the output from HTMT analysis. The results show that all values are below the threshold of 0.90 suggesting that all the HTMT values are significantly different. Thus, discriminant validity has been established.

Table 4.15
Heterotrait-Monotrait Ratio of Correlations (HTMT) (n=304)

	Cloud Comp Adopt	**Effort Expc**	**Facilitating Cond**	**Gender Segr**	**Perf Excp**	**Social Ifl**
Cloud Comp Adopt						
Effort Expc	0.556					
Facilitating Cond	0.263	0.349				
Gender Segr	0.275	0.290	0.143			
Perf Excp	0.895	0.562	0.285	0.245		
Social Ifl	0.377	0.307	0.197	1.157	0.276	

4.7.2 Assessment of Path Coefficient (Structural Model)

Once the measurement model (outer model) is satisfied and the reliability and validity of the model are ascertained, the next step was to assess the outer model (structural model). This involved evaluating the structural model's predictive abilities and relationships between the constructs. The fundamental criteria for evaluating a structural model in PLS-SEM are the significance of the path coefficients, coefficient determination (R^2), effect size (F^2) and predictive relevance (Q^2) (Hair et al., 2014).

A path coefficient, denoted by the symbol (β) represents a hypothesized relationship between constructs in the model, and its significance that ranges between -1 and +1 represents the hypothesis significance. A positive value closer to +1 means a stronger positive relationship and a negative value closer to -1 means a stronger negative relationship (Hair et al, 2019). A systematic model analysis of the structural model was carried out to provide a detailed understanding of the results and to test Hypotheses H_1 to H_9. In addition, standard bootstrapping procedure with-5,000 bootstrap samples and 304 cases in the original sample was used to assess the significance of the path coefficients (Hair, Hult, Ringle, & Sarstedt, 2017; Henseler et al., 2009). Figure 4.5 and Table 4.16 show the estimates for the full structural model which includes Gender as moderator.

Figure 4.5 focused on the analysis of the relationship between the independent variables and the dependent variable (Hypotheses H_1 to H_5).

Table 4.16
Structural Model Assessment

Hypothesis	Relationship	Beta, β	Standard Deviation	T Values	P Values	Basic Confidence Interval Lower Levels	Basic Confidence Interval Upper Levels	F^2
H1	Performance Excp -> Cloud Comp Adopt	0.175	0.079	2.214	0.027**	0.014	0.315	0.679
H2	Effort Expc -> Cloud Comp Adopt	0.323	0.064	5.063	0.000***	0.190	0.440	0.048
H3	Social Influence -> Cloud Comp Adopt	-0.164	0.070	2.346	0.019**	-0.273	-0.003	0.026
H4	Facilitating Cond -> Cloud Comp Adopt	0.406	0.058	6.977	0.000***	0.287	0.519	0.003
H5	Gender -> Cloud Comp Adopt	0.105	0.047	2.221	0.027**	0.019	0.208	0.009

*Note: In One-tailed test of significance p < 0.01***, p <0.05** p <0.1** 99% 95%, 90% confidence level, the t- statistics level is 2.33, 1.65, and 1.28 respectively.*

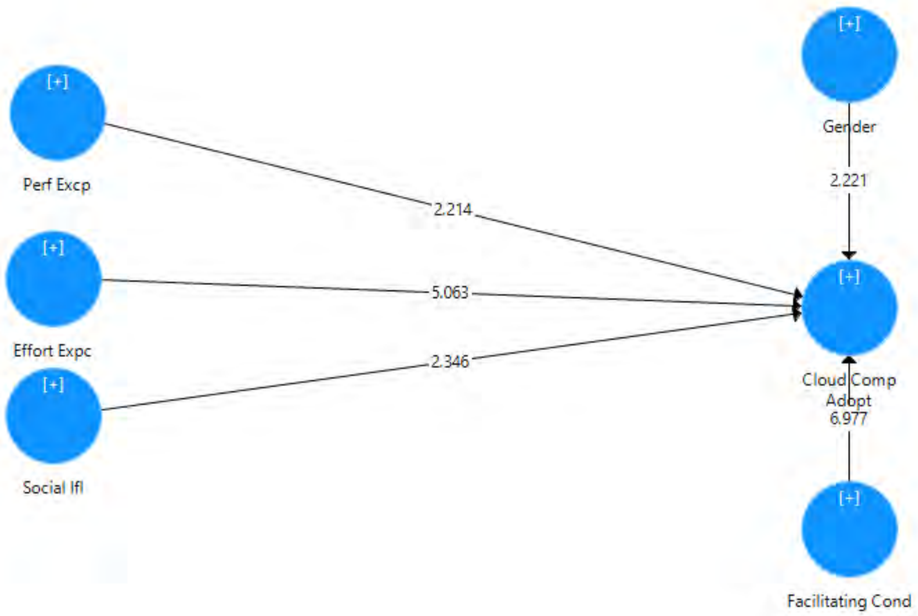


Figure 4.5
PLS-SEM Bootstrapping
Sources: Author 2025

The structural model in table 4.16 and figure 4.5 examined the hypothesized relationships influencing cloud computing adoption in Saudi Arabian health sector. The results show varying levels of support for the hypotheses.

Hypothesis (H1): Performance expectancy → Cloud Computing Adop

Hypothesis (H2): Effort expectancy → Cloud Computing Adoption

Hypothesis (H3): Social influence → Cloud Computing Adoption..

Hypothesis (H4): Facilitating condition → Cloud Computing Adoption.

Hypothesis (H5): Gender Segregation → Cloud Computing Adoption. Gender segregation

Hypothesis ***H_1*** was developed to examine if there is positive significant relationship between the perceived performance expectancy of cloud computing and the decision to adopt cloud computing in the Saudi Arabian health sector. The result in Table 4.16 and Figure 4.5 shows that relative advantage has a positive and significant influence on cloud computing adoption ($\beta = 0.175$, $t = 2.214$, $p < 0.05$) with the confidence interval [0.014, 0.315] supporting the hypothesis.

This implies that when organizations perceive cloud computing as more advantageous than existing technologies, the likelihood of adoption increases. This entails that perceived performance expectancy play an important role in encouraging cloud adoption. The effect size ($f^2 = 0.679$) indicates a large impact, highlighting performance as a strong determinant of cloud computing, supporting Hypothesis H_1. The results support the previous findings such as (Alnassar & Baashirah, 2024; Alshamaileh, 2013; Baishya & Samalia, 2020; Dash & Sahoo, 2022a; Gangwar et al., 2015; Uddin et al., 2024). Hence, e-health cloud computing consulting service providers should design their products to perform various tasks and emerge as a productive and multi-tasking offering.

These findings align with the Technology–Organization–Environment (TOE) framework, which emphasizes that perceived technological benefits are strong predictors of adoption (Gangwar et al., 2015). Prior research has shown that firms in developing economies are particularly sensitive to relative advantages like reduced IT costs, flexibility, and improved data management, which are critical factors in overcoming infrastructural limitations (Gangwar et al., 2015). However, the relatively smaller coefficient compared to other variables (e.g., security and privacy) suggests that while benefits are important, they may not be the sole determinant in the adoption decision.

Previous research on healthcare shows that performance expectancy, the belief that cloud computing enhances efficiency, service quality, and cost-effectiveness remains a dominant predictor of adoption. This implies that future studies must focus on quantifying measurable outcomes of cloud integration, such as reduced operational costs, enhanced patient data accessibility, and improved clinical decision-making. Emphasizing performance expectancy in empirical models will allow researchers to capture how hospital administrators and clinicians weigh tangible benefits against adoption risks (Alassafi et al., 2017).

Moreover, since private and public hospitals differ in their emphasis on efficiency versus compliance, research should investigate the contextual moderating effect of hospital ownership on the strength of performance expectancy's influence. For instance, private hospitals may prioritize ROI and competitive advantage, while public hospitals may link PE to alignment with national health transformation plans. Testing such differences can refine theoretical extensions of UTAUT in healthcare contexts (Alharbi et al., 2016).

Similarly, **Hypothesis H_2** was developed to examine if effort expectancy has a negative effect on the adoption of cloud computing in the Saudi Arabian health sector. Results in Table 4.16 and Figure 4.6 revealed that technical complexity shows a strong positive and highly significant effect on cloud computing adoption ($\beta = 0.323$, $t = 5.063$, $p < 0.001$) with the confidence interval [0.190, 0.440] thereby not supporting the hypothesis. This finding suggests that organizations that perceive cloud technologies as less complex are more likely to adopt them. Complexity here refers to the degree of difficulty in implementing, managing, and integrating cloud solutions into existing systems (Rogers, 2007). This suggests that technical complexity significantly influence adoption.

This is consistent with prior studies that identify technical challenges as both barriers and motivators for adoption. Gangwar et al. (2015) found that complexity in integrating cloud systems with legacy infrastructure often influences firms' readiness to adopt. In Nigeria, where many firms face infrastructural and skills-related constraints, the perception of manageable complexity significantly drives adoption decisions (Abdullah et al., 2015). The effect size ($f^2 = 0.048$) shows a moderate contribution, meaning technical complexity is an important predictor of cloud computing in Saudi Arabia, hence, rejecting Hypothesis H_2.

The results support the previous findings. For instance, Adebo et al., (2025); Alnassar & Baashirah, (2024); Dash & Sahoo, (2022); Gu et al., (2021) revealed positive relationship between perceived effort expectancy and adoption of cloud computing. This implying that, when the adoption of cloud computing services is perceived as simple, transparent and reasonable, it enhances the likelihood of its adoption. This is based on the assumption that cloud computing adoption will be more inclined toward adopting technology that demands minimal effort for effective utilization.

Hence, the usability of a new system including the design and the attribute of user experience affects its acceptance and use. Thus degree of ease of use associated with the adoption of e-health cloud computing system is one of the most important factors that positively influenced the decision to use the system. This means the involvement of potential users during the development of the e-health cloud computing system to integrate their needs and preference is highly influential to the acceptability and use of the system.

Therefore, effort expectancy (perceived complexity) is an important factor influencing adoption of cloud computing because clinical and non-technical staff mostly resists systems they view as complex. Previous research in healthcare suggests that usability perceptions significantly affect adoption, especially among non-expert staff (Sadoughi et al., 2020). This means that policy makers should consider how effort expectancy interacts with facilitating conditions such as IT support and training programs. For example, in public hospitals with bureaucratic structures, high effort expectancy may not translate into adoption unless sufficient support structures are in place, The strength of this relationship also indicates that technical training, IT expertise, and vendor support are critical for organizations. Without simplifying adoption processes and reducing integration difficulties, even organizations recognizing cloud benefits may be reluctant to migrate. This finding reinforces the need for capacity building and technical support as enablers of cloud adoption in developing economies (Abdullah et al., 2015).

In addition, **Hypothesis *H_3*** was developed to examine if social influence has a positive effect on the adoption of cloud computing in the Saudi Arabian health sector. Results in Table 4.16 and Figure 4.5 reveal that regulation and policies negatively and significantly influence cloud computing adoption ($\beta = -0.164$, $t = 2.346$, $p < 0.05$) with the interval [-0.273, -0.003] there by not supporting the hypothesis. This suggests that restrictive, unclear, or inconsistent regulatory frameworks may hinder adoption decisions. Organizations may perceive legal uncertainties around data protection, compliance requirements, and cross-border data transfers as risks that outweigh cloud benefits (Gu et al., 2021). This finding is consistent with existing literature highlighting regulatory environments as major determinants of adoption in developing economies (Low et al., 2011; Tam & Oliveira, 2016). This indicates that restrictive or unclear regulatory frameworks hinder cloud computing adoption in Saudi Arabia. The effect size ($f^2 = 0.026$) shows a small effect, but the direction highlights policy challenges as a barrier, rejecting Hypothesis *H_3*. The results support the previous findings. For instance, Alsahafi et al., (2020); Alshammari et al., (2021); Alsharo et al., (2021); Hamzat & Mabawonku, (2018); Sharma et al., (2021) revealed a significant positive relationship between perceived social influence and decision to adopt cloud computing.

The results of this study revealed that the attitudes and behaviours of other individuals in a user's social and work circles significantly impact that user's adoption of cloud computing. This is because in middle eastern countries, people are more dependent on each other and more influenced by living within extended families, hence, behaviour of an individual is motivated by the perception of how others will recognize him/her after using services of E-health cloud computing. Accordingly, friends, families, and groups in society may influence the decision of a user towards E- health cloud computing.

The negative coefficient emphasizes that policymakers must prioritize developing robust regulatory frameworks that address privacy, security, and data localization concerns. Without such frameworks, uncertainty persists, limiting adoption despite the recognized advantages of cloud computing.

However, previous research also indicates that social influence pressure from peers, professional associations, or regulatory bodies shapes adoption intentions in Saudi hospitals. Hence, regulators and policy makers should look at how social influences affect cloud adoption to highlight the macro-level drivers of individual behavioral intention and extend UTAUT to account for top-down regulatory contexts (Alharbi et al., 2016).

Hypothesis *H_4* was developed to examine if facilitating conditions have a positive effect on the adoption of cloud computing in the Saudi Arabian health sector. The results in Table 4.16 and Figure 4.6, that the strongest predictor in this study is security and privacy ($\beta = 0.406$, $t = 6.977$, $p < 0.001$) with the confidence interval [0.287, 0.519], showing a highly significant positive effect there by supporting the hypothesis. This indicates that organizations prioritize secure and privacy-compliant cloud services when deciding to adopt. In contexts where cyber threats, data breaches, and privacy violations are prevalent, security assurances are key determinants of adoption (Zissis & Lekkas, 2012),

This result aligns with findings by Gangwar et al. (2015), who observed that firms in emerging economies emphasize security and trustworthiness when considering cloud services. However, the effect size ($f^2 = 0.003$) is very small, indicating limited incremental contribution beyond other identified factors influencing cloud computing in Saudi Arabian health sector, supporting the Hypothesis H_4. This is consistent with previous finding. For instance, Abdelwahed et al., (2024); De Veer et al., (2015); Idoga et al., (2018); Sair & Danish, (2018) revealed appositive significant impact of facilitating conditions and cloud computing adoption.

The present study's positive and significant relationship revealed that an individual believes organizational and technical infrastructure exists to support the adoption of could computing. This shows facilitating condition is among the factors affecting the adoption of cloud computing in the health sector. This is because of the believe that having the resources and support needed for the use of a particular technology could make users to adopt cloud computing system. Hence, it is of out-most importance for e-health cloud computing providers to make adequate provision/maintenance of facilitating conditions and ensure that healthcare data are well secured as the success of cloud based health system is hinged on these two constructs. Thus the availability of required IT infrastructures, technological know-how and technical support could influence the adoption of cloud computing in Saudi Arabian health sector.

Facilitating conditions availability of infrastructure, and regulatory alignment has strong implications for healthcare research in Saudi Arabia. Active regularly framework can influence the adoption of cloud computing, public healthcare's reliance on government regulations makes FC particularly salient (Alassafi et al., 2017). Having a robust facilitating conditions mitigate concerns around privacy and security (Alshahrani, 2022).

Hypothesis *H_5* was developed to examine if there is a negative significant relationship between Gender Segregation and the decision to adopt cloud computing. As shown in Table

4.16 and Figure 4.5, a positive significant association between Gender Segregation and the decision to adopt cloud computing was found with β = 0.105, t = 2.221, and p < 0.027 shows a positive and significant effect (β = 0.105, t = 2.221, p = 0.027), with confidence interval [0.019, 0.208] thereby not supporting the hypothesis. Although the effect size (f^2 = 0.009) is small, the results suggest that gender differences modestly influence cloud adoption decisions., supporting the Hypothesis H_5. The finding is consistent with previous research. For instance, (Alqattan et al., 2022; Dajani & Yaseen, 2016; Hamzat & Mabawonku, 2018; Prasanna & Huggins, 2016) revealed a positive relationship between gender segregation and adoption of cloud computing in health sector.

Considering the nature and religious practice of the study area, the results revealed that high levels of gender segregation in health sector may encourage collaborative decision-making and improve the acceptance of new technologies.

Therefore, the findings confirm that relative performance, technical complexity, security and privacy concerns, and gender positively influence cloud computing adoption in Saudi Arabian health sector, while regulation and policies act as a negative factor. Among these, social and privacy concerns exert the strongest influence, while regulation and gender have weaker impacts. This underscores the need for policymakers and managers to strengthen supportive regulations, reduce complexity barriers, and address social and privacy considerations to drive wider adoption of cloud computing.

UTAUT defines voluntariness of use as the degree to which use of a system is perceived as being of free will, and it moderates how social influence affects behavioral intention (i.e., voluntariness matters when adoption is seen as optional).In settings where end users choose freely, voluntariness amplifies individual perceptions (usefulness, and ease of use) into genuine intention (Li et al., 2013). However, UTAUT's voluntariness assumption meets a structural barrier in Saudi public hospitals because healthcare technology decisions are often mandated from the top (hospital executives, ministry directives) within a high-power-distance organizational culture (Venkatesh & Davis, 2000). Hofstede's country profile and organizational studies consistently report Saudi Arabia's very high power-distance norms (acceptance of hierarchical authority), which reduce individual decision latitude in institutions (Khoja et al., 2017).

Empirical reviews of eHealth adoption in Saudi Arabia show that organizational mandates, management support and facilitating conditions (infrastructure; policy mandates) are repeatedly among the dominant determinants often outweighing individual attitudes tied to voluntariness (Al-Shorbaji et al., 2018; Lehto et al., 2012).

Consequently, where adoption is essentially an innovation-decision made by authorities (not an optional individual choice), UTAUT's voluntariness effects is less predictive or must be reinterpreted as a contextual continuum rather than an active causal lever.

Practically and theoretically, this mismatch matters: implementation strategies that assume voluntariness (e.g., persuasion, incentive-based change at the individual level) may misfire when staff comply because of mandate rather than conviction producing superficial use, workarounds, or resistance in practice (Kumar, 2023). Saudi-context research therefore recommends augmenting UTAUT with organizational-level constructs (power distance, mandate strength, top-management support, and facilitating conditions) or treating voluntariness as contingent on decision type (mandated vs. optional) (Fan et al., 2020).

Rogers' Diffusion of Innovations (DOI) classifies adopters by innovativeness and emphasizes attributes like relative advantage, compatibility, and perceived risk as drivers of diffusion (Rogers, 2007). DOI's adopter categories presume that conservatism toward an innovation primarily reflects individual or social risk/uncertainty preferences (Adlung et al., 2025). But in contexts where religious-normative concerns affect whether a technology is deemed permissible, hesitancy toward an innovation especially innovations involving external data hosting can stem from moral, religious or sovereignty considerations rather than simple risk aversion or lack of innovativeness (Adlung et al., 2025).

Saudi healthcare studies and cloud-adoption research show this pattern: concerns about data control, privacy, cross-border hosting, and compliance (including expectations about local/Islamic norms of accountability) are major barriers to cloud adoption even among technically capable organizations. Quantitative and qualitative work on Saudi healthcare cloud adoption finds that data privacy, legal/regulatory uncertainty and data-sovereignty concerns strongly suppress intention to move patient data to external/cloud providers (Rahman & Al-Borie, 2020).

