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Exploring Emotional Intelligence in Jordan's Artificial Intelligence (AI) Healthcare Adoption: A UTAUT Framework

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Abstract: **-** The integration of Artificial Intelligence (AI) has been reshaping healthcare globally. However, the AI adoption in Jordan is met with cautious progress. AI has shown substantial potential to enhance healthcare services and foster Emotional Intelligence (EI), especially in advanced economies. Despite its proven effectiveness elsewhere, the Jordanian populace is reluctant to adopt AI in the healthcare sector, with predictions for hospitalizations, medical consultations, and treatment recommendations being sluggish to gain acceptance. This study investigates the combination of Emotional Intelligence and AI adoption in the healthcare system in Jordan, guided by the Unified Theory of Acceptance and Use of Technology (UTAUT) model. While UTAUT typically considers performance expectancy, effort expectancy, social influence, and facilitating conditions as key determinants of technology acceptance, this study argues that emotional intelligence, including self-regulated, self-awareness, motivation, empathy, and social skills, should be integrated as direct determinants of behavioural intention. In this study, a quantitative approach has been employed, whereby questionnaires were delivered through email and messaging apps to evaluate the impact of emotional intelligence on Jordanians' willingness to adopt AI technology in the healthcare sector. The findings suggested that the UTAUT model should be further expanded to encompass emotional intelligence as its fifth construct, particularly in developing countries like Jordan, where user models for AI adoption are less explored. The implications of the study extend to healthcare planners and developers in Jordan, providing insights into factors, which influence the successful adoption of AI technologies among diverse user groups. This study has provided valuable recommendations for developers of AI-based healthcare systems, enabling them to align their assistance with the perceptions and behaviours of Middle Eastern users. By doing so, they can foster increased acceptance of AI-based healthcare systems in the Middle East and other developing regions to improve healthcare services.

Keywords: recommendations, UTAUT, healthcare, intelligence

1.0 Introduction

The utilization of AI-based healthcare systems in Jordan is characterized by both promises and challenges. AI has the potential to enhance patient care, improve diagnosis and therapy, and streamline healthcare operations. However, its adoption in Jordan has been slower compared to more technologically advanced nations. The utilization of AI in clinical practice has increased and contributed to improving diagnostic accuracy, optimized treatment planning, and improved patient outcomes (Sesha et al., 2023). AI and machine learning algorithms can process and analyze large amounts of data, leading to the development of new diagnostic and treatment tools that improve patient outcomes (Kaur et al., 2023). AI-based computer-assisted diagnosis tools can be affordable in developing nations and address the problem of a lack of expert medical practitioners (Emre, 2023). One significant challenge is the prevalent reluctance among healthcare professionals and patients regarding the effectiveness and safety of AI in healthcare. Concerns about data security, patient privacy, and job security may be the reason for such reluctance, thereby emphasizing the dire need for education and awareness programs to address these concerns. Empirical evidence indicates that user reluctance is prevalent and, therefore, further investigations are essential to identify and address the factors, which drive this reluctance (Alexander & Mark, 2021). Furthermore, regulatory hurdles and concerns related to technological sovereignty are obstacles that must be navigated to ensure the successful integration of AI-based healthcare systems in Jordan. The slow-paced

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adoption of AI technologies highlights the need for comprehensive strategies and policy frameworks to promote AI in the Jordanian healthcare sector to optimize the quality and efficiency of healthcare services.

In Jordan, the users of AI-based healthcare systems include a broad spectrum, covering individual patients, who seek personalized care and healthcare professionals, who aspire to improve diagnosis and patient outcomes. Both public and private hospitals are incorporating AI-based solutions, but the extent of utilization can vary among these institutions. While private hospitals are typically quicker to adopt AI technologies due to their resources and infrastructure, public hospitals, which serve a significant portion of the population, may face budget constraints and infrastructure limitations that impact the rate of adoption. Jordan's healthcare landscape reflects the broader global trend of embracing AI in healthcare, and as the country seeks to overcome these challenges, it can harness the transformative potential of AI to enhance healthcare services for its population.