At the same time, scholarship on digital health ethics in Islamic contexts highlights how religious and cultural norms influence perceptions of what is acceptable (e.g., concerns about custody and proper governance of sensitive personal information), meaning that resistance may be framed as religious/ethical caution (perceptions of "haram" risk) rather than being reducible to the DOI category.

Therefore, applying DOI in Saudi public hospitals without accounting for religious-compatibility or data-governance legitimacy risks misclassifying adopters and misunderstanding the root causes of reluctance. Policy responses that proved successful elsewhere (e.g., demonstration projects, early-adopter champions) must be complemented by context-specific measures: robust local data governance (Al-Anezi, 2022; Khoja et al., 2017),

4.7.3 Assessment of Variance Explained in the Endogenous Latent Variables

PLS-SEM structural model recommends using *R*-squared (R^2) which is also called coefficient of determination as a value assessment criterion (Hair et al., 2012; Henseler et al., 2009). The R^2 value represents the ratio of variation in the dependent variable(s) that could be explained by one or more independent variable(s) (Hair et al., 2012; Hair Jr et al., 2010). Falk and Miller (1992) suggested that an R^2 value of 0.10 is acceptable. In addition, Chin (1998) recommended that in PLS-SEM, an R^2 value of 0.19 is considered as weak, 0.33 as moderate and 0.60 as substantial. The R^2 value from the endogenous latent construct in this study is 0.508 which is moderate.

As such, this study's model explains 0.582 (58.2%) of the total variance in the adoption of cloud computing suggesting that the five exogenous latent constructs (performance expectancy, effort expectancy, social influence, facilitation condition, and gender segregation) including their dimensions jointly explained 58.2% of the variance of the endogenous latent construct, adoption of cloud computing. Thus, following Falk and Miller (1992), and Chin (1998), this study's endogenous latent construct (dependent variable) showed an acceptable level of R^2. Chin (1998) noted that even a model with a low R^2 can still yield excellent goodness of fit.

4.7.4 Evaluation of Effect Size (F^2)

After assessing R^2 and according to Hair. *et. al*. (2013), the next criterion to be assessed is effect size (F^2). Effect size is the difference in R^2 between the main effects when the particular exogenous construct is omitted from the model and when it is in the model. This is done purposely to evaluate whether the omitted exogenous construct has a substantial impact on the endogenous variables (Hair et al., 2013). Equation 4.1 below is used to calculate the effect size for the exogenous construct. Cohen (1988) proposed that effect size of 0.35, 0.15, and 0.02 as large effects, moderate, and small, respectively. However, Chin et al. (2003) noted that even the smallest strength of F^2 should be considered as it can influence the dependent variables (endogenous variables).

$$F^2 = \frac{R^2 \text{ Included- } R^2 \text{ Excluded}}{1 - R^2 \text{ Included}} \qquad \text{(Equation 4.1)}$$

Table 4.17 below shows effect size of the latent variable in the structural model. It shows that effect size for independent variables and gender is 0.06 and 0.095, respectively. Thus, following Cohen's (1988) recommendation, the effect size of these two exogenous variables on adoption of cloud computing can be regarded as small.

Table 4.17
Effect Size on the Endogenous Latent Construct Cohen (1988)

Latent Construct	F-Squared	Effect Size
Effort Expectancy	0.048	Small
Facilitating Cond	0.003	Small
Gender Segregation	0.009	Small
Perf Expectancy	0.679	Large

Social Influence	0.026	Small

4.9.3 Predictive Relevance of the Model

Another assessment of the structural model involves the model's capacity to predict. In addition to assessments of R^2 and effect size of all the exogenous latent variables on the endogenous latent variable, researchers suggested evaluating the level of predictive relevance of the model, Q^2 (Geisser, 1974; Stone, 1974). The value of Q^2 shows how well the observed values had formed the model as well as its parameter estimations (Chin, 1998). Hair et al. (2010) assumed that the model should be able to effectively predict each dependent latent variable indicator. The leading measure of predictive relevance is Stone-Geisser‘s Q^2 test using blindfolding procedures (Geisser, 1974; Hair et al., 2014; Stone, 1974). This test is mostly used to complement goodness-of-fit assessment in PLS-SEM modelling (Duarte, Alves, & Raposo, 2010).

Therefore, blindfolding procedure was employed in this study and a cross-validated redundancy result was used to observe predictive relevance (Q^2) of the exogenous latent constructs on the endogenous latent construct (Geisser, 1974; Hair et al., 2014; Ringle, Sarstedt, & Straub, 2012). A model with Q^2 above zero is assumed to have predictive relevance (Chin, 1998a; Henseler, Ringle, & Sinkovics, 2009) and thus the higher the Q^2, the higher the predictive relevance (Duarte et al., 2010). This is consistent with Hair et al. (2013) who suggested that if $Q^2 > 0$, the model has predictive relevance while if $Q^2 < 0$, the model has no predictive ability.

Table 4.19 shows that the cross-validation redundancy measure, Q^2, for the endogenous latent variable (Adoption of cloud computing) has a value of 0.371, which is above zero. This implies that the model has predictive relevance for this construct (Chin, 1998; Henseler et al., 2009).

Table 4.18
Construct Cross-Validated Redundancy

Total	SSO	SSE	1-SSE/SSO
Cloud Comp	915.000	575.941	0.371

4.7.4 Testing Moderating Effect

When the effect of an exogenous constructs (independent variables) on an endogenous construct (dependent variable) is contingent upon the value of another variable, then, a moderating effect exists where such variable moderates the relationship between the exogenous (for example, in this study, relative advantage, technical complexity, regulation and policies, and security and privacy) (Hair et al., 2013). Previous literature indicated several dimensions to be used in measuring the exogenous variables (F. Alharbi, Atkins, & Stanier, 2016; Venkatesh, 2000; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). Hence, this study adopted these dimensions in measuring (for example, in this study, performance expectancy, effort expectancy, social influence and facilitating condition) and developed hypotheses which represented the moderating effect of gender on the relationship between exogenous variables and endogenous variable.

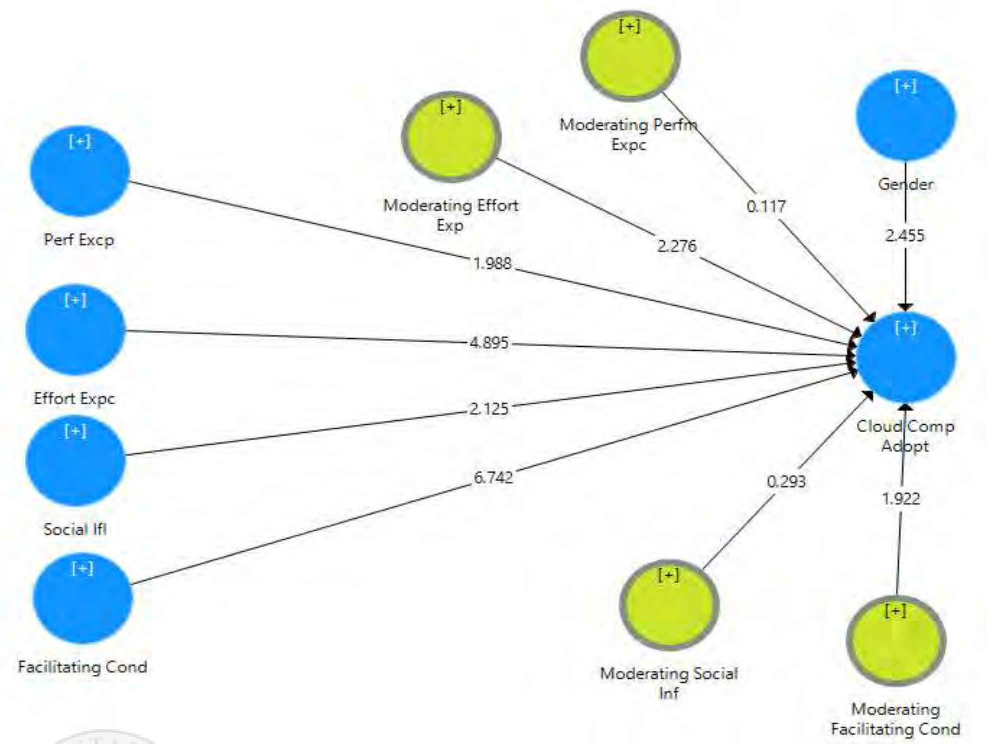


Figure 4.6
PLS-SEM Bootstrapping Interactions
Sources: Author 20265

Table 4.19
Results of Moderation Test

Hyp	Relationship	β	Standard Dev.	T Statistics	P Values
H6	Moderating Performance Expc -> Cloud Comp Adopt	-0.012	0.099	0.117	0.907
H7	Moderating Effort Exp -> Cloud Comp Adopt	0.160	0.070	2.276	0.023
H8	Moderating Social Influence -> Cloud Comp Adopt	-0.029	0.100	0.293	0.770
H9	Moderating Facilitating Cond -> Cloud Comp Adopt	-0.121	0.063	1.922	0.055

Note: $p < 0.1$*, $p < 0.05$**, $p < 0.01$***,

The presence of a moderator is to examine if there is any change in the relationship between two variables. In this study, Gender was hypothesized to moderate the relationship between performance expectancy, effort expectancy, social influence and facilitating condition and adoption of e-health cloud computing in Saudi Arabia (Hypotheses H_6, H_7, H_8, H_9 respectively).

The study applied a product term approach using PLS-SEM to estimate and detect the strength of the moderating effect of gender on the relationship between between exogenous variables and endogenous variable.(Chin, Lo, & Ramayah, 2013; Chin, Marcolin, & Newsted, 2003; Henseler & Fassot, 2010). Henseler and Fassot (2010) suggested that to assess moderation, firstly, one has to examine only the main effects of the independent variable(s) on the dependent variables, followed by an examination of the effect of the independent variable(s) including the moderator on the dependent variables, and lastly, to include the interaction terms.

The product term approach is considered suitable in the current study because the moderating variable is continuous (Henseler & Fassot, 2010). This is in line with recommendation of Henseler and Fassot (2010) that given the results of the product term approach are usually equal or superior to those of the group comparison gender on the relationship between exogenous variables and endogenous variable. The product terms between the indicators of the latent independent variable and the indicators of the latent moderator variable was created, hence, these product terms were used as indicators of the interaction term in the structural model (Kenny & Judd, 1984).

The moderation model in Figure 4.6 test whether the prediction of cloud computing adoption can be enhanced when gender as a moderating variable become significant. Hence, the moderating effect holds only when these interaction terms are significant (Hair. et al., 2013). Previous research revealed that gender has an influence on cloud computing adoption. Hence, hypotheses H_6, H_7, H_8, H_9 Were tested to show the moderating effect of gender.

The results of the moderating effects of gender on the relationship between exogenous variables and endogenous variable were examined and reported. The study revealed that hypotheses H_7, and H_9 were supported. While H_6, and H_8 were not supported.

Hypothesis $\boldsymbol{H_7}$ was developed to examine if gender segregation moderates the relationship between negative significant effect of effort expectancy and the adoption of e-health cloud computing. The result revealed that gender segregation positively significantly moderate the relationship between the perceived effort expectancy of cloud computing and the decision to adopt cloud computing in the Saudi Arabian health sector at 5 %. The parameters are β=0.160, t-2.276 and P= 0.023. This led to rejecting of hypothesis (H_7). The results support the previous findings such as (Almazroi et al., 2019; Calegari et al., 2023; Zhang et al., 2014) all revealed gender can significantly moderate the relationship bet effort expectancy and decision to adopt of cloud computing. Hence, e-health cloud computing consulting service providers should design their products to perform various tasks and emerge as a productive and multi-tasking offering.

following the procedures recommended by Dawson (2014), and Marcus, Schuler, Quell, and Humpfner (2002). Information from path coefficients was used to plot the moderating effect of gender on the relationship on the relationship between independent variables and dependent variable. Hence, it was used to plot the moderating effect of gender on the relationship between effort expectancy, facilitating condition and cloud computing adoption..

Figure 4.7 below shows that the moderating effect of gender segregation on the relationship between effort expectancy and decision to adopt cloud computing, the decision to adopt cloud is stronger (i.e. positive) revealing high cloud computing adoption with gender segregation and low cloud computing adoption without gender segregation. Hence, Gender strengthens the positive relationship between Effort expectancy and Cloud computing. Below is the plot graph of the hypothesis H_7.

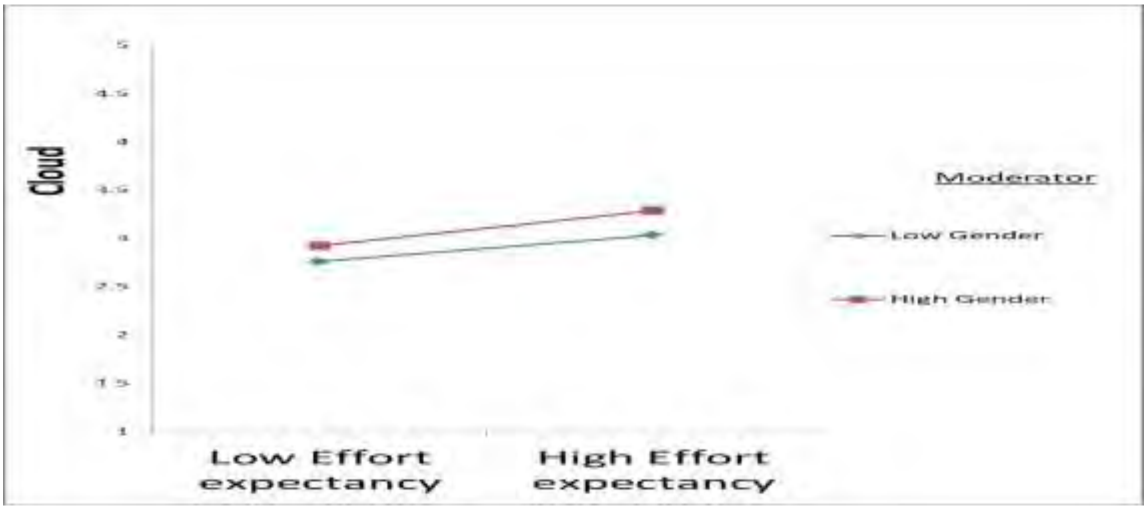


Figure 4.7
Interaction Effect of perceived compatibility and the decision to adopt cloud computing
Sources: Author 2025

Hypothesis *H₉* was developed to examine if significant positive effect of facilitating conditions on the adoption of cloud computing in the Saudi Arabian health sector can be moderated by gender segregation. Adequate support enhances adoption of cloud computing but gender segregation may determine who can access such resources, thus moderating the relationship between facilitating conditions and adoption. The results in Table 4.16 and Figure 4.6, revealed that gender segregation negatively and significantly affect the relationship between facilitating condition and the decision to adopt cloud computing at 5%. The result revealed that gender weakens the positive relationship between facilitating conditions and the decision to adopt cloud computing, where the interaction terms were statistically significant at β = -0.121, t = 1.922, and $p < 0.055$ rejecting the Hypothesis H_9. The results are consistent with previous finding. For instance, Abdelwahed et al., (2024); De

Veer et al., (2015); Idoga et al., (2018); Mojtahed et al., (2014); Sair & Danish, (2018) revealed the significant impact of facilitating conditions and cloud computing adoption.

following the procedures recommended by Dawson (2014), and Marcus, Schuler, Quell, and Humpfner (2002). Information from path coefficients was used to plot the moderating effect of gender on the relationship on the relationship between independent variables and dependent variable. Hence, it was used to plot the moderating effect of gender on the relationship between effort expectancy, facilitating condition and cloud computing adoption.. Figure 4.8 below shows that the moderating effect of gender segregation on the relationship between facilitating condition and decision to adopt cloud computing, the decision to adopt cloud is weaker (i.e negative) revealing low cloud computing adoption with gender segregation and high cloud computing adoption without gender segregation. Hence, Gender dampens the negative relationship between Facilitating Condition and Cloud Computing. Below is the plot graph of the hypothesis H_9.

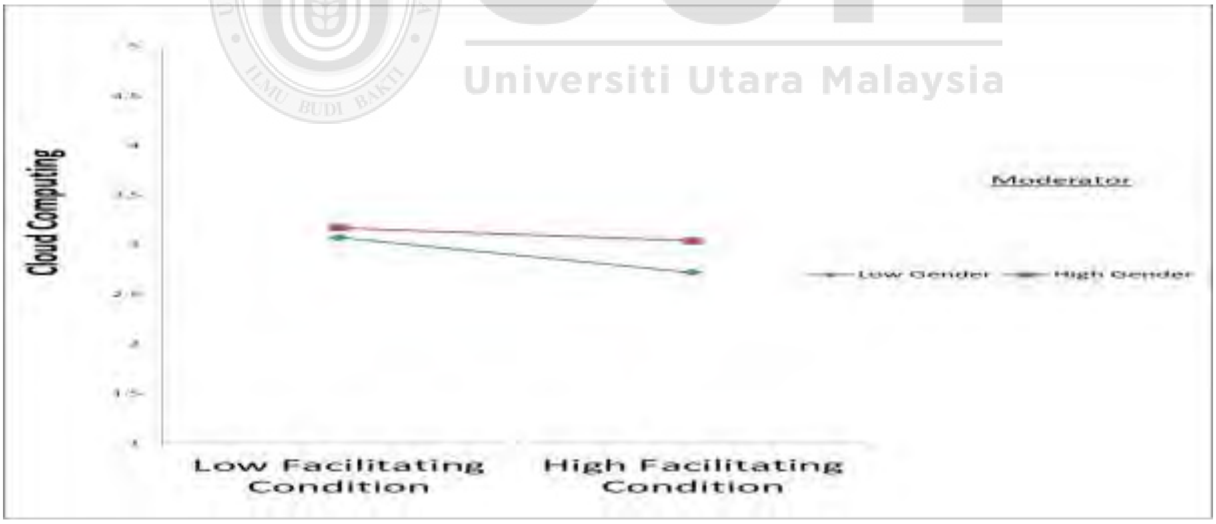


Figure 4.7
Interaction facilitating condition and the decision to adopt cloud computing
Sources: Author 2025

4.7.5 Determining the Strength of the Moderating Effects

In order to determine the strength of the moderating effect of gender on the relationship between exogenous constructs (independent variables) on an endogenous construct (dependent variable), Cohen's (1988) effect size was calculated. Furthermore, the strength of the moderating effect can be assessed by comparing the coefficient of determination, R^2 value of the main effect model with the R^2 value of the full model that incorporates both exogenous latent variables and moderating variable (Henseler & Fassot, 2010; Wilden, Gudergan, Nielsen, & Lings, 2013). Thus, the strength of the moderating effects could be expressed using the formula (Cohen, 1988; Henseler & Fassot, 2010) as in Equation 4.2.

$$\text{Effect size, } f^2 = \frac{R^2 \textit{ Model with moderator} - R^2 \textit{ Model without moderator}}{1 - R^2 \textit{ Model with Moderator}} \qquad \text{(Equation 4.2)}$$

Moderating effect size (f^2) with a value of 0.02 can be considered as weak, effect sizes of 0.15 as moderate while the effect sizes above 0.35 may be regarded as strong (Cohen, 1988; Henseler & Fassot, 2010). However, according to Chin et al. (2003, p211), a low effect size does not necessarily mean that the moderating effect is insignificant when Even a small interaction effect can be meaningful under extreme moderating conditions, if the resulting beta changes are meaningful, then it is important to take these conditions into account. Results of the strength of the moderating effects of gender are presented in Table 4.19.

Following Henseler and Fassot (2010) and Cohen's (1988) rule of thumb for determining the strength of moderating effects, Table 4.19 shows that the effect size for cloud computing adoption was 0.032, suggesting that the moderating effect was weak (Wilden et al., 2013; Wilson et al., 2007).

Table 4.19
Strength of the Moderating Effects Based on Cohen (1988); Henseler and Fassot (2010) Guideline

Endogenous Latent Variables	*R*-squared Included	*R*-squared Excluded	F^2	Effect Size
Cloud computing adoption	0.589	0.582	0.002	Weak

4.8 Evaluation of the proposed model for cloud computing adoption in the Saudi Arabian healthcare sector.

The integration of cloud computing into healthcare has emerged as a transformative innovation, offering opportunities for improved efficiency, scalability, and patient care delivery (Alharthi, 2017). Hence, evaluating the drivers of cloud computing adoption in Saudi Arabian healthcare is therefore crucial for both practitioners and policymakers. This study seeks to evaluate the validity and explanatory power of the proposed model in the Saudi context.

H1: Performance Expectancy → Cloud Computing Adoption ($\beta = 0.175$, $p = 0.027$)

The findings reveal that performance expectancy significantly and positively influences cloud computing adoption in the Saudi Arabian healthcare sector ($\beta = 0.175$, $p < 0.05$). This indicates that healthcare professionals and organizations perceive cloud solutions as beneficial in improving efficiency, patient record management, and service delivery. Although the coefficient is relatively modest, it aligns with the Unified Theory of Acceptance and Use of Technology (UTAUT), where performance expectancy is a major determinant of technology adoption (Venkatesh et al., 2003a).

The confidence interval (0.014–0.315) excludes zero, reinforcing the robustness of the effect. This suggests that healthcare providers are more inclined to adopt cloud systems when they recognize tangible improvements in job performance, productivity, and patient care outcomes. Similar studies in healthcare settings emphasize that perceived performance benefits, such as enhanced collaboration and data accessibility, strongly drive adoption (Alharthi, 2017).

The effect size ($f^2 = 0.679$) suggests a large contribution of performance expectancy to the variance explained in cloud computing adoption. This highlights its critical role in Saudi Arabia's healthcare digitization agenda, supporting the vision of advancing e-health services under national transformation initiatives.

H2: Effort Expectancy → Cloud Computing Adoption (β = 0.323, p = 0.000)

Effort expectancy shows a strong positive and highly significant effect on adoption ($\beta = 0.323$, $p < 0.001$). This finding indicates that the ease of use and simplicity of cloud computing solutions encourage adoption in healthcare organizations. Healthcare professionals, who often face heavy workloads, are more likely to accept technologies that are user-friendly with less complexity (Venkatesh et al., 2012).

The confidence interval (0.190–0.440) confirms the reliability of this relationship. This result underscores that adoption is not only about the perceived benefits but also about minimizing the effort required for learning and implementation. Studies in healthcare IT adoption have shown that new technologies that are less complex are significant motivators for technology acceptance (Hoque et al., 2017).

However, the effect size ($f^2 = 0.048$) is small, suggesting that while effort expectancy is significant, its standalone contribution to explaining adoption variance is limited compared to other predictors such as facilitating conditions. This implies that user-friendly systems must be complemented by data security to maximize adoption in healthcare.

H3**: Social Influence → Cloud Computing Adoption (β = -0.164, p = 0.019)**

The results indicate a significant but negative relationship between social influence and adoption ($\beta = -0.164$, $p < 0.05$). This suggests that, in the Saudi Arabian healthcare context, external pressures from colleagues, management, or regulatory bodies may actually discourage adoption (Venkatesh & Davis, 2000).

The confidence interval (–0.273 to –0.003) supports the significance of this negative effect. This finding aligns with previous research suggesting that in professionalized settings such as healthcare, mandatory pressure may reduce perceived autonomy and foster resistance (Li et al., 2013). The effect size ($f^2 = 0.026$) is small, indicating a weak but noteworthy contribution. This highlights that in Saudi Arabia's healthcare sector, adoption is more strongly shaped by individual perceptions of usefulness and infrastructure readiness than by regulations and policy.

H4: Facilitating Conditions → Cloud Computing Adoption (β = 0.406, p = 0.000)

Facilitating conditions emerge as the strongest predictor of adoption ($\beta = 0.406$, $p < 0.001$). This implies that availability of resources; security and privacy play a decisive role in encouraging healthcare providers to adopt cloud solutions (Venkatesh et al., 2003). The confidence interval (0.287–0.519) indicates a robust and consistent effect. This aligns with earlier studies that highlight the role of security and privacy of data in driving healthcare cloud adoption (Alharthi et al., 2017). Despite its strong coefficient, the effect size ($f^2 = 0.003$) is negligible, which might indicate multicollinearity with other predictors (e.g., performance and effort expectancy). Nevertheless, its significance suggests that without security and privacy, even the most user-friendly or beneficial systems may fail to be adopted.

H5: Gender → Cloud Computing Adoption (β = 0.105, p = 0.027)

The findings show a small but significant positive effect of gender on adoption ($\beta = 0.105$, $p < 0.05$). This indicates that gender segregation may play a role in cloud adoption decisions within healthcare organizations, with one group (likely males in managerial roles) being more inclined to adopt compared to others. This coincide with UTAUT findings that gender moderates the impact of other constructs like performance and effort expectancy (Venkatesh et al., 2003).

The confidence interval (0.019–0.208) confirms the stability of the effect. This suggests that gender segregation strategies may be necessary to ensure balanced adoption across healthcare staff. The effect size ($f^2 = 0.009$) is very small, suggesting that while gender has a statistically significant effect, it contributes little to explaining adoption variance.

Hence, the model is statistically valid with most of the hypotheses being significant, confidence intervals confirm reliability, and effect sizes provide deeper insight into the weight of each factor. Facilitating conditions and performance expectancy emerge as the most impactful predictors for cloud adoption in healthcare, while social influence shows an unexpected negative role.

4.9 Multi-Group Analysis (MGA):

Multigrain analysis was performed to assess whether the impact of factors influencing the adoption of cloud computing in Saudi Arabian health sector differs between different hospital (Private and Others) and hospital official (expert and Non-expert).

4.9.1 Private vs Public hospitals

4.9.1.1 Assessment of Measurement Model

Measurement model assessment includes establishing construct reliability and validity. Construct reliability was established through Cronbach's Alpha and Composite Reliability (CR). Construct reliability and convergent validity for the hospital-specific sample and the complete sample are presented in table table 20. The Cronbach alpha values and CR for all the constructs were higher than the recommended value of 0.700 for the sample from Private hospital and the overall sample. The Average Variance Extracted (AVE) for the constructs was higher than 0.500 for the sample from private hospitals and the overall sample, which corroborates convergent validity. The dimensions in others were found to have low reliability and lack convergent validity.

However, the composite reliability for factors influencing the adoption of cloud computing adoption was found to be fairly reliable (> 0.50). Furthermore, the overall dataset has better quality characteristics than for hospitals separately. Discriminant validity was assessed through cross-loadings. The results show that the factor loading of the items on their underlying construct was greater than their cross-loadings on the other construct in each sample, thus establishing discriminant validity.

Table 4.20
Cronbach's Alpha and Composite Reliability Values **(Private Vs Other Hospitals)**

	Private Hospital				**Other Hospital**			
	Alpha	**rho_A**	**CR**	**AVE**	**Alpha**	**rho_A**	**CR**	**AVE**
Perf Excp	0.629	0.731	0.778	0.545	0.626	0.732	0.783	0.553
Effort Expc	0.576	0.573	0.787	0.560	0.447	0.495	0.746	0.518
Facilitating Cond	0.788	0.813	0.865	0.620	0.771	0.795	0.855	0.600
Social Ifl	0.741	0.950	0.809	0.552	0.655	0.918	0.771	0.515
Gender Segr	0.835	0.840	0.888	0.666	0.847	0.883	0.890	0.670
Cloud Comp Adopt	0.916	0.917	0.947	0.857	0.911	0.912	0.944	0.850

Note. CR: Composite Reliability, AVE: Average Variance Extracted

4.9.1.2 Assessment of Structural model

The multi-group analysis in table 21 below compared the factors influencing cloud computing adoption between private hospitals and other hospitals. The results reveal important similarities and differences in how the two groups respond relate to the identified determinants. For Private Hospitals, the results indicate that

H1: Performance expectancy→ Cloud Computing ($\beta = 0.132$, $t = 2.185$, $p = 0.029$), social influence ($\beta = 0.332$, $t = 4.455$, $p < 0.001$), and facilitating conditions ($\beta = 0.358$, $t = 5.205$, $p < 0.001$) are significant predictors of cloud adoption. This suggests that private hospitals are more likely to adopt cloud technologies when they perceive performance benefits, experience peer or managerial encouragement, and have adequate infrastructural support.

H2: Effort expectancy → Cloud Computing Adoption, effort expectancy ($\beta = 0.049$, $p = 0.608$) and gender segregation ($\beta = 0.002$, $p = 0.978$) do not significantly influence adoption in private hospitals, indicating that ease of use and gender-related factors are less relevant in this context. In Other Hospitals, the results highlight that effort expectancy ($\beta = 0.358$, $t = 5.941$, $p < 0.001$), **H3**: Social influence → Cloud Computing Adoption ($\beta = 0.317$, $t = 3.475$, $p = 0.001$), and **H**4: Facilitating condition → Cloud Computing Adoption ($\beta = 0.330$, $t = 3.971$, $p < 0.001$) significantly impact cloud adoption. This means that in public or other types of hospitals, cloud adoption is strongly influenced by the perceived ease of use, social pressure, and the availability of supportive resources. Conversely, performance expectancy ($\beta = 0.082$, $p = 0.095$) and H5: gender segregation → cloud computing adoption ($\beta = 0.047$, $p = 0.636$) are not significant, showing that performance benefits and gender factors are less critical in shaping adoption decisions in these settings.

Therefore, from the above analysis the findings revealed that social influence and facilitating conditions consistently drive cloud adoption across both hospital types, while the roles of performance expectancy and effort expectancy differ. Performance benefits matter more for private hospitals, whereas ease of use is more critical in other hospitals. Gender segregation does not play a meaningful role in either group. These insights provide context specific guidance for policymakers and managers seeking to improve cloud technology adoption in healthcare institutions.

Table 4.21:
Path Coefficient (Private hospitals vs Other hospitals) **(Private Vs Other Hospitals)**

	Private Hospitals				Other Hospitals			
	β	**STDEV**	**t-Values**	**p-Values**	**STDEV**	**β**	**t-Values**	**p-Values**
Perf Excp -> Cloud Comp Adopt	0.060	0.132	2.185	0.029	0.082	0.049	1.672	0.095
Effort Expc -> Cloud Comp Adopt	0.096	0.049	0.513	0.608	0.358	0.072	5.941	0.000
Social Ifl -> Cloud Comp Adopt	0.332	0.075	4.455	0.000	0.091	0.317	3.475	0.001
Facilitating Cond -> Cloud Comp Adopt	0.358	0.069	5.205	0.000	0.083	0.330	3.971	0.000
Gender Segr -> Cloud Comp Adopt	0.002	0.079	0.027	0.978	0.099	0.047	0.474	0.636

4.9.2 Experts vs Non-experts

4.9.2.1 Assessment of Multi-Group Measurement model

Measurement model assessment includes establishing construct reliability and validity. Construct reliability was established through Cronbach's Alpha and Composite Reliability (CR). Construct reliability and convergent validity for the hospital-specific sample and the complete sample are presented in table 4.22. The Cronbach alpha values and CR for all the constructs were higher than the recommended value of 0.700 for the sample from Expert and the overall sample. The Average Variance Extracted (AVE) for the constructs was higher than 0.500 for the sample from expert officials and the overall sample, which corroborates convergent validity. The dimensions in non-experts were found to have low reliability and lack convergent validity. However, the composite reliability for factors influencing the adoption of cloud computing adoption was found to be fairly reliable (> 0.50). Furthermore, the overall dataset has better quality characteristics than for officials (expert and non-experts) separately. Discriminant validity was assessed through cross-loadings. The results show that the factor loading of the items on their underlying construct was greater than their cross-loadings on the other construct in each sample, thus establishing discriminant validity.

Table 22:
Discriminant validity (expert vs non-expert)

	Non-Expert				Expert			
	Alpha	**rho_A**	**CR**	**AVE**	**Alpha**	**rho_A**	**CR**	**AVE**
Cloud Comp Adopt	0.914	0.916	0.946	0.855	0.916	0.917	0.947	0.857
Effort Expc	0.576	0.574	0.787	0.561	0.576	0.573	0.787	0.560
Facilitating Cond	0.777	0.802	0.859	0.610	0.788	0.813	0.865	0.620
Gender Segr	0.833	0.834	0.887	0.666	0.835	0.840	0.888	0.676
Perf Excp	0.641	0.762	0.785	0.554	0.629	0.731	0.778	0.545
Social Ifl	0.703	0.937	0.789	0.532	0.741	0.950	0.809	0.555

Note. CR: Composite Reliability, AVE: Average Variance Extracted
Note:
Experts: *IT managers, CIOs, clinical officers, decision-makers familiar with cloud architectures, security standards, and procurement processes.*
Non-experts*: clinical staff (doctors, nurses), admin staff and other end users with limited technical knowledge.*

4.9.2.2 Assessment of Structural model

The multi-group analysis assessed in table 23 whether the determinants of cloud computing adoption differ between experts and non-experts. The results show both similarities and differences in the way these groups relate to the identified factors..

For Experts in the health sectors, the analysis shows that facilitating conditions ($\beta = 0.362$, $t = 5.853$, $p < 0.001$) and social influence ($\beta = 0.323$, $t = 5.709$, $p < 0.001$) are significant drivers of cloud adoption in Saudi Arabia. This means that experts are more likely to adopt cloud computing when they have adequate infrastructure, resources, and external encouragement from peers or organizations. However, performance expectancy ($\beta = 0.077$, $p = 0.074$) and effort expectancy ($\beta = 0.073$, $p = 0.325$) are not significant, implying that experts are less concerned with performance improvements or technical complexity, this is because they already possess technical knowledge. Similarly, gender segregation (β = 0.001, p = 0.786) has no influence.

For Non-Experts, the results reveal that effort expectancy (β = 0.067, t = 2.211, p = 0.027), facilitating conditions (β = 0.358, t = 5.648, $p < 0.001$), and social influence (β = 0.332, t = 3.804, $p < 0.001$) significantly predict cloud adoption in Saudi Arabia. This indicates that non-experts rely more on ease of use, external support, and social encouragement when deciding to adopt cloud computing in health sectors. Performance expectancy is also significant (β = 0.082, t = 2.026, p = 0.045), suggesting that perceived performance benefits influence non-experts more than experts. Like in the expert group, gender segregation (β = 0.002, p = 0.978) remains insignificant.

Therefore, the analysis in table 23 below revealed that both experts and non-experts are strongly influenced by facilitating conditions and social influence in adopting cloud computing in Saudi Arabian health sector. However, differences emerge in effort expectancy and performance expectancy, which are more considered for non-experts than for experts. This suggests that while experts prioritize infrastructure and peer influence, non-experts also require systems that are easy to use and demonstrate clear performance benefits. Gender segregation plays no significant role in either group. Previous literature on Health IT adoption literature supports that user groups differ in which UTAUT constructs is most predictive. The results of the multi-group analysis are summarized in table 23 below.

Table 23:
Multi-group path analysis (expert vs Non-expert)

	Expert				Non-Expert			
	β	**STDEV**	**t-Values**	**p-Values**	**B**	**STDEV**	**T**	**P**
Perf Excp -> Cloud Comp Adopt	0.077	0.043	1.791	0.074	0.082	0.050	2.026	0.045
Effort Expc -> Cloud Comp Adopt	0.073	0.074	0.984	0.325	0.067	0.041	2.211	0.027

Facilitating Cond -> Cloud Comp Adopt	0.362	0.062	5.853	0.000	0.358	0.061	5.648	0.000
Social Ifl -> Cloud Comp Adopt	0.323	0.069	5.709	0.000	0.332	0.069	3.804	0.000
Gender Segr -> Cloud Comp Adopt	0.001	0.077	0.018	0.786	0.002	0.079	0.027	0.978

4.10 Summary of Results of the Hypotheses

As shown in Table 4.16 revealed five direct hypotheses namely, *H_1, H_2, H_3, H_4, and H_5,* were all significant. Furthermore, in moderation hypotheses table 4.16 revealed that gender segregation were found to be significantly related in *H_7,* and *H_9*. On the other hand *H_6 and H_8* were found to be not significantly moderated by gender segregation. With discussions of the results of the main and moderating effects presented in earlier sections, Table 4.24 below provides a summary of results of all hypotheses.

Table 4.24
Summary of Hypotheses Testing

Hyp	Relationship	β	Standard Dev.	T Statistics	P Values
H1	Performance Excp -> Cloud Comp Adopt	0.175	0.079	2.214	0.027**
H2	Effort Expc -> Cloud Comp Adopt	0.323	0.064	5.063	0.000***
H3	Social Influence -> Cloud Comp Adopt	-0.164	0.070	2.346	0.019**
H4	Facilitating Cond -> Cloud Comp Adopt	0.406	0.058	6.977	0.000***
H5	Gender -> Cloud Comp Adopt	0.105	0.047	2.221	0.027**
H6	Moderating Performance Expc -> Cloud Comp Adopt	-0.012	0.099	0.117	0.907
H7	Moderating Effort Exp -> Cloud Comp Adopt	0.160	0.070	2.276	0.023**
H8	Moderating Social Influence -> Cloud Comp Adopt	-0.029	0.100	0.293	0.770
H9	Moderating Facilitating Cond -> Cloud Comp Adopt	-0.121	0.063	1.922	0.055**

Note: $p < 0.1$*, $p < 0.05$**, $p < 0.01$***,

4.11 Summary of the Chapter

Key findings of the study were presented following the assessment of the significance of the path coefficients. Generally, previous literature showed that self-report techniques provided considerable support for the moderating effect of gender on the relationships between exogenous latent constructs (Performance expectancy, effort expectance, social influence and facilitating condition) and adoption of cloud computing in the e-health sector.

More importantly, with the moderating effect of gender on the relationship between the exogenous latent variables and the endogenous latent variable, PLS path coefficients revealed that of the five direct formulated hypotheses (H_1, H_2, H_3, H_4, H_5) all were significant. In addition, gender was shown to moderate the relationship between (1) effort expectancy and adoption of cloud computing, (2) facilitating conditions and adoption of cloud computing,

CHAPTER FIVE
Discussion of Results and Conclusion

5.1 Introduction

Chapter four presented the findings of this study. Chapter five includes a summary of the study's findings and a discussion of the results in the light of underpinning theories and previous literature. Additionally, the theoretical, methodological, and managerial implications of the study are discussed. The limitations of the study are noted, and suggestions for future research directions in the area of performance expectancy, effort expectancy, social influence, facilitating condition, gender segregation and clod computing adoption, are made based on these limitations. Finally, this chapter ends with a conclusion of the study.

5.2 Recapitulation of the Study

This study examined the factors influencing e-health cloud computing adoption in Saudi Arabia. With moderating effect of gender segregation on the relationship between the independent variables (performance expectancy, effort expectancy, social influence, facilitating condition and gender segregation) and a dependent variable (clod computing adoption). Overall, this study provided answers to the following research questions:

RQ1 What are the factors necessary for the successful adoption of cloud computing in the Saudi Arabian healthcare sector?

RQ2. Does gender segregation moderate the relationship between the identified factors and cloud computing adoption in the Saudi Arabian healthcare sector?

RQ3. Does the proposed model constructs significantly explain and predict cloud computing adoption n the Saudi Arabian healthcare sector?

The theoretical framework underlying this study was based on the Unified Theory of Acceptance and Use of Technology (UTAUT). After an extensive literature review, scale items from previous studies were adapted to suit this present study, followed by a pilot test study with a total participation of 44 health personnel representatives. A survey questionnaire, developed based on a 5-point interval scale, was validated through several statistical measures (for item reliability and validity). The pilot-testing was conducted to confirm that there was no ambiguity in the questions and the respondents could understand the questions the way they were designed and intended (Sekaran, 2003). The pilot-testing process rectifies any inadequacies, thus, reduces biases before being administered to survey respondents.

Furthermore, after data collection was carried out in the Saudi Arabian health sector, the data was screened via SPSS, estimation of content validity, factor loading significance, outer model specification, convergent and discriminant validities, with the aid of SmartPLS 3 SEM software. After the establishment of the measurement model, further examination for effect size and predictive relevance of the study model were done.

Upon satisfactory examination of these statistical measures, the inner model specification (structural model), used for testing the hypothesized paths, was evaluated. In this study, a variance of 0.032 (Table 4.19) for the adoption of cloud computing is considered "weak" following the suggestions of Falk and Miller (1992) and Chin (1998). According to Chin (1988) *R*-squared (R^2) values of 0.67, 0.33, and 0.19 are considered as substantial, moderate, and weak, respectively. However, Chin (1998) noted that even models with low R^2 can still yield excellent goodness of fit.

Hence, this study's hypotheses' consisted of direct and moderating paths were calculated using several statistical analyses to determine the significance of their results. Individually, the moderating effects of gender segregation on the relationships between exogenous latent constructs (performance expectancy, effort expectancy, social influence, facilitating condition and gender segregation) and endogenous variable (adoption of cloud computing) were tested through the bootstrap method.

Regarding the relationship between the (performance expectancy, effort expectancy, social influence, facilitating condition and gender segregation) and endogenous variable (adoption of cloud computing) were tested through the bootstrap method, the findings of this study indicated that (H_1, H_2, H_3, H_4, and H_5) were all significant. In other words, the results of the PLS path model showed that factors identified (performance expectancy, effort expectancy, facilitating condition and gender segregation) were significantly and positively related to adoption of e-health cloud computing. While social influence were found to be negatively influence the adoption of e-health cloud computing.

5.3 Discussion of the Research Results

In this study, factors such as performance expectancy, effort expectancy, social influence, facilitating condition and gender segregation were measured and analyzed to determine their influence on the adoption of cloud computing.

To identify the factors necessary for the successful adoption of cloud computing in the Saudi Arabian healthcare sector.

The first objective of the study was to identify the factors necessary for the successful adoption of cloud computing in the Saudi Arabian healthcare sector. Previous literature indicated that factors necessary for the successful adoption of cloud computing comprises of performance expectancy, effort expectancy, social influence, facilitating condition and gender segregation as a moderating variable (Abdullah et al., 2015; Al-Ruithe et al., 2017; F. Alharbi, Atkins, & Stanier, 2016; Alkurdi, 2022; Alsenea, 2015; Meri et al., 2019; Sharma et al., 2021). Therefore, this study adopted the four dimensions in measuring cloud computing adoption in the health sector.

Hence, five hypotheses were develop, which represented the relationship between factors necessary for the adoption of cloud computing in the health sector and cloud computing adoption.

Hypothesis H_1 suggested that there is a positive relationship between the perceived performance expectancy of cloud computing and the decision to adopt cloud computing and as postulated, the relationship existed and was found to be positively significant with indicators (β = 0.175, t = 2.214, and p = 0.014). Performance expectation refers to an individual's belief that adopting cutting-edge technologies will enhance their ability to meet specific goals or perform better (Apfel & Herbes, 2021).

This empirical result support the findings of previous studies which showed a positive relationship between performance expectancy and cloud computing adoption (F. Alharbi, Atkins, Stanier, et al., 2016; Alsenea, 2015; Karim & Rampersad, 2017; Sharma et al., 2021). Therefore, these results validate the empirical linkage between perceived performance expectancy and cloud computing adoption. Hence, Hypothesis H_1 is supported.

Additionally, having a positive relationship with performance expectancy revealed the relative advantage of cloud computing by enhancing the quality of health services. As the finding validates the hypothesis by having a positive relationship it also provided an answer to the respective research question. In general, the result gives further support to the assertion of the UTAUT model as a theory by confirming the positive influence of performance expectancy on the adoption of clod computing. The results also further revealed that cloud computing can increase productivity and scalability to meet growing demand of health sector.

Hypothesis H_2 suggested that there is a negative relationship between the perceived effort expectancy of cloud computing and the decision to adopt cloud computing. It is important to note that effort expectancy is the degree of ease associated with the use of the system" (Venkatesh et al., 2003) that is the degree to which an innovation is perceived to be relatively difficult to understand and use. Therefore, the likelihood of adoption is increased if the technology is regarded as relatively straightforward by the intended users'. The relationship between effort expectancy and e-health cloud computing adoption was thus, examined.

The results of the study indicated a positive relationship between effort expectancy and adoption of cloud computing in the health sector, thereby rejecting the hypothesis that read there is a negative relationship between the effort expectancy of cloud computing and the decision to adopt cloud computing with $\beta = 0.323$, $t = 5.063$, and $p = 0.000$ thereby not supporting the previous research that reported a negative relationship (Abdullah et al., 2015; Alsenea, 2015; Karim & Rampersad, 2017; Tornatzky & Klein, 1982).

However, the results support the previous findings. For instance, Adebo et al., (2025); Alnassar & Baashirah, (2024); Borgman et al., (2013); Dash & Sahoo, 2022a; Gu et al., 2021) revealed positive relationship between perceived effort expectancy and adoption of cloud computing. This implying that, when the adoption of cloud computing services is perceived as simple, transparent and reasonable, it enhances the likelihood of its adoption. This is based on the assumption that cloud computing adoption will be more inclined toward adopting technology that demands minimal effort for effective utilization. Meaning the likelihood of adoption is increased if the technology is regarded as relatively straightforward by the intended users, hence, relative complexity is an important driver in the acceptance of cloud technology.

Hence, the results revealed that effort expectancy should be given close consideration, especially in the government sector where most employees are not very familiar with new technologies. The variety of cloud settings, tools, techniques and software is getting increasingly hard to test and maintain and that raises the complexity. Cloud has some complexity in handling technical features, customizing software, operating services, virtualisation issues, and optimizing performance.

Thus previous studies in the literature (Klug, 2014; Low et al., 2011; Tan & Teo, 2000) have highlighted this factor and its importance as a barrier to adopting cloud computing if effort expectancy is not considered while adopting new technology. Hence, IT specialists suggested solutions to overcome this challenge such as providing intensive training and financial support. Thus, this study shows how effort expectancy are capable of influencing cloud computing in the health sector.

Hypothesis H_3 suggested that there is a positive relationship between social influences/societal attitudes towards technology and the decision to adopt e-health cloud computing.

Hypothesis H_3 postulated that social influence has a positive effect on the adoption of cloud computing in the Saudi Arabian health sector. It is important to note that social influence is one the factors that affect the adoption of cloud computing in health sector. The results of this study revealed that there is a negative significant relationship between societal influences and adoption of cloud computing in the health sector with β = -0.164, t = 2.346, and p = 0.019. Thereby rejecting the hypothesis H_3.

Though, the hypothesis is not supported the results of the study supports the previous findings which revealed a significant relationship between social influence and cloud computing adoption in the health sector (Alsahafi et al., 2020; W. M. G. Alshammari et al., 2021; Alsharo et al., 2021; Dash & Sahoo, 2022b; De Veer et al., 2015; Hamzat & Mabawonku, 2018; Jawad et al., 2023; Meri et al., 2019; Sahoo et al., 2023). In developing nations like Saudi Arabia, people usually live in joint families and are interdependent in socioeconomic settings. Hence, the usage of e-health services, in this case, would not only be observed by their close friends and family, but it would also encourage them to do so. Therefore, in general, the result gives further support to the assertion of the UTAUT model on cloud computing adoption

Hypothesis H_4 was developed to examine if facilitating conditions have a positive effect on the adoption of e-health cloud computing in the Saudi Arabian health sector. The results of the study revealed a positive and significant relationship between facilitating condition and the decision to adopt cloud computing was found at 1%, with parameters as $\beta = 0.406$, $t = 6.979$, and $p < 0.000$ supporting the Hypothesis H_{21}. This is consistent with previous finding. For instance, Abdelwahed et al., (2024); De Veer et al., (2015); Idoga et al., (2018); Sair & Danish, (2018) revealed appositive significant impact of facilitating conditions and cloud computing adoption.

The present study's positive and significant relationship revealed that an individual believes organizational and technical infrastructure exists to support the adoption of could computing. This shows facilitating condition is among the factors affecting the adoption of cloud computing in the health sector. Thus the availability of required IT infrastructures, technological know-how and technical support could influence the adoption of cloud computing in Saudi Arabian health sector.

Hypothesis *H_5* was developed to examine if there is a negative significant relationship between Gender Segregation and the decision to adopt cloud computing. However, the results of the study revealed a positive significant association between Gender Segregation and the decision to adopt cloud computing was found with $\beta = 0.105$, $t = 2.221$, and $p < 0.027$ supporting the Hypothesis H_5. The finding is consistent with previous research. For instance, (Alqattan et al., 2022; Dajani & Yaseen, 2016; Hamzat & Mabawonku, 2018; Prasanna & Huggins, 2016) revealed a positive relationship between gender segregation and adoption of cloud computing in health sector. Considering the nature and religious practice of the study area, the results revealed that high levels of gender segregation in health sector may encourage collaborative decision-making and improve the acceptance of new technologies.

Hypothesis H_7: There is a negative relationship between Gender Segregation and the decision to adopt cloud computing. H_9 suggested that there is a negative relationship between Gender Segregation and the decision to adopt cloud computing. Previous research's acknowledged that gender influences the use of any information system in both mandatory and voluntary settings (Al-Harethi & Garfan, 2018; Jawad et al., 2023).

The results of the study indicated a positive and significant relationship between gender and adoption of cloud computing in the health sector, thereby rejecting the hypothesis that read there is a negative relationship between, the gender and the decision to adopt cloud computing with $\beta = 0.092$, $t = 1.912$, and $p = 0.056$ and accept the alternative hypothesis. However, it supported the previous research that assert that gender has a positive relationship with cloud computing (Al-Harethi & Garfan, 2018; Almarazroi et al., 2019; Alqattan et al., 2022; Jawad et al., 2023). Therefore, this result validates the previous empirical linkage between gender segregation and cloud computing adoption.

Being Saudi Arabia a Muslim dominated country segregation of gender will make the adoption of cloud computing possible and successful. Hence, to adopt cloud computing in the health sector there is need to segregate between the genders so that the adoption of cloud computing in the health sector will be successful.

To examine the moderating effect of gender segregation on the relationship between the identified factors and cloud computing adoption in the Saudi Arabian healthcare sector.

The second objective of the study was to examine the moderating effect of gender segregation on the relationship between the identified factors and cloud computing adoption in the Saudi Arabian healthcare sector. Previously gender is been tested as a moderator on new technology acceptance (Moores, 2012; Prasanna & Huggins, 2016; Sharma et al., 2023). Previous literature indicated that adoption of cloud computing in the health sector can be influence by factors such as relative advantage, Cost, Cultural Society, Infrastructure, Regulation, Compatibility, Security, Technical Exp (Hassan et al., 2017; Jianwen & Wakil, 2020; Karim & Rampersad, 2017; Prasanna & Huggins, 2016; Tawfik et al., 2023). Therefore, this study adopted eight factors in measuring the moderating effect of gender on these factors influencing the adoption of cloud computing. The moderating effect of gender segregation was analyzed using SmartPLS. This study employed bootstrapping method to test the hypotheses.

Firstly, a direct relationship was examined between gender and cloud computing adoption in the health sector in line with Baron and Kenny (1986) proposition, that to test moderator, the moderating variable must be significant with dependent variable. This study revealed a significant positive relationship between gender and cloud computing adoption with indicators β = 0.105, t =2.221, and p = 0.027. This supports the hypothesis that gender influence the adoption of cloud computing consistent with previous studies (Al-Harethi & Garfan, 2018; Almarazroi et al., 2019; Alqattan et al., 2022; Jawad et al., 2023). Thus, the findings suggest that health sector should have a strong gender segregation to adopt a successful cloud computing.

This study test the moderating effects of Gender on the identified factors influencing the adoption of cloud computing. Hence, four hypotheses were develop, which represented the relationship between identified factors influencing cloud computing adoption (performance expectancy, effort expectancy, social influence and facilitating condition) and cloud computing adoption in the Saudi Arabian health sector.

Out of the four direct hypotheses that were postulated only two (H_7 & H_9) were found to be significantly related to adoption of cloud computing in the Saudi Arabian health sector. **Hypothesis *H_7*** was developed to examine if gender segregation moderates the relationship between negative significant effect of effort expectancy and the adoption of e-health cloud computing. The result revealed that gender segregation positively significantly moderate the relationship between the perceived effort expectancy of cloud computing and the decision to adopt cloud computing in the Saudi Arabian health sector at 5 %. %. The parameters are β=0.160, t=2.276 and P= 0.023. This led to rejecting of hypothesis (H_7). The results support the previous findings such as (Almazroi et al., 2019; Calegari et al., 2023; Zhang et al., 2014) all revealed gender can significantly moderate the relationship bet effort expectancy and decision to adopt of cloud computing. Hence, e-health cloud computing consulting service providers should design their products to perform various tasks and emerge as a productive and multi-tasking offering.

Hypothesis H_9 was developed to examine if significant positive effect of facilitating conditions on the adoption of cloud computing in the Saudi Arabian health sector can be moderated by gender segregation. Adequate support enhances adoption of cloud computing but gender segregation may determine who can access such resources, thus moderating the relationship between facilitating conditions and adoption. The results of the study revealed gender segregation negatively and significantly moderate the relationship between facilitating condition and the decision to adopt cloud computing at 5%.

The result revealed that gender weakens the positive relationship between facilitating conditions and the decision to adopt cloud computing, where the interaction terms were statistically significant at β = -0.121, t = 1.922, and p < 0.055 rejecting the Hypothesis H_9. The results are consistent with previous finding. For instance, Abdelwahed et al., (2024); De Veer et al., (2015); Idoga et al., (2018); Mojtahed et al., (2014); Sair & Danish, (2018) revealed the significant impact of facilitating conditions and cloud computing adoption. Hence, facilitating condition is necessary for advancing any breakthrough technology. In general, the result gives further support to the assertion of the UTAUT model on cloud computing adoption.

In general, the empirical evidence of this study indicated that gender segregation to a certain extent moderate the relationship between factors influencing the adoption of cloud computing and cloud computing adoption in E-health sector of Saudi Arabia. The findings also suggest the need for the Saudi Arabia Health sector to have gender segregation and to focus on cloud computing adoption in strengthening their services.

However, Hypothesis (H6): performance expectancy has a positive significant effect on the adoption of e-health cloud computing, and this relationship is moderated by gender segregation and Hypothesis (H8): Social influence has a positive effect on the adoption of e-health cloud computing, and this relationship is moderated by gender segregation were not supported by the study.

5.4 Implications of the Study

Generally, the study has several contributions to the body of knowledge, namely, theoretical and managerial contributions, which are discussed further in the following sub-sections.

5.4.1 Theoretical Contributions

The conceptual framework of this study was based on the theoretical gaps and prior empirical studies that were identified in the extant literature. The framework was supported and explained from two theoretical perspectives, which are, Venkatesh's Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) and the Roger's Innovation Diffusion Theory (Rogers, 1995). The Unified Theory of Acceptance and Use of Technology is important in that it vividly identifies critical components that influence adopting of technology (Cloud computing adoption). Furthermore, it shows what factors organization shall look into before adopting a new technology. The present study incorporated gender segregation as a moderating variable to explain and understand the relationship between exogenous variables and adoption of cloud computing in E-Health sector of Saudi Arabia. Thus, based on the findings this study was able to make several theoretical contributions to the field of cloud computing and cloud computing adoption.

In general, this study found empirical evidence for theoretical relationships posited in the research framework. The present findings have contributed to literature and development of theory which includes; (1) establishing the positive influence of performance expectancy and cloud computing adoption; (2) establishing the positive influence of effort expectancy and cloud computing adoption; (3) establishing the negative influence of social influence and cloud computing adoption; (4) establishing the positive influence of security dimension and cloud computing adoption; (5) establishing the positive influence of gender segregation and cloud computing adoption; (6) establishing the moderating influence of gender segregation between effort expectancy and cloud computing adoption; (7) establishing the moderating influence of gender segregation between facilitating condition and cloud computing adoption; and (8) finally expanding the theories of Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003a). and Diffusion of Innovations Theory (M. Tan & Teo, 2000).

This study provides some theoretical implications by giving additional empirical evidence in the domain of UTAUT. Previous literature has highlighted the UTAUT in the context of health sector, indicating how performance expectancy, effort expectancy, social influence and facilitating condition influence adoption of technology (Dash & Sahoo, 2022a; Jawad et al., 2023; C. Kim et al., 2010; Martins et al., 2014; Meri et al., 2019; Sahoo et al., 2023; Song et al., 2020). The use of UTAUT in adoption of cloud computing in Saudi Arabia studies is rare. Therefore, one of the major contributions of this study is the application of UTAUT to the context of cloud computing adoption in e-Health sector. To this end, this study has significantly contributed to cloud computing adoption theory.

Furthermore, this study contributed to the methodology adopted, the questionnaire used as an instrument for data collection and the specific items (proxies) were adapted from previous studies conducted in other parts of' the world (F. Alharbi, Atkins, & Stanier, 2016; Alkurdi, 2022; Brown & Venkatesh, 2005; Meri et al., 2019; Venkatesh & Davis, 2000). The present study has contributed to testing these instruments in an Arabian countries context, which was not previously done.

Another methodological contribution of this study is the assessment of psychometric properties of each latent variable via PLS path modelling. The present study has evaluated psychometric properties of each latent variable in terms of convergent validity and discriminant validity. The study also examined composite reliability and individual item reliability of each latent variable. Furthermore, convergent validity was evaluated by examining the value of average variance explained (AVE) for each latent variable.

Furthermore, Square roots of AVE with correlations among the latent variables were compared to determine the discriminant validity. The cross loadings matrix results were also examined to find support for discriminant validity in the conceptual model. Thus, one of the more robust approaches, namely, PLS path modelling was used to assess the psychometric properties of each latent variable illustrated in the conceptual model of this study.

Previous studies have shown how performance expectancy, effort expectancy, social influence and facilitating condition relate to cloud computing adoption. However, this study considers another variable (gender segregation) to moderate the relationship. This study extended the body of knowledge in providing empirical evidence by combining the four dimensions of factors influencing cloud computing adoption as UTAUT model factors as well adding gender segregation as moderator which other studies did not consider.

Therefore, measuring UTAUT model factors via four dimensions (Effort Expectancy, Performance Expectancy, Facilitating condition and Social Influence) and inclusion of gender segregation to examine the moderating effect on the relationship between factors influencing cloud computing adoption and adoption of cloud computing in the health sector has its contribution to the body of knowledge.

To this end, the results of the study confirmed that there is a positive moderating effect of gender segregation between performance expectancy, social influence, facilitating condition and cloud computing adoptions. Hence, this study is expected to make a significant contribution to the body of knowledge.

5.4.2 Managerial Implications

Based on the findings of the study, the present study has contributed to several practical implications regarding cloud computing adoption in the context of the Saudi Arabian health sector. The findings would be relevant to policymakers such as the IT practitioners, Ministry of Health, and policymakers involved in cloud computing activities across the Saudi Arabia in designing programs and policies related to the health sector.

The result of this study can benefit specialists to understand and present adequate indication for confirming a significant relationship between the variables (identified factors such as performance expectancy, effort expectancy, social influence, facilitating condition, gender segregation, and cloud computing adoption).

This study provides the management and regulatory bodies of health sector with recommendations to have an understanding of the implication of their commitment and considering the identified factors in designing cloud computing that will enhance the performance of health sector, since the practical recommendations was drawn logically from the empirical findings. Consequently, this research gives statistical evidence that factors identified, and gender segregation are significantly related to cloud computing adoption.

This shows that regulatory authorities and management of hospitals, ministry of health should be more concerned with factors identified to influence the adoption of cloud computing in designing cloud computing in health sector that will influence their service performance.

Furthermore, gender segregation was found to have a significant positive impact on adoption of cloud computing in health sector. The implication of this is that hospitals with a high gender segregation strategy tend to perform better than those with a weak gender segregation strategy. Therefore, management and regulatory authorities of hospitals, and policymakers can enhance the health sector service efficiency by adopting cloud computing with a high gender segregation. A weak gender segregation suppresses the adoption of cloud computing and adversely affects its adoption. The challenge for top management is to proactively plan for a strong gender segregation strategy.

5.5 Limitation and Suggestions for Future Research

5.5.1 Limitations

Firstly, the study was performed at a certain point in time and therefore the results obtained only indicated the level of acceptance at that point and the experience variable, which requires a longitudinal study, could not be effectively measured. Secondly, the sample selected and in fact the entire sample population did not contain enough female end-users to be able to analyse gender as a moderating variable. This limited the study.

Though this study has provided support for a number of the hypothesized relationships between the endogenous and exogenous variables, the results have to be interpreted with consideration of the study's limitations which were identified as follows.

Firstly, the current study relied on a single method of data collection and adopted a quantitative method. Precisely, in gathering the data for this study, questionnaire was the only instrument used. The respondents may not always be willing to answer questions properly. Therefore, the responses may not accurately and consistently measure the study variables. It will be of interest if future studies will adapt Mix-Method by combining both qualitative and quantitative methods to conduct an in-depth investigation into adoption of cloud computing in e-health sector.

Secondly, this study examined only health sector where other sectors such as the banks, educational sector and manufacturing industries were not included. Future researches are recommended to consider the need to examine other sectors which may provide more in-depth results.

Thirdly, the study adopted a cross-sectional design for the survey in which the opinions of respondents was captured at one specific point in time. Thus, it does not allow causal inferences to be made from the population due to the cross-sectional nature of this study, (Sekaran & Bougie, 2009b). In view of these limitations, a longitudinal study is therefore recommended for future research. This may help researchers validate the findings from cross-sectional studies.

Lastly, no significant moderating influence of gender segregation on the relationship between relative advantages, technical efficiency, cost, culture, regulation, security and effort expectancy and cloud computing adoption was found. Thus, more research is needed to investigate such moderating effects. Hence, it's necessary for the future research to verify whether other moderating variables may strengthen this relationship.

5.5.2 Suggestions for Future Research

In order to overcome these limitations discussed above, future research should adopt a longitudinal study with enough time for data collection. Since the study is limited to the Saudi Arabian health sector only; future research should look at other servicing sector like banks, educational sector rather than selecting the health sector alone in the country to examine if results will be different.

In addition, since the study is conducted in Saudi Arabia, an Asian country, it cannot be generalized to other countries with different settings and different cultures with Asian countries. Thus, future studies should replicate this study in other countries so as to compare if there are differences. Finally, future researches are also recommended to consider combining both qualitative and quantitative methods (mixed methods) to have an in-depth investigation into cloud computing adoption in Saudi Arabia.

5.6 Conclusions

The main objective of the study was to identify the factors necessary for the successful adoption of cloud computing in the Saudi Arabian healthcare sector. In addition, it examined the moderating role of gender segregation on the relationship between the identified factors and cloud computing adoption in Saudi Arabia health sector. The study has achieved all these objectives as discussed in Chapter One.

The first objective was to identify the factors necessary for the successful adoption of cloud computing in the Saudi Arabian healthcare sector. This objective was achieved through the use of PLS-SEM measurement and structural model, revealed the identified factors to be performance expectancy, effort expectancy, social influence and facilitating condition. The study provides empirical evidence of a significant relationship between the identified factors and adoption of cloud computing in e-health sector of Saudi Arabian.

The second objective was to examine moderating effect of gender segregation on the relationship between the identified factors and cloud computing adoption in the Saudi Arabian healthcare sector. In particular, the current study has successfully achieved this objective. The study provides empirical evidence of moderating effect of gender on the significant relationship between effort performance and facilitating conditions and cloud computing adoption in health sector of Saudi Arabia.

The second objective of this study was to examine the moderating effect of gender segregation on the relationship between the identified factors and cloud computing adoption in the Saudi Arabian healthcare sector. Four moderating hypotheses were examined to achieve this objective. Results showed two (effort expectancy and facilitating condition) significant relation on the moderating of gender segregation on the relationship between identified factors affecting the adoption of cloud computing and cloud computing adoption of health sector in Saudi Arabia.

The third objective of this study was to evaluate the proposed model for cloud computing adoption in the Saudi Arabian healthcare sector. This objective was achieved; the model was evaluated via empirical testing using of PLS-SEM model.

Additionally, the study provides managerial and theoretical contributions in terms of the influence of these variables on cloud computing adoption in the health sector. Based on the limitations of the study, several directions for future research are outlined. Conclusively, this research work has added valuable implications in both theoretical and managerial in cloud computing adoption and to the growing body of knowledge in the field of gender segregation literature.

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APPENDIX A

The Questionnaire Title

FACTORS INFLUENCING E-HEALTH CLOUD COMPUTING ADOPTION IN SAUDI ARABIA

SECTION ONE

This questionnaire aims to evaluate the model of cloud computing adoption in Saudi Arabia, developed based on various factors influencing adoption in health organizations across the country. Your responses will provide valuable insights into the current state of cloud computing adoption, helping to identify key drivers and barriers.

Dear Sir/Madam

We would like to invite you to participate in the Study of FACTORS INFLUENCING E-HEALTH CLOUD COMPUTING ADOPTION IN SAUDI ARABIA. being conducted by Ebtesam Jibreel, School of Computing UUM Malaysia, for the purpose of his Doctorate degree (PhD).

In order to develop an E-Health Cloud Computing Adoption model in Saudi Arabia that will help health organizations assess their strengths and weaknesses in terms of designing, implementing, and measuring appropriate strategies to support their cloud computing adoption activities, this research aims to survey the opinions and experiences of IT/health informatics practitioners, policy makers and top management in e-health. regarding the factors that can play a positive or negative role in the adoption of cloud computing by health organizations. We would like to extend an invitation to you to take part in the research survey for this reason.

All data collected during the survey will only be used for research. Such data will be handled with the utmost confidentiality, and any publications resulting from this research will only include aggregate data that makes it impossible to identify specific organizations or research participants. Throughout this project, you are free to stop participating whenever you want. Furthermore, these transcripts will only be accessible to the supervisory team.

Your involvement in this study is completely voluntary, and it will only take an hour of your time to complete the research survey..

You can contact Ebtesam Jibreel at 00966 (0) 565589204 or email iisam_abdelrahman@ahsgs.uum.edu.my if you have any concerns about the research. You are not required to provide a reason for your withdrawal from this research project at any point in time.

Yours sincerely

SECTION TWO

2.1. Demographics Data

(Please tick as appropriate)

	(Please tick as appropriate)
Indicate your Gender	Male Female
How long have you been working in healthcare?	Less than 2 years Between 2 and 5 years Between 6 and 10 years More than 10 years
What is your level of knowledge and experience in using computer software at work?	Absent /Poor Fair Satisfactory Very good Excellent
Rate your personal experience using cloud computing in business (in general)?	Absent /Poor Fair Satisfactory Very good Excellent

2.2. General information about your institution

(Please tick as appropriate)

Indicate the type of your institution.	Ministry of Health organizations Private healthcare organization (please specify) Other (please specify..)
Which stage of the adoption of cloud computing is your organization presently in?	Nothing Exploration and Awareness Has evaluated but not planned Cloud Computing Adoption Has evaluated and is planning adoption Already adopted cloud computing. Advanced usage

SECTION THREE

No.	**Statement**	**Strongly Agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
1	**Performance expectancy**					
1.1	**Relative advantage**					
1	Cloud computing technology helps you to access data in real-time.	**5**	**4**	**3**	**2**	**1**
2	Cloud computing technology helps you to improve accuracy and reduce errors.	**5**	**4**	**3**	**2**	**1**
3	Cloud computing technology help in increases business productivity.	**5**	**4**	**3**	**2**	**1**
4	Cloud computing technology help in enhance the quality of service for patients.	**5**	**4**	**3**	**2**	**1**
2	**Effort Expectancy**	**Strongly Agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
2.1	**Technical Complexity**					
1	The implementation of cloud computing technology involves complexities in usage.	**5**	**4**	**3**	**2**	**1**
2	The technical skills that you need for using cloud computing technology can be challenging.	**5**	**4**	**3**	**2**	**1**
3	Cloud computing technology will require a number of specialized technical staff in your organization to manage it.	**5**	**4**	**3**	**2**	**1**
4	The technical staff may face technical challenges in the implementation of cloud computing technology.	**5**	**4**	**3**	**2**	**1**
3	**Social Influence**	**Strongly Agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
3.2	**Regulations and Policies**					

1	You believe there is a significant deficiency in regulations concerning cloud computing technology.	**5**	**4**	**3**	**2**	**1**
2	The well-established rules and policies in your organization leads to adopt Cloud Computing technology in a proper way.	**5**	**4**	**3**	**2**	**1**
3	Regulatory concerns prevent your organization from adopting cloud computing technology.	**5**	**4**	**3**	**2**	**1**
4	Your organization is facing pressure from certain government agencies to adopt cloud computing technology.	**5**	**4**	**3**	**2**	**1**
4	**Facilitating Conditions**	**Strongly Agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
4.2	**Security and privacy**					
1	Your organization is concern about security issues for information within the realm of cloud computing technology.	**5**	**4**	**3**	**2**	**1**
2	Your organization is concern about privacy issues for information within the realm of cloud computing technology.	**5**	**4**	**3**	**2**	**1**
3	Our organization is worried about the idea of cloud providers misusing the data for commercial purposes.	**5**	**4**	**3**	**2**	**1**
4	Your organization decision to adopt cloud computing technology depends on the security and privacy that cloud computing can ensure for the organization information.	**5**	**4**	**3**	**2**	**1**

	Gender Segregation	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
1	In your organization females cannot work in male workplaces	5	4	3	2	1
2	In your organization separates males and females as much as possible	5	4	3	2	1
3	Gender segregation affects the perceived benefits of adopting cloud computing technology in your organization.	5	4	3	2	1
4	Gender segregation affects how perceive the technical complexity of adopting cloud computing technology in your organization	5	4	3	2	1

	Cloud Computing	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
1	E-Health Management in your organization invests resources in cloud computing technology.	5	4	3	2	1
2	Your organization activities require the use of cloud computing technology.	5	4	3	2	1
3	Your organization functional areas require the use of cloud computing technology.	5	4	3	2	1

SECTION FOUR

Are there any additional factors or considerations that you believe influence the adoption of cloud computing within your organization or industry? Please feel free to share any insights, experiences, or perspectives you think are relevant?

APPENDIX B

Researchers CVs

This appendix contains the curriculum vitae (CVs) of the researchers who reviewed the questionnaire for face and content validity. Their expertise and experience in cloud computing, data analysis, and research methodology ensure that the questionnaire is robust, reliable, and relevant. The reviewers' detailed backgrounds and qualifications are presented here to provide transparency and confidence in the validity of the questionnaire used in this study. Their comprehensive evaluation has played a crucial role in refining the questions to accurately capture the factors influencing cloud computing adoption in Saudi Arabia.

Dr. Ismail M. Keshta

Associate Professor, Computer science & Information Systems Department, AlMaarefa University

imohamed@um.edu.sa

Education

Ph.D. in Computer Science and Engineering, 2016
Dissertation Title: "Towards achieving CMMI Level 2 for small and medium sized software development organizations."

King Fahd University of Petroleum and Minerals (**KFUPM**), Saudi Arabia

Master of Science degree in Computer Engineering, June 2011
Thesis Title: "Performance Analysis of Real-Time Publish/Subscribe Middleware For Wireless Sensor Networks."

King Fahd University of Petroleum and Minerals (**KFUPM**), Saudi Arabia

Bachelor of Science degree in Computer Engineering, February 2009

King Fahd University of Petroleum and Minerals (**KFUPM**), Saudi Arabia

Academic Work Experience

Associate Professor
AlMaarefa University Riyadh - KSA
July. 2023-Present

Assistant Professor
AlMaarefa University Riyadh - KSA
Sept. 2018-June. 2023

Lecturer B
King Fahd University of Petroleum and Minerals (KFUPM)
Dhahran, KSA
Sept. 2012-Dec. 2016

Lecturer (Part Time)
Princess Nora Bint Abdulrahman University (PNU)
Riyadh, Saudi Arabia
Jan. 2012-Aug. 2012

Research Assistant
King Fahd University of Petroleum and Minerals(KFUPM)
Dhahran, KSA
Feb. 2009-June. 2011

Journal and Conference Publications

No.	Title	Year
1.	Artificial intelligence-Enabled deep learning model for multimodal biometric fusion H Byeon, V Raina, M Sandhu, M Shabaz, **I Keshta**, M Soni, K Matrouk, ... Multimedia Tools and Applications, 1-24	2024
2.	Few-shot learning-based human behavior recognition model V Mahalakshmi, M Sandhu, M Shabaz, **I Keshta**, KDV Prasad, N Kuzieva, Computers in Human Behavior 151, 108038	2024
3.	Deep Learning Model for Interpretability and Explainability of Aspect-Level Sentiment Analysis Based on Social Media NK Singh, S Agal, TR Gadekallu, M Shabaz, **I Keshta**, L Jindal, M Soni, ... IEEE Transactions on Computational Social Systems	2024
4.	Anonymity and security improvements in heterogeneous connected vehicle networks SA Sivasankari, D Gupta, **I Keshta**, CVK Reddy, PP Singh, H Byeon International Journal of Data Science and Analytics, 1-14	2024
5.	Enhancing Stock Price Prediction with Deep Cross-Modal Information Fusion Network RC Mandal, R Kler, A Tiwari, **I Keshta**, MR Abonazel, EM Tageldin, ... Fluctuation and Noise Letters	2024
6.	Non-sample fuzzy based convolutional neural network model for noise artifact in biomedical images H Byeon, RK Patel, DA Vidhate, S Kiyosov, SA Rahin, **I Keshta**, ... Discover Applied Sciences 6 (1), 16	2024
7.	Intelligent dynamic spectrum access using fuzzy logic in cognitive radio networks KK Kishore, AS Rajasekaran, **I Keshta**, H Byeon, MW Bhatt, A Irshad, ... Discover Applied Sciences 6 (1), 18	2024
8.	Deep learning model to detect deceptive generative adversarial network generated images using multimedia forensic H Byeon, M Shabaz, K Shrivastava, A Joshi, **I Keshta**, R Oak, PP Singh, ... Computers and Electrical Engineering 113, 109024	2024
9.	A Blockchain-based AI approach towards smart home organization security SF Khan, SS Priya, M Soni, **I Keshta**, IR Khan Artificial Intelligence, Blockchain, Computing and Security Volume 1, 589-596	2024
10.	A logic Petri net model for dynamic multi-agent game decision-making H Byeon, C Thingom, **I Keshta**, M Soni, SA Hannan, H Surbakti Decision Analytics Journal 9, 100320	2023
11.	An advanced approach for fig leaf disease detection and classification: Leveraging image processing and enhanced support vector machine methodology S Alzoubi, M Jawarneh, Q Bsoul, **I Keshta**, M Soni, MA Khan Open Life Sciences 18 (1), 20220764	2023
12.	Self-Attention Mechanism Based Federated Learning Model for Cross Context Recommendation System NK Singh, DS Tomar, M Shabaz, **I Keshta**, M Soni, DR Sahu, M Bhende, ... IEEE Transactions on Consumer Electronics	2023
13.	Cloud-based non-invasive cognitive breath monitoring system for patients in health-care system M Soni, M Shabaz, RR Maaliw, **I Keshta**, R Altaee, S Das International Journal of Data Science and Analytics, 1-12	2023
14.	Smart robots’ virus defense using data mining technology J Ye, HN Patel, S Meena, RR Maaliw III, SSM Ajibade, **I Keshta** Journal of Intelligent Systems 32 (1), 20230065	2023

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15.	An effective framework to improve the managerial activities in global software development S Siddique, M Naveed, A Ali, **I Keshta**, MI Satti, A Irshad, Z Alomari, ... Nonlinear Engineering 12 (1), 20220312	2023
16.	Application of Artificial Neural Network Unified with Fuzzy Logic for Systematic Stock Market Prediction A Kumar, **I Keshta**, J Bhola, MW Bhatt, SA AlQahtani, M Gali Fluctuation and Noise Letters, 2440001	2023
17.	An Efficient Brain Tumor Segmentation Method Based on Adaptive Moving Self-Organizing Map and Fuzzy K-Mean Clustering S Dalal, UK Lilhore, P Manoharan, U Rani, F Dahan, F Hajjej, **I Keshta**, ... Sensors 23 (18), 7816	2023
18.	Medical Image Despeckling Using the Invertible Sparse Fuzzy Wavelet Transform with Nature-Inspired Minibatch Water Wave Swarm Optimization A Amarnath, P Manoharan, B Natarajan, R Alroobaea, M Alsafyani, **I Keshta** Diagnostics 13 (18), 2919	2023
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20.	A probability-based fuzzy algorithm for multi-attribute decision-analysis with application to aviation disaster decision-making AV Agrawal, M Soni, **I Keshta**, V Savithri, PS Abdinabievna, S Singh Decision Analytics Journal 8, 100310	2023
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22.	Check for updates The Use of Digital Educational Resources in the Educational Process DS García¹, I Otcheskiy, MA Alkhafaji, **I Keshta**, S Gabriyelyan, ... Networks and Systems in Cybernetics: Proceedings of 12th Computer Science On …	2023
23.	CNN Based Self Attention Mechanism for Cross Model receipt Generation for Food Industry **I Keshta**, M Soni Journal of Engineering, Science and Mathematics (JESM), 22-22	2023
24.	Generic Edge Computing System for Optimization and Computation Offloading of Unmanned Aerial Vehicle P Panwar, M Shabaz, S Nazir, **I Keshta**, A Rizwan, R Sugumar Computers and Electrical Engineering 109, 108779	2023
25.	Spatio–temporal attention based real-time environmental monitoring systems for landslide monitoring and prediction MVS Babu, N Ashokkumar, A Joshi, PS Deshpande, **I Keshta**, ... Spatial Information Research, 1-14	2023
26.	Rectal Cancer Prediction and Performance Based on Intelligent Variational Autoencoders Machine Using Deep Learning on CDAS Dataset G Kaur, **I Keshta**, M Shabaz, HS Batra, TV Sagar, BK Singh, VS Lakshmi Journal of Artificial Intelligence and Technology	2023
27.	A computer-aided feature-based encryption model with concealed access structure for medical Internet of Things S Vaidya, A Suri, V Batla, **I Keshta**, SSM Ajibade, G Safarov Decision Analytics Journal, 100257	2023
28.	Blockchain aware proxy re-encryption algorithm-based data sharing scheme **I Keshta**, Y Aoudni, M Sandhu, A Singh, PA Xalikovich, A Rizwan, M Soni, ... Physical Communication 58, 102048	2023
29.	Multi-stage biomedical feature selection extraction algorithm for cancer detection	2023

No.	Title	Year
	I Keshta, PS Deshpande, M Shabaz, M Soni, M Bhadla, Y Muhammed SN Applied Sciences 5 (5), 131	
30.	Policy conflict detection approach for decision-making in intelligent industrial Internet of Things PK Tripathy, M Shabaz, A Zaidi, **I Keshta**, U Sharma, M Soni, AV Agrawal, ... Computers and Electrical Engineering 108, 108671	2023
31.	Support Vector Machine based Multi-Class Classification for Oriented Instance Selection SK Davuluri, D Srivastava, M Aeri, M Arora, **I Keshta**, R Rivera 2023 International Conference on Inventive Computation Technologies (ICICT …	2023
32.	Optimized LightGBM model for security and privacy issues in cyber-physical systems S Dalal, M Poongodi, UK Lilhore, F Dahan, T Vaiyapuri, **I Keshta**, ... Transactions on Emerging Telecommunications Technologies, e4771	2023
33.	Comparative Analysis of Supervised Machine and Deep Learning Algorithms for Kyphosis Disease Detection AS Chauhan, UK Lilhore, AK Gupta, P Manoharan, RR Garg, F Hajjej, **I Keshta** Applied Sciences 13 (8), 5012	2023
34.	Solving the Global Optimization Problem with Swarm Intelligence A Aljarbouh, M Sabugaa, MA Alkhafaji, **I Keshta**, EDF Benites, ... Computer Science On-line Conference, 451-457	2023
35.	The Use of Digital Educational Resources in the Educational Process DS García, I Otcheskiy, MA Alkhafaji, **I Keshta**, S Gabriyelyan, ... Computer Science On-line Conference, 478-485	2023
36.	A convolutional neural network for face mask detection in IoT-based smart healthcare systems T Vaiyapuri, TA Ahanger, F Dahan, F Hajjej, **I Keshta**, M Alsafyani, ... Frontiers in Physiology 14, 314	2023
37.	Support Vector Machine for Multiclass Classification of Redundant Instances H Surbakti, AN Kumar, S Tara, **I Keshta**, A khare, GNR Prasad International Conference on Intelligent Computing and Networking, 413-423	2023
38.	Probabilistic Scheme for Intelligent Jammer Localization for Wireless Sensor Networks AP Yadav, SK Davuluri, P Charan, **I Keshta**, JCO Gavilán, G Dhiman International Conference on Intelligent Computing and Networking, 453-463	2023
39.	PUF-Based Lightweight Authentication Protocol for IoT Devices A Shah, H Pandya, M Soni, A Karimov, RR Maaliw, **I Keshta** International Conference on Intelligent Computing and Networking, 401-412	2023
40.	Security model to identify block withholding attack in blockchain **I Keshta**, FA Reegu, A Ahmad, A Saxena, RR Chandan, V Mahalakshmi Artificial Intelligence, Blockchain, Computing and Security Volume 1, 621-629	2023
41.	Energy efficient indoor localisation for narrowband internet of things **I Keshta**, M Soni, MW Bhatt, A Irshad, A Rizwan, S Khan, RR Maaliw III, ... CAAI Transactions on Intelligence Technology	2023
42.	Deep Learning and SVM-Based Approach for Indian Licence Plate Character Recognition. N Sharma, MA Haq, PK Dahiya, BR Marwah, R Lalit, N Mittal, **I Keshta** Computers, Materials & Continua 74 (1)	2023
43.	Project Management for Cloud Compute and Storage Deployment: B2B Model J Tanwar, T Kumar, AA Mohamed, P Sharma, S Lalar, **I Keshta**, V Garg Processes 11 (1), 7	2022
44.	Evaluating One-Dimensional Definite Integrals using Excel-Based Monte Carlo Simulation Method **I Keshta** Computer Integrated Manufacturing Systems 28 (12), 648-662	2022
45.	A Secure and Resilient Scheme for Telecare Medical Information Systems With Threat Modeling and Formal Verification SS Ahamad, M Al-Shehri, **I Keshta**	2022

No.	Title	Year
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46.	IoT-based federated learning model for hypertensive retinopathy lesions classification M Soni, NK Singh, P Das, M Shabaz, PK Shukla, P Sarkar, S Singh, **I Keshta** IEEE Transactions on Computational Social Systems	2022
47.	Enhanced Route Discovery Mechanism Using Improved CH Selection Using Q-Learning to Minimize Delay. N Kaur, IK Aulakh, S Tharewal, **I Keshta**, AW Rahmani, TD Ta Scientific Programming	2022
48.	An Optimized Systematic Approach to Identify Bugs in Cloud-Based Software. S Marappan, A Kollu, **I Keshta**, SM Beram, S Bhende, K Kaliyaperumal Scientific Programming 2022	2022
49.	Visual Object Tracking Using Machine Learning A Odeh, **I Keshta**, M Al-Fayoumi International Conference on Science, Engineering Management and Information …	2022
50.	ISF: Security Analysis and Assessment of Smart Home IoT-based Firmware A Bhardwaj, K Kaushik, M Alshehri, AAB Mohamed, **I Keshta** ACM Transactions on Sensor Networks	2022
51.	Analysis of Blockchain in the Healthcare Sector: Application and Issues A Odeh, **I Keshta**, QA Al-Haija Symmetry 14 (9), 1760	2022
52.	Techniques of medical image encryption taxonomy MA Al-Fayoumi, A Odeh, **I Keshta**, A Ahmad Bulletin of Electrical Engineering and Informatics 11 (4), 1990-1997	2022
53.	Machine vision-based human action recognition using spatio-temporal motion features (STMF) with difference intensity distance group pattern (DIDGP) J Arunnehru, S Thalapathiraj, R Dhanasekar, L Vijayaraja, R Kannadasan, **I Keshta** Electronics 11 (15), 2363	2022
54.	Analytic Hierarchy Process Based Land Suitability for Organic Farming in the Arid Region P Mangan, D Pandi, MA Haq, A Sinha, R Nagarajan, T Dasani, **I Keshta**, ... Sustainability 14 (8), 4542	2022
55.	An experimental analysis of various machine learning algorithms for hand gesture recognition S Bhushan, M Alshehri, **I Keshta**, AK Chakraverti, J Rajpurohit, ... Electronics 11 (6), 968	2022
56.	Smart water management framework for irrigation in agriculture A Bhardwaj, M Kumar, M Alshehri, **I Keshta**, A Abugabah, SK Sharma Environmental Technology, 1-15	2022
57.	A novel approach to face pattern analysis S Bhushan, M Alshehri, N Agarwal, **I Keshta**, J Rajpurohit, A Abugabah Electronics 11 (3), 444	2022
58.	A model for defining project lifecycle phases: Implementation of CMMI level 2 specific practice **I Keshta** Journal of King Saud University-Computer and Information Sciences 34 (2 …	2022
59.	Efficient Email phishing detection using Machine learning R Abdulraheem, A Odeh, M Al Fayoumi, **I Keshta** 2022 IEEE 12th Annual Computing and Communication Workshop and Conference …	2022
60.	Privacy and security in mobile health technologies: Challenges and concerns A Odeh, **I Keshta**, A Aboshgifa, E Abdelfattah 2022 IEEE 12th Annual Computing and Communication Workshop and Conference …	2022
61.	Email phishing detection based on naïve Bayes, Random Forests, and SVM classifications: A comparative study M Al Fayoumi, A Odeh, **I Keshta**, A Aboshgifa, T AlHajahjeh, ...	2022

No.	Title	Year
	2022 IEEE 12th Annual Computing and Communication Workshop and Conference …	
62.	A Novel Approach to Face Pattern Analysis. Electronics 2022, 11, 444 S Bhushan, M Alshehri, N Aggarwal, **I Keshta**, J Rajpurohit MDPI Electronics	2022
63.	Autonomous Unmanned Aerial Vehicles Based Decision Support System for Weed Management AK Dutta, Y Albagory, ARW Sait, **IM Keshta** CMC-COMPUTERS MATERIALS & CONTINUA 73 (1), 899-915	2022
64.	Impact of COVID-19 pandemic on education: Moving towards e-learning paradigm A Odeh, **I Keshta** Int J Eval & Res Educ ISSN 2252 (8822), 8822	2022
65.	AI-driven IoT for smart health care: Security and privacy issues **I Keshta** Informatics in Medicine Unlocked 30, 100903	2022
66.	Phishing website detection using multilayer perceptron A Odeh, A., **Keshta, I.**, Alhaol, A.I., & Abushakra Journal of Management Information and Decision Sciences (Print ISSN: 1524 …	2022
67.	A Model for Understanding Project Requirements based on CMMI Specifications A Odeh, A El-Hassan, **I Keshta**, T AlHajahjeh 2021 International Conference on Engineering and Emerging Technologies …	2021
68.	Security and privacy of electronic health records: Concerns and challenges **I Keshta**, A Odeh Egyptian Informatics Journal 22 (2), 177-183	2021
69.	PHIBOOST-a novel phishing detection model using Adaptive boosting approach A Odeh, **I Keshta**, E Abdelfattah Jordanian Journal of Computers and Information Technology (JJCIT) 7 (01)	2021
70.	Machine learningtechniquesfor detection of website phishing: A review for promises and challenges A Odeh, **I Keshta**, E Abdelfattah 2021 IEEE 11th Annual Computing and Communication Workshop and Conference …	2021
71.	Developing and Pre-Processing a Dataset using a Rhetorical Relation to Build a Question-Answering System based on an Unsupervised Learning Approach AK Dutta, **IM Keshta**, A Elhalles International Journal of Computer Science & Network Security 21 (11), 199-206	2021
72.	Big data management: Security and privacy concerns I Atoum, **I Keshta** International Journal of Advanced and Applied Sciences 8 (5), 73-83	2021
73.	Efficient prediction of phishing websites using multilayer perceptron (MLP) A Odeh, A Alarbi, **I Keshta**, E Abdelfattah Journal of Theoretical and Applied Information Technology 98 (16), 3353-3363	2020
74.	Efficient detection of phishing websites using multilayer perceptron A Odeh, **I Keshta**, E Abdelfattah International Association of Online Engineering	2020
75.	Towards the implementation of requirements management specific practices (SP 1.1 and SP 1.2) for small-and medium-sized software development organisations **IM Keshta**, M Niazi, M Alshayeb IET Software 14 (3), 308-317	2020
76.	Security and privacy of electronic health records: Concerns and challenges. Egyptian Informatics Journal, 22 (2), 177–183 **I Keshta**, A Odeh	2020

Books

No.	Book Title
1	Aadam Quraishi , Shajeni Justin , **Ismail Keshta** ,Haewon Byeon "INTERPRETABLE AI: TECHNIQUES FOR MAKING MACHINE LEARNING MODELS TRANSPARENT" January 2024
2	Aadam Quraishi , Pinki Nayak, **Ismail Keshta**, T. Saju Raj MACHINE LEARNING FOR NATURAL LANGUAGE PROCESSING: TEXT AND SPEECH ANALYSIS January 2024
3	Nidhi, **Ismail Keshta** , Abhishek Agarwal , Vandana Rathore "QUANTUM COMPUTING FOR BEGINNERS" December 2023
4	Aadam Quraishi , Khair Ul Nisa , Vaibhav Bhatnagar , **Ismail Keshta** "DEEP LEARNING FOR DATA MINING: UNVEILING COMPLEX PATTERNS WITH NEURAL NETWORKS" December 2023
5	Gargishankar Verma , Aadam Quraishi , **Ismail Keshta** , Byeon Haewon "BLOCKCHAIN AND THE INTERNET OF THINGS (IOT): A CONVERGENCE OF TECHNOLOGIES" October 2023
6	Santosh Kumar Sahu, Herison Surbakti, **Ismail Keshta** "Foundation of Data Science Perfect" August 2023
7	Gunawan Widjaja , Niraj Upadhayaya , **Ismail Keshta** , Haewon Byeon "BLOCKCHAIN FUNDAMENTALS CORE AND CONCEPTS AND DECENTRALIZED LEDGER TECHNOLOGY" September 2023
8	Gunawan Widjaja , Dr Seema, **Ismail Keshta**, Haewon Byeon APPLICATIONS BEYOND CRYPTOCURRENCIES - NON-FINANCIAL USE CASES FOR BLOCKCHAIN TECHNOLOGY September 2023
9	Sachin R. Jadhav , Pritam Mondal, **Ismail Keshta**, Haewon Byeon "PRACTICAL MACHINE LEARNING APPLICATIONS" September 2023
10	Sushil Dohare , **Ismail Keshta** , Ashish Kumbhare , Piyush Kumar Thakur "HEALTHCARE SOLUTIONS USING MACHINE LEARNING " January 2023

Management Positions

Chairman of the Examination Committee
Department of Computer Science and Information Systems
AlMaarefa University Riyadh - KSA
2020 - Present

Assistant Head
Department of Computer Science and Information Systems
AlMaarefa University Riyadh - KSA
February 2021 - February 2022

Coordinator of the Quality Unit for the German Accreditation of the Programs
Department of Computer Science and Information Systems
AlMaarefa University Riyadh - KSA
2020 – 2022

Awards

1. Awarded the Shield of Excellence for outstanding contributions to the work and activities of the Department of Computer Science at AlMaarefa University, recognized by the German academic accreditation body ASIIN.
2. Received the Certificate of Excellence in recognition of exceptional efforts in supporting AlMaarefa University's work and activities, leading to the institutional accreditation of the university.

Committees

Member of the Scientific Research Committee, College of Applied Sciences AlMaarefa University Riyadh - KSA	**2018 - 2019**
Member of the Advisory Board of the Information Systems Program Department of Computer Science and Information Systems AlMaarefa University Riyadh - KSA	**2021 - Present**
Member of the Advisory Board of the Computer Science Program Department of Computer Science and Information Systems AlMaarefa University Riyadh - KSA	**2021 - Present**
Member of the Committee of the Master's Program in Cyber Security AlMaarefa University Riyadh - KSA	**2021 - Present**

Languages

Arabic

English

Skills

- Operating Systems: MS Windows, UNIX (Linux).
- Programming: Java, C, C++
- Software's used: LaTeX, MATLAB, Logisim, LogicWorks 4.0

جامعة المعرفة
ALMAAREFA UNIVERSITY

Curriculum Vitae

Name: **Prof.Dr.ASHIT KUMAR DUTTA**

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College of Applied Sciences
Almaarefa University, Riyadh, 11597
Kingdoms of Saudi Arabia
Mobile: 00966558637380
Email: adotta@um.edu.sa

Educational Qualifications: Ph.D.(Computer Science) **MCA(**Master in Computer Applications) **B.E**(Computer Science and Engineering)

- Ph.D. in Computer Science from the "Department of Computer Science", Jamia Hamdard University, in 2006, New Delhi (India)
  Research area: Artificial Intelligence and Searching Technique.
- Master in Computer Application (MCA) from Utkal University.
- B.E (Computer Science and Engineering) From Sarvepalli Radhakrishnan University

Experiences:

(More than 21 years of teaching experience in India, Jordan and Saudi Arabia.)
Currently working as **Professor** in Department of Computer Science and Information Systems, College of Applied Sciences, Almaarefa University, Riyadh, 11597 Kingdom of Saudi Arabia from January 2021 till-date

Associate Professor And Head of Department College of Computing and Information Technology, Department of Computer Science,Shaqra University Saudi Arabia.(From October 2012- August 2019).

Assistant Professor College of Computing and Information Technology, Department of Computer Science,Shaqra University Saudi Arabia.(From September 2009 – September 2012).

Assistant Professor in the Faculty of prince Al-Hussein Bin Abdullah II – for Information Technology, Department of Computer Science and Applications, **Hashemite University** (Government university), Zarka, **Jordan**.(From February 2007 – August 2009).

Honors and Awards:

- Almaarefa University Rector Excellence Award in Artificial Intelligence.
- Best Researcher Award by the Nature Science Foundation 2022 NSF/BRA/083/2022

- Best Patent Award by the Nature Science Foundation 2022 NSF/BRA/085/2022

Institutional and Professional Services.

- Member of the Scientific Research Committee at Almaarefa University from Jun 2021 July 2022.
- Member of the Quality Committee for German Academic Accreditation Azin for the Programs of the Department of Computer Science and Information Systems at Al-Maarefa University , from February 1 2021 December 2021.

Recent Professional Development Activities.

1. Dutta, Ashit Kumar "Tracking Climatic Variations through Smart IoT driven Approach: An Exploratory Analysis" 3rd International Conference on Computing and Communication Networks(ICCCNet-2023) organised by : manchester metropolitan university, united kingdom. 17-18th NOVEMBER, 2023.
2. International Conference "Recent developments in research and teaching towards the united nation sustainable development goal "organized by WASD, united kingdom.
3. Successfully completed course on **Certified Ethical Hacker v11** at an EC Council,USA

Principal Publications from the Past Five Years

1. Dutta, A.K., 2021. Detecting phishing websites using machine learning technique. PloS one, 16(10), p.e0258361.
2. Manickam P, Girija M, Sathish S, Dudekula KV, Dutta AK, Eltahir YA, Zakari NM, Gilkaramenthi R. Billiard based optimization with deep learning driven anomaly detection in internet of things assisted sustainable smart cities. Alexandria Engineering Journal. 2023 Nov 15;83:102-12. (ISI –Web of Science-Q1).
3. Zhong Y, Qin Z, Alqhatani A, Metwally AS, Dutta AK, Rodrigues JJ. Sustainable Environmental Design Using Green IOT with Hybrid Deep Learning and Building Algorithm for Smart City. Journal of Grid Computing. 2023 Dec;21(4):72. (ISI –Web of Science-Q1).
4. Alabdulkreem E, Alruwais N, Mahgoub H, Dutta AK, Khalid M, Marzouk R, Motwakel A, Drar S. Sustainable groundwater management using stacked LSTM with deep neural network. Urban Climate. 2023 May 1;49:101469. (ISI –Web of Science-Q1).

Funded Research Projects and Patents from the Past Five Years

1. Co-PI in a project proposal titled entitled "Stroke identification and Rehabilitation" reference no KSRG-2022-064 approved by King Salman Center for Disability Research for funding.
2. PI in a project entitled entitled "Developing and pre-processing a dataset using a rhetorical relation to build a Question-Answering system based on an unsupervised learning approach" completed by Almaarefa University
3. AI Based Camera For Healthcare Monitoring Intellectual Property Office, GB, Design number: 6319810

PROF.DR. ASHIT KUMAR DUTTA

ALMAAREFA UNIVERSITY,SAUDI ARABIA

Arificial Intelligence
Machine Learning
Deep Learning
Internet of Things
Cyber Security

	All	Since 2019
Citations	1186	1035
h-index	17	15
i10-index	24	22

1 article 1 article

not available available

Based on funding mandates

TITLE	CITED BY	YEAR
Hybrid Sine-Cosine Chimp optimization based feature selection with deep learning model for threat detection in IoT sensor networks MA Alkhonaini, A Al Mazroa, M Aljebreen, SBH Hassine, R Allafi, ... Alexandria Engineering Journal 102, 169-178		2024
Enhancing privacy and security in IoT-based smart grid system using encryption-based fog computing S Rani, M Shabaz, AK Dutta, EA Ahmed Alexandria Engineering Journal 102, 66-74		2024
Waste-to-energy poly-generation scheme for hydrogen/freshwater/power/oxygen/heating capacity production; optimized by regression machine learning algorithms S Li, Y Leng, AM Abed, AK Dutta, O Ganiyeva, Y Fouad Process Safety and Environmental Protection 187, 876-891		2024
Modeling of traffic at a road crossing and optimization of waiting time of the vehicles SC Dimri, R Indu, M Bajaj, RS Rathore, V Blazek, AK Dutta, S Alsubai Alexandria Engineering Journal 98, 114-129		2024
Intellectual Assessment of Amyotrophic Lateral Sclerosis Using Deep Resemble Forward Neural Network A Alqahtani, S Alsubai, M Sha, AK Dutta, YD Zhang Neural Networks, 106478		2024
Bio-inspired Deep Learning-Personalized Ensemble Alzheimer's Diagnosis Model for Mental Well-being A Kiran, M Alsaadi, AK Dutta, M Raparthi, M Soni, S Alsubai, H Byeon, ... SLAS Technology, 100161		2024
Hybrid Feature Extraction Technique-based Alzheimer's Disease Detection Model Using MRI Images HS Al-Rawashdeh, A Usman, AK Dutta, ARW Sait Journal of Disability Research 3 (6), 20240073		2024
Brain-Computer Interfaces Inspired Spiking Neural Network Model for Depression Stage Identification MA Ponrani, M Anand, M Alsaadi, AK Dutta, R Fayaz, S Mathew, ... Journal of Neuroscience Methods, 110203		2024

TITLE	CITED BY	YEAR
Trusted Personalized and Contextualized E-Commerce Services for Consumer Electronics over Wireless Sensor Network AA Deshmukh, M Alsaadi, RV Pamba, A Suri, R Khan, AK Dutta, ... IEEE Transactions on Consumer Electronics		2024
Ensemble Learning-based Alzheimer's Disease Diagnosis Using Magnetic Resonance Imaging HS Al-Rawashdeh, A Usman, AK Dutta, AR Wahab Sait Journal of Disability Research 3 (6), 20240067		2024
A Systematic Review of Genetics-and Molecular-Pathway-Based Machine Learning Models for Neurological Disorder Diagnosis NA Aljarallah, AK Dutta, ARW Sait International Journal of Molecular Sciences 25 (12), 6422		2024
Sustainable Freshwater/Energy Supply through Geothermal-Centered Layout Tailored with Humidification-Dehumidification Desalination Unit; Optimized by Regression Machine … S Li, Y Leng, R Chaturvedi, AK Dutta, BS Abdullaeva, Y Fouad Energy, 131919		2024
Artificial intelligence based virtual assistant for hospital management S Alsubai, A Alqahtani, A Alanazi, AK Dutta US Patent App. 18/437,577		2024
Ensemble Learning-based Brain Stroke Prediction Model Using Magnetic Resonance Imaging AW Abulfaraj, AK Dutta, ARW Sait Journal of Disability Research 3 (5), 20240061		2024
Feature fusion-based food protein subcellular prediction for drug composition H Byeon, M Shabaz, JVN Ramesh, AK Dutta, R Vijay, M Soni, JC Patni, ... Food Chemistry, 139747	20	2024
Feature Fusion-based Brain Stroke Identification Model Using Computed Tomography Images AW Abulfaraj, AK Dutta, ARW Sait Journal of Disability Research 3 (5), 20240060		2024
Trailblazing ASD Behavioral Research: Leveraging Modified MLP with Cross-Weighted Attention Mechanism at the Forefront M Sha, A Alqahtani, S Alsubai, AK Dutta Journal of Disability Research 3 (4), 20240053		2024
Empowering Cybersecurity Using Enhanced Rat Swarm Optimization with Deep Stack-Based Ensemble Learning Approach P Manickam, M Girija, AK Dutta, PR Babu, K Arora, MK Jeong, S Acharya IEEE Access		2024
Design of Artificial Intelligence Driven Crowd Density Analysis for Sustainable Smart Cities S Alsubai, AK Dutta, F Alghayadh, BH Alamer, RM Pattanayak, ...		2024

TITLE	CITED BY	YEAR
IEEE Access		
Optimizing User Association, Power Control and Beamforming for 6G Multi-IRS Multi-UAV NOMA Communications in Smart Cities N Sehito, Y Shouyi, HM Alshahrani, M Alamgeer, AK Dutta, S Alsubai, ... IEEE Transactions on Consumer Electronics		2024
Federated-Reinforcement Learning-Assisted IoT Consumers System for Kidney Disease Images MA Mohammed, A Lakhan, KH Abdulkareem, M Deveci, AK Dutta, ... IEEE Transactions on Consumer Electronics	1	2024
Developing a Pain Identification Model Using a Deep Learning Technique AR Wahab Sait, AK Dutta Journal of Disability Research 3 (3), 20240028		2024
Brain tumor segmentation using neuro-technology enabled intelligence-cascaded U-Net model H Byeon, M Al-Kubaisi, AK Dutta, F Alghayadh, M Soni, M Bhende, ... Frontiers in Computational Neuroscience 18, 1391025	1	2024
A Fine-Tuned CatBoost-Based Speech Disorder Detection Model AK Dutta, AR Wahab Sait Journal of Disability Research 3 (3), 20240027	1	2024
A Speech Disorder Detection Model Using Ensemble Learning Approach AK Dutta, AR Wahab Sait Journal of Disability Research 3 (3), 20240026		2024
Thermo-environmental multi-investigation and ANN-based optimization of a novel heat integration criteria system integrated with a marine engine generating liquefied hydrogen TUK Nutakki, MA Alghassab, AK Dutta, BS Abdullaeva, S Alkhalaf, ... Case Studies in Thermal Engineering 56, 104240		2024
Ensemble Learning-Based Pain Intensity Identification Model Using Facial Expressions AR Wahab Sait, AK Dutta Journal of Disability Research 3 (3), 20240029		2024
Deep learning-based multi-head self-attention model for human epilepsy identification from EEG signal for biomedical traits AK Dutta, M Raparthi, M Alsaadi, MW Bhatt, SB Dodda, M Sandhu, ... Multimedia Tools and Applications, 1-23	41	2024
A Systematic Review on Developing Computer Programming Skills for Visually Impaired Students NA Aljarallah, AK Dutta Journal of Disability Research 3 (2), 20240018		2024
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IEEE Access		
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Enhanced slime mould optimization with convolutional BLSTM autoencoder based malware classification in intelligent systems S Alsubai, AK Dutta, A Rahaman Wahab Sait, YAA Jaish, BH Alamer, ... Expert Systems, e13557		2024
Artificial Intelligence-driven Remote Monitoring Model for Physical Rehabilitation M Jleli, B Samet, AK Dutta Journal of Disability Research 3 (1), 20230065		2024
Battery-Based Energy Storage and Solar Technologies Integrated for Power Matching and Quality Improvement Using Artificial Intelligence AK Dutta, L Bharathi Krishna, K Rayudu, D Vedhagiri, NR Medikondu, ... Electric Power Components and Systems 52 (2), 322-336	2	2024
Investigating the role of internet-based educational application in the dental sciences SA Alsaleh, AS Alzawawi, AA Alzuhair, SA Kalagi, EM Al-Madi, AK Dutta Heliyon 10 (1)		2024
Convergence results for cyclic-orbital contraction in a more generalized setting with application H Ahmad, S Shahab, WFM Mobarak, AK Dutta, YM Abolelmagd, ... AIMS Mathematics 9 (6), 15543-15558		2024
Gamified approach towards optimizing supplier selection through Pythagorean Fuzzy soft-max aggregation operators for healthcare applications S Shahab, M Anjum, AK Dutta, S Ahmad AIMS Mathematics 9 (3), 6738-6771		2024
Detecting cardiovascular diseases from radiographic images using deep learning techniques MAAK Dutta Expert Systems, 17		2024
An Innovative Approach Using TKN-Cryptology for Identifying the Replay Assault SW Zahra, M Nadeem, A Arshad, S Riaz, MA Bakr, AK Dutta, Z Alzaid, ... Computers, Materials & Continua 78 (1)		2024
Tree Seed Algorithm-based Feature Selection with Optimal Deep Learning Model for Supply Chain Management JS Alzahrani, M Maashi, HM Alshahrani, AQA Hassan, J Khan, AK Dutta, ... Fluctuation and Noise Letters 23 (2), 2440019-170		2024

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Dynamic resource management in integrated NOMA terrestrial–satellite networks using multi-agent reinforcement learning A Nauman, HM Alshahrani, N Nemri, KM Othman, NO Aljehane, ... Journal of Network and Computer Applications 221, 103770	1	2024
Modified Meta Heuristic BAT with ML Classifiers for Detection of Autism Spectrum Disorder M Sha, A Alqahtani, S Alsubai, AK Dutta Biomolecules 14 (1), 48	1	2023
Sustainable Environmental Design Using Green IOT with Hybrid Deep Learning and Building Algorithm for Smart City Y Zhong, Z Qin, A Alqhatani, ASM Metwally, AK Dutta, JJPC Rodrigues Journal of Grid Computing 21 (4), 72	1	2023
Empowering smart cities: High-altitude platforms based Mobile Edge Computing and Wireless Power Transfer for efficient IoT data processing A Nauman, N Alruwais, E Alabdulkreem, N Nemri, NO Aljehane, AK Dutta, ... Internet of Things 24, 100986	6	2023
Billiard based optimization with deep learning driven anomaly detection in internet of things assisted sustainable smart cities P Manickam, M Girija, S Sathish, KV Dudekula, AK Dutta, YAM Eltahir, ... Alexandria Engineering Journal 83, 102-112	3	2023
Predicting Functional Recovery of Stroke Rehabilitation Using a Deep Learning Technique N Ali Aljarallah, AK Dutta, AR Wahab Sait, AKM Alanaz, RA Absi Journal of Disability Research 2 (3), 60-69	1	2023
Scaled Conjugate-Artificial Neural Network-Based novel framework for enhancing the power quality of Grid-Tied Microgrid systems GK Sahoo, S Choudhury, RS Rathore, M Bajaj, AK Dutta Alexandria Engineering Journal 80, 520-541	12	2023
Smart urban planning: Intelligent cognitive analysis of healthcare data in cloud-based IoT Z Gong, J Ji, P Tong, ASM Metwally, AK Dutta, JJPC Rodrigues, ... Computers and Electrical Engineering 110, 108878	4	2023
An efficient hybrid approach for optimization using simulated annealing and grasshopper algorithm for IoT applications F Sajjad, M Rashid, A Zafar, K Zafar, B Fida, A Arshad, S Riaz, AK Dutta, ... Discover Internet of Things 3 (1), 7	4	2023
Automated red palm weevil detection using gorilla troops optimizer with deep learning model AA Albraikan, M Khalid, N Alruwais, T Hasanin, AK Dutta, H Mohsen, ... IEEE Access	2	2023
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Artificial intelligence-driven malware detection framework for internet of things environment S Alsubai, AK Dutta, AM Alnajim, R Ayub, AM AlShehri, N Ahmad PeerJ Computer Science 9, e1366	2	2023
SCREENING OF AGGLUTINATION ACTIVITIES OF COMMON VEGETABLES IN BANGLADESH R Mitra, R Rouf, AK Dutta, JA Shilpi, SJ Uddin Khulna University Studies, 62-71		2023
Hybrid deep learning with improved Salp swarm optimization based multi-class grape disease classification model S Alsubai, AK Dutta, AH Alkhayyat, MM Jaber, AH Abbas, A Kumar Computers and Electrical Engineering 108, 108733	25	2023
Hill Matrix and Radix-64 Bit Algorithm to Preserve Data Confidentiality. A Arshad, M Nadeem, S Riaz, SW Zahra, AK Dutta, Z Alzaid, R Alabdan, ... Computers, Materials & Continua 75 (2)	1	2023
An automated hyperparameter tuned deep learning model enabled facial emotion recognition for autonomous vehicle drivers DK Jain, AK Dutta, E Verdú, S Alsubai, ARW Sait Image and Vision Computing 133, 104659	20	2023
Sustainable groundwater management using stacked LSTM with deep neural network E Alabdulkreem, N Alruwais, H Mahgoub, AK Dutta, M Khalid, R Marzouk, ... Urban Climate 49, 101469	10	2023
Internet of agents system for age and gender classification using grasshopper optimization with deep convolution neural networks AK Dutta, B Qureshi, Y Albagory, M Alsanea, D Gupta, A Khanna Expert Systems 40 (4), e13115		2023
Sailfish Optimizer with EfficientNet Model for Apple Leaf Disease Detection. MM Alqahtani, AK Dutta, S Almotairi, M Ilayaraja, AA Albraikan, ... Computers, Materials & Continua 75 (1)	8	2023
A systemic review on medicinal plants and their bioactive constituents against avian influenza and further confirmation through in-silico analysis AK Dutta, MS Gazi, SJ Uddin Heliyon	3	2023
Colliding Bodies Optimization with Machine Learning Based Parkinson's Disease Diagnosis. AK Dutta, N Zakari, Y Albagory, ARW Sait Computer Systems Science & Engineering 44 (3)	6	2023
Cat and Mouse Optimizer with Artificial Intelligence Enabled Biomedical Data Classification.	2	2023

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B Kalpana, S Dhanasekaran, T Abirami, AK Dutta, MI Obayya, ... Comput. Syst. Sci. Eng. 44 (3), 2243-2257		
An Optimization Approach for Convolutional Neural Network Using Non-Dominated Sorted Genetic Algorithm-II. A Zafar, M Aamir, NM Nawi, A Arshad, S Riaz, A Alruban, AK Dutta, ... Computers, Materials & Continua 74 (3)	1	2023
Optimal Weighted Extreme Learning Machine for Cybersecurity Fake News Classification. AK Dutta, B Qureshi, Y Albagory, M Alsanea, M Al Faraj, ARW Sait Computer Systems Science & Engineering 44 (3)	8	2023
Ensemble Deep Learning with Chimp Optimization Based Medical Data Classification. AK Dutta, Y Albagory, M Alsanea, HI Almohammed, AR Wahab Sait Intelligent Automation & Soft Computing 35 (2)	1	2023
An Efficient Technique to Prevent Data Misuse with Matrix Cipher Encryption Algorithms. M Nadeem, A Arshad, S Riaz, SW Zahra, AK Dutta, M Al Moteri, ... Computers, Materials & Continua 74 (2)	8	2023
Intelligent Smart Grid Stability Predictive Model for Cyber-Physical Energy Systems. AK Dutta, M Al Faraj, Y Albagory, ARW Sait Computer Systems Science & Engineering 44 (2)	2	2023
ANTIBIOTIC SENSITIVITY TEST OF GRAM NEGATIVE BACTERIAL ISOLATES FROM MEDICAL AND SURGICAL INTENSIVE CARE UNIT AT TERTIARY CARE HOSPITAL MS Alam, SK Mehi, R Kumar, A Kumar Int J Acad Med Pharm 5 (3), 548-551		2023
A Study On Catheter Associated Urinary Tract Infections (Cauti) In A Tertiary Care Hospital Of Bihar AA Hassan, R Kumar, A Kumar, A Kumar Int J Acad Med Pharm 5 (3), 68-71	1	2023
Discover Internet of Things F Sajjad, M Rashid, A Zafar, K Zafar, B Fida, A Arshad, S Riaz, AK Dutta, ...		2023
THROMBOCYTOSIS AND ITS EFFECT ON MORBIDITY AND MORTALITY IN CHILDREN OF 2 MONTHS TO 5 YEARS WITH PNEUMONIA M Priyadarshi, N Kumar, D Kumar, A Kumar, AK Bharti, KS Nath, ... Int J Acad Med Pharm 5 (3), 814-817		2023
ROLE OF NEUROIMAGING IN PRETERM INFANTS TO PREDICT NEUROLOGICAL OUTCOMES N Kumar, D Kumar, M Priyadarshi, A Kumar, AK Bharti, KS Nath, ... Int J Acad Med Pharm 5 (3), 660-663		2023

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LEVEL OF SERUM IRON AND ZINC IN CHILDREN AND ASSESSING ITS CORRELATION WITH SIMPLE FEBRILE SEIZURE-A PROSPECTIVE OBSERVATIONAL STUDY D Kumar, M Priyadarshi, N Kumar, A Kumar, RP Bharti, A Kumar, ... Int J Acad Med Pharm 5 (3), 818-822	1	2023
CORRELATION OF OAE WITH NEUROIMAGING IN ASPHYXIATED NEWBORN A Riyaz, KS Nath, AK Bharti, A Kumar, M Saleem, S Nandan, GS Ahmad Int J Acad Med Pharm 5 (2), 1104-1107		2023
CORRELATION OF ACUTE KIDNEY INJURY IN NEONATES OF PERINATAL ASPHYXIA WITH AND WITHOUT SHOCK MZ Ashrafi, K Shambhunath, A Kumar, A Riyaz Int J Acad Med Pharm 5 (2), 49-52		2023
Methodical Systematic Review of Abstractive Summarization and Natural Language Processing Models for Biomedical Health Informatics: Approaches, Metrics and Challenges PK Katwe, A Khamparia, D Gupta, AK Dutta ACM Transactions on Asian and Low-Resource Language Information Processing	3	2023
Developing a Deep-Learning-Based Coronary Artery Disease Detection Technique Using Computer Tomography Images AKD Abdul Rahaman Wahab Sait diagnostics 13 (7)	7	2023
Optimal Deep Belief Network Enabled Cybersecurity Phishing Email Classification. AK Dutta, T Meyyappan, B Qureshi, M Alsanea, AW Abulfaraj, M Al Faraj, ... Comput. Syst. Sci. Eng. 44 (3), 2701-2713	1	2023
Optimal Machine Learning Enabled Performance Monitoring for Learning Management Systems. AK Dutta, MM Alqahtani, Y Albagory, ARW Sait, M Alsanea Comput. Syst. Sci. Eng. 44 (3), 2277-2292		2023
Cat Swarm with Fuzzy Cognitive Maps for Automated Soil Classification. AK Dutta, Y Albagory, M Al Faraj, M Alsanea, ARW Sait Comput. Syst. Sci. Eng. 44 (2), 1419-1432	7	2023
Intelligent Student Mental Health Assessment Model on Learning Management System. NA Aljarallah, AK Dutta, M Alsanea, ARW Sait Comput. Syst. Sci. Eng. 44 (2), 1853-1868	7	2023
Optimal Sparse Autoencoder Based Sleep Stage Classification Using Biomedical Signals. AK Dutta, Y Albagory, M Al Faraj, YAM Eltahir, ARW Sait Comput. Syst. Sci. Eng. 44 (2), 1517-1529		2023

TITLE	CITED BY	YEAR
Fuzzy with Metaheuristics Based Routing for Clustered Wireless Sensor Networks. AK Dutta, Y Albagory, M Alsanea, AR Wahab Sait, HS AlRawashdeh Intelligent Automation & Soft Computing 35 (1)	2	2023
Development of Security Rules and Mechanisms to Protect Data from Assaults SW Zahra, A Arshad, M Nadeem, S Riaz, AK Dutta, Z Alzaid, R Alabdan, ... Applied Sciences 12 (24), 12578	6	2022
Chaotic Krill Herd with Fuzzy Based Routing Protocol for Wireless Networks. AK Dutta, Y Albagory, FM Obesat, AW Abulfaraj Intelligent Automation & Soft Computing 34 (3)		2022
A generalized laser simulator algorithm for mobile robot path planning with obstacle avoidance A Muhammad, MAH Ali, S Turaev, R Abdulghafor, IH Shanono, Z Alzaid, ... Sensors 22 (21), 8177	3	2022
Building construction based on video surveillance and deep reinforcement learning using smart grid power system KM Alhamed, C Iwendi, AK Dutta, B Almutairi, H Alsaghier, S Almotairi Computers and Electrical Engineering 103, 108273	11	2022
Bird Swarm Algorithm with Fuzzy Min-Max Neural Network for Financial Crisis Prediction. K Kumar, S Dhanasekaran, IS Punithavathi, P Duraipandy, AK Dutta, ... Computers, Materials & Continua 73 (1)	2	2022
Deep Learning Enabled Disease Diagnosis for Secure Internet of Medical Things. S Ahmad, S Khan, MF AlAjmi, AK Dutta, LM Dang, GP Joshi, H Moon Computers, Materials & Continua 73 (1)	29	2022
Detecting Lung Cancer Using Machine Learning Techniques AK Dutta Intelligent Automation & Soft Computing 31 (No.2), 18	9	2022
Two-Layer Security Algorithms to Prevent Attacks on Data in Cyberspace M Nadeem, A Arshad, S Riaz, SW Zahra, AK Dutta, A Alruban, B Almutairi, ... Applied Sciences 12 (19), 9736	4	2022
Intelligent rider optimization algorithm with deep learning enabled hyperspectral remote sensing imaging classification AK Dutta, M Alsanea, B Qureshi, FY Alghayadh, ARW Sait Canadian Journal of Remote Sensing 48 (5), 649-662	4	2022
A comparison of pooling methods for convolutional neural networks A Zafar, M Aamir, N Mohd Nawi, A Arshad, S Riaz, A Alruban, AK Dutta, ... Applied Sciences 12 (17), 8643	127	2022
A secure architecture to protect the network from replay attacks during client-to-client data transmission	5	2022

TITLE	CITED BY	YEAR
M Nadeem, A Arshad, S Riaz, SW Zahra, AK Dutta, S Almotairi Applied Sciences 12 (16), 8143		
Intelligent Feature Selection with Deep Learning Based Financial Risk Assessment Model. T Vaiyapuri, K Priyadarshini, A Hemlathadhevi, M Dhamodaran, AK Dutta, ... Computers, Materials & Continua 72 (2)	7	2022
Preventing the Cloud Networks through Semi-Supervised Clustering from Both Sides Attacks M Nadeem, A Arshad, S Riaz, SW Zahra, AK Dutta, S Almotairi Applied Sciences 12 (15), 7701	6	2022
An automated hyperparameter tuning recurrent neural network model for fruit classification K Shankar, S Kumar, AK Dutta, A Alkhayyat, AJM Jawad, AH Abbas, ... Mathematics 10 (13), 2358	25	2022
Hybrid Deep Learning Enabled Air Pollution Monitoring in ITS Environment. AK Dutta, J Sampson, S Ahmad, T Avudaiappan, K Narayanasamy, ... Computers, Materials & Continua 72 (1)	6	2022
Chaotic sparrow search algorithm with deep transfer learning enabled breast cancer classification on histopathological images K Shankar, AK Dutta, S Kumar, GP Joshi, IC Doo Cancers 14 (11), 2770	19	2022
Oppositional chaos game optimization based clustering with trust based data transmission protocol for intelligent IoT edge systems M Padmaa, T Jayasankar, S Venkatraman, AK Dutta, D Gupta, ... Journal of Parallel and Distributed Computing 164, 142-151	15	2022

ALMAAREFA UNIVERSITY

Dr. Mohammed M. Al Gabri

Assistant Professor, Department of computer science and information systems, College of Applied Sciences, AlMaarefa University

Education

Degree	***Field***	***Institution***	***Year***
PhD	Computer Science	King Saud University	2022
MS	Computer Science	King Saud University	2014
BS	Computer Science	Umm Al-Qura University	2009

Experience

From	*To*	*Institution*	*Rank*
2022	Present	AlMaarefa University	Assist. Prof.
2019	2022	King Saud University	*Lecturer (Part-time)*
2015	2022	King Saud University	Researcher.

Honors and Awards

1. Winning Third Place in Innovation in E-learning (Faculty members track), Global Trends in E-Learning (GTEL) 2023, Saudi Electronic University.

Institutional and Professional Services *(administration, committees, units, etc.)*

1. Head of the Quality Committee in the Department of Computer Science and Information Systems, AlMaarefa University, 2022-present
2. Member of the University President's Excellence Committee, AlMaarefa University, 2022-present
3. Member of the Innovation and Entrepreneurship Committee, AlMaarefa University, 2022-present
4. Member of the Graduation Projects Committee, AlMaarefa University, 2022-present
5. Member of the Preparing students for standardized exams Committee, AlMaarefa University, 2022-present
6. Member of the E-Learning Committee in the College of Applied Sciences, AlMaarefa University, 2022-present
7. Member of the Technical and Administrative Committee for the Humanitarian Work and Sustainable Development Hackathon accompanying the Third Riyadh Humanitarian Forum 2023, organized by the King Salman Humanitarian Aid and Relief Center.
8. Member of the Scientific Committee for the AlMaarefa Hackathon for Health Innovation 2023, held at AlMaarefa University.

Recent Professional Development Activities *(Workshops, training, etc.)*

1. Participation in a Self-Study Report (SSR) Workshop, held by Almaarefa University's Quality Center, 2024.
2. Presenting a workshop entitled :"Computer-Aided Pronunciation Training System for Non-Naïve learners of the Arabic Language", NPST-KSU, 2023.
3. Presenting a workshop entitled :"Generative AI and its applications", Almaarefa University, 2023.
4. Participation in the 3rd International Conference on Computing and Information Technology, 2023 ICCIT, University of Tabuk [Type of participation: paper presentation]
5. Participation in the Sixth International Traffic Safety Forum and Exhibition- Artificial intelligence and big data for transportation and traffic safety, December 2023 [Type of participation: poster presentation]
6. Presenting a training course entitled :"Programming with C#", King Saud University, 2023.
7. Presenting a training course entitled: "Artificial Intelligence and its Applications in the Healthcare", Almaarefa University, 2022.
8. Presenting a workshop entitled: "End-to-End deep learning based automatic speech recognition system using NEMO", KCST Kuwait College of Science and Technology, 2022.
9. Member of the Team that participated in MCIT challenge "Our hearts hear you", and was among the top ten selected teams, Ministry of Communications and Information Technology, December 23, 2019.
10. Attended the conference "Teaching Holy Quran to people with disabilities" King Fahd Glorious Qur'an Printing Complex, Almadinah Al-Munawwrah, October 1-3, 2019.
11. Participation as a mentor at MIT Hacking Medicine (Virtual Care and Telemedicine Track), Princess Noura University, Riyadh, November 29 - December 1, 2018.

Principal Publications from the Past Five Years

1. Faisal, Mohammed, Mansour Alsulaiman, Mohamed Mekhtiche, Bencherif Mohamed Abdelkader, Mohammed Algabri, Tariq Bin Saleh Alrayes, Ghulam Muhammad et al. "Enabling Two-Way Communication of Deaf Using Saudi Sign Language." IEEE Access 11 (2023): 135423-135434.
2. Alsulaiman, M., Algabri, M., Mathkour, H., Bencherif, M.A., Muhammad, G., Al-Gahtani, S., Faisal, M., Mekhtiche, M.A. and Alfakih, T., 2023, September. Development and Analysis of a Versatile Dataset of Speech, Real and Synthesized, of Arabic Learners. In 2023 3rd International Conference on Computing and Information Technology (ICCIT) (pp. 155-159). IEEE.
3. Algabri, M., Mathkour, H., Alsulaiman, M., & Bencherif, M. A. (2022). Mispronunciation detection and diagnosis with articulatory-level feedback generation for non-native arabic speech. Mathematics, 10(15), 2727.
4. Al-Hammadi, M., Bencherif, M.A., Alsulaiman, M., Muhammad, G., Mekhtiche, M.A., Abdul, W., Alohali, Y.A., Alrayes, T.S., Mathkour, H., Faisal, M. and Algabri, M., 2022. Spatial attention-based 3d graph convolutional neural network for sign language recognition. Sensors, 22(12), p.4558.
5. Musallam, Y.K., AlFassam, N.I., Muhammad, G., Amin, S.U., Alsulaiman, M., Abdul, W., Altaheri, H., Bencherif, M.A. and Algabri, M., 2021. Electroencephalography-based motor imagery classification using temporal convolutional network fusion. Biomedical Signal Processing and Control, 69, p.102826.
6. Al-Qershi, F., Al-Qurishi, M., Aksoy, M.S., Faisal, M. and Algabri, M., 2021. A time-series-based new behavior trace model for crowd workers that ensures quality annotation. Sensors, 21(15), p.5007.
7. Faisal, M., Albogamy, F., ElGibreen, H., Algabri, M., Alvi, S.A.M. and Alsulaiman, M., 2021. COVID-19 Diagnosis Using Transfer-Learning Techniques. Intelligent Automation & Soft Computing, 29(3).
8. Elgibreen, H., Faisal, M., Al Sulaiman, M., Abdou, S., Mekhtiche, M.A., Moussa, A.M., Alohali, Y.A., Abdul, W., Muhammad, G., Rashwan, M. and Algabri, M., 2021. An incremental approach to corpus design and construction: application to a large contemporary saudi corpus. IEEE Access, 9, pp.88405-88428.
9. Bencherif, M.A., Algabri, M., Mekhtiche, M.A., Faisal, M., Alsulaman, M., Mathkour, H., Al-Hammadi, M. and Ghaleb, H., 2021. Arabic sign language recognition system using 2D hands and body skeleton data. IEEE Access, 9, pp.59612-59627.
10. Algabri, M., Mathkour, H., Alsulaiman, M.M. and Bencherif, M.A., 2021. Deep learning-based detection of articulatory features in arabic and english speech. Sensors, 21(4), p.1205.
11. Faisal, M., Albogamy, F., Elgibreen, H., Algabri, M. and Alqershi, F.A., 2020. Deep learning and computer vision for estimating date fruits type, maturity level, and weight. IEEE Access, 8, pp.206770-206782.
12. Algabri, M., Mathkour, H., Bencherif, M.A., Alsulaiman, M. and Mekhtiche, M.A., 2020. Towards deep object detection techniques for phoneme recognition. IEEE Access, 8, pp.54663-54680.

Funded Research Projects and Patents from the Past Five Years

Patents:

1. "Robotic system for harvesting and maintaining date palms", U.S. Patent No. US 11910751B1. Granted at February 27, 2024.
2. "Tree harvesting tool", U.S. Patent No. US10485171B1. Granted at November 26, 2019

Funded Research Projects:

1. Research Project #:3-17-09-001-0003 "Computer-Aided Pronunciation Training System for Non-native Learners of the Arabic Language", Sponsored by NPST-KSU, 2020-2022.
2. Research Project #:5-18-03-001-0003 "Saudi Sign Language Translation Companion System", Sponsored by NPST-KSU, 2020-2022.
3. Research Project: "A Framework for Arabic Media Mining and Information Extraction Using Continuous Domain Semantic Representation", Sponsored by Ministry of Education, 2020-2023.

جامعة المعرفة
ALMAAREFA UNIVERSITY

DR. Nasriah Zakaria

Associate Professor, Department of computer science and information systems, College of Applied Sciences, AlMaarefa University

Education

Degree	*Field*	*Institution*	*Year*
PhD	Information Science and Technology	Syracuse University, NY	2006
MS	Biomedical Engineering	Rensselaer Polytechnic Institute, NY	2002
BS	Biomedical Engineering	Rensselaer Polytechnic Institute, NY	1997

Experience

From	*To*	*Institution*	*Rank*
2023	Present	Al Maarefa University	Assoc. Prof.
2021	2022	University of Malaya	Assoc. Prof.
2012	2020	King Saud University	Assist. Prof

Honors and Awards

1. Adjunct Professor, Faculty of Medicine, University of Malaya, May 2023- Present

Institutional and Professional Services *(administration, committees, units, etc.)*

1. Health Information System coordinator, AlMaarefa University, 2023-present
2. Master of Digital Health Committee, University of Malaya, 2021-present
3. Deputy Head, Medical Informatics and E-learning Unit, Medical Education Department, College of Medicine, King Saud University, 2012-2020

Recent Professional Development Activities *(Workshops, training, etc.)*

1. Data Documentation and Management to enhance patient quality of care, Ministry of Health, Saudi Arabia, November 5-8, 2023 [Speaker]

Principal Publications from the Past Five Years

1. AlFaris, E., Irfan, F., Abouammoh, N. Zakaria, N, Abdullah MA Ahmed, Kasule, O., Aldosari, D.M., AlSahli, N.A., Alshibani. M.G., Ponnaperuma, G. (2023). Physicians' professionalism from the patients' perspective: a qualitative study at a single-family practice in Saudi Arabia. BMC Med Ethics 24, 39. https://doi.org/10.1186/s12910-023-00918-9 (SCI Impact factor 2.7) (Q1).

2. Dhamanti, I., Juliasih, N. N., Semita, I. N., Zakaria, N., Guo, H. R., & Sholikhah, V. (2023). Health Workers' Perspective on Patient Safety Incident Disclosure in Indonesian Hospitals: A Mixed-Methods Study. Journal of Multidisciplinary Healthcare, *16*, 1337-1348. https://doi.org/10.2147/JMDH.S412327. (SCI Impact factor 3.3) (Q2).

3. Zakaria N., Zakaria N., Alnobani O., AlMalki M., El-Hassan O., Alhefzi M.I., Househ M., Jamal A. Unlocking the eHealth professionals' career pathways: A case of Gulf Cooperation Council countries. Int J Med Inform. 2022 Nov 11; 170:104914 (SCI Impact factor 3.210) (Q1).

4. Alnobani, O. Zakaria, N., Temsah M.H., Alkamel N.,Jamal, A. Tharkar S. (2021).Knowledge, attitude and perception of healthcare personnel working in intensive care units of mass gatherings toward the application telemedicine-robotic remote presence of technology: a cross-sectional multicenter study.Telemedicine Journal and e-health.(SCI Impact factor 5.428) (Q1).

5. Albarrak, A.I, Zakaria N., Almulhem J., Khan S., Abdul Karim N. (2021). Modified team-based and blended learning perception: a cohort study among medical students at King Saud University. BMC Medical Education, 21, 199. (SCI Impact factor 1.831) (Q1).
6. Mohd Salleh M.I., Abdullah R., Zakaria N. (2021).Evaluating the effects of electronic medical record systems adoption on the performance of Malaysian health care providers. *BMC Med Inform Decis Mak* 21:75. (SCI Impact factor 2.067) (Q1).

7. Jamal A., Aldawsari S., Almufawez K., Barri R., Zakaria N., Tharkar S. (2020) Twitter as a promising microblogging application for psychiatric consultation - Understanding the predictors of use, satisfaction and e-health literacy. Int J Med Inform.Sep;141:104202. (SCI Impact factor 3.210) (Q1).

8. Alkamel N., Jamal A., Alnobani O., Househ M., Zakaria N., Qawamseh M., Tharkar S.(2020). Understanding the stakeholders' preferences on a mobile application to reduce door to balloon time in the management of ST-elevated myocardial infarction patients – a qualitative study. *BMC Med Inform Decis Mak* 20, 205 (SCI Impact factor 2.067) (Q1).

9. Wahabi H.A., Zakaria N. (2020). Building capacity of evidence-based public health practice at King Saud University: perceived challenges and opportunities. Journal of Public Health Management and Practice. (SCI Impact factor 1.420) (Q1).

10. Zakaria N., Wahabi H.A., AlQahtani M. (2020). Development and Usability Testing of Riyadh Mother and Baby Multi-Center Cohort Study Registry. Journal of Infection and Public Health. (SCI Impact factor 2.487) (Q1).

11. Wahabi H.A., Esmaeil S.A, Bahkali K.H., Titi M.A., Amer Y.S.; Fayed A.A., Jamal A., Zakaria N., Siddiqui A.R., Semwal M., Car L.T., Posadzki P., Carr,J. (2019) Medical Doctors' Offline Computer-Assisted Digital Education: Systematic Review by the Digital Health Education Collaboration. Journal of Medical Internet Research (SCI Impact factor 4.945) (Q1).

12. Zakaria N., Fakhri O., Alzahrani A.,Matbuli A., Arab N., Madani A., AlShehri N., Albarrak A. Development of a Saudi e-Health Literacy scale (SeHL) for non-communicable diseases (NCD) in Saudi Arabia: Using Integrated Health Literacy Dimensions. International Journal for Quality in Healthcare. 2018 (SCI Impact factor 1.829) (Q3)

Funded Research Projects and Patents from the Past Five Years

1. Al Maarefa University Internal Grant, SAR 50,000, "Mental Health Literacy among Adolescents using Reusable Learning Object: A cross-comparison study Saudi Arabia and Malaysia" 2023-2024 [Principal Investigator]