The transformation of healthcare by artificial intelligence (AI) is, thus, crucial. Applications of medical AI are numerous and widespread. Emotional intelligence (EI) and artificial intelligence (AI) have been a debated topic in corporate and organizational leadership, as well as in the healthcare industry (R. Hoque & Sowar, 2017), becoming a hugely contested topic since its inception, with differing perspectives on its adoption for a general purpose and applicability. The results of previous studies on Emotional Intelligence (EI) and the use of Artificial Intelligence (AI) in the health-care system showed that AI and EI play a significant role in transforming the sector and improving health-care services, particularly in advanced economies (Wang H. et al., 2020). A health care system that uses artificial intelligence has significantly improved the system and promoted EI abilities in several ways, including technology acceptance among users, applicability and adoption, staff training, and welfare system improvement (Nightingale et al., 2018). An improved learning process for AI base knowledge contributes to improving overall organizational performance by defining improved interactions between physicians and patients (Arefeh Kalavani, Maryam Kazerani, Maryam Shekofteh, 2018).

The AI global market share for healthcare in the United States is expected to grow from $663.8 million in 2014 to $6.66 billion in 2021, saving the US health-care industry $150 billion per year by 2026 (Regis, 2021). Fewer hospitalizations, medical visits, and treatments are expected as a result. Through ongoing coaching and monitoring, as well as earlier diagnosis, individualized treatments, and more effective follow-ups, artificial intelligence-based technology will be essential in helping people maintain their health. There are several useful applications for the ongoing EI research. From a security perspective, cybersecurity and fraud detection may be aided by EI in the AI dimension. By reducing prescription mistakes, expediting administrative procedures, and serving as virtual nursing assistants, it may also be used to help nurses and employees (Hailiang Wang, Da Taoa, Na Yu, Xingda Qu, 2020). Advanced tasks, including robot-assisted surgery, automatic image diagnosis, early diagnoses, and the identification of clinical trial participants may all benefit from applying AI. All AI components can be connected, which might provide coherence. The AI system can help cancer patients with currently available clinical trials, drug treatment, surgery, radiation, and supportive care. This might free up doctors' time to give their patients more attention. The performance of healthcare organizations will benefit from having employees that are emotionally intelligent. Adding EI to one's professional skill set will be beneficial for managers and employees at all levels (Manar Algahtani, Abdullah Altameem, and Abdul Rauf Baig, 2021). In essence, this can only be accomplished if a well-developed model for integrating EI and AI in measuring user acceptance of new technology exists. The emergence of new technology causes some level of rejection among individuals in society, as does the use of AI machines to improve hospital services. In Jordan, the acceptance rate is moving slowly in comparison to advanced economies like the US and Europe, despite its importance in improving efficiency, cost reduction, and physician-patient relationships.

Jordan has one of the most advanced healthcare systems among the Middle East countries. The international community, including the World Health Organisation, is constantly studying Jordan's healthcare system in the hope of adopting some of its more successful components, such as extensive insurance coverage and increased investment. Jordan's legislature has adopted a national e-health system to keep up with the country's rising population and enhance the Jordanian healthcare system. This e-health system aims to connect all public and private hospitals, keep records organized, and make them available to everybody (Hidayah Sulaiman & Asma I. Magaireah, 2018).

The country has one of the most advanced systems in the region. Jordan distinguishes itself from other nations due to its substantial healthcare expenditures, which are directed toward the development of novel treatment procedures and the expansion of healthcare accessibility. In 2003, healthcare expenditures accounted for approximately 10.4% of Jordan's GDP (Yorulmaz, O, 2016). Jordan's health information systems and human resources teams were modified and enhanced during the previous decade. As a result, Jordan has considerably improved its level of treatment during the last decade as a result of recent changes in the healthcare system's emphasis. Therefore, Jordan's sophisticated healthcare system sets it as a distinguished system compared with other Middle Eastern countries.

By analyzing patients' emotions and sentiments via verbal cues, inflections, and gestures, an integrated model of AI and EI has the potential to further revolutionize Jordanian healthcare. The tone of one's voice may also be used to detect melancholy and emotional health. Real-time feedback makes it possible, which might lessen the burden of patient clinical studies (Nightingale et al., 2018). Overall, automating input and discharge operations might improve the client's experience, which is associated with the technology acceptance level in Jordan. The development of AI system base and EI in the healthcare system involves user acceptance and intention to use as it is getting popular among practitioners and researchers (Backfisch et al., 2021; Hanham et al., 2021; Sprenger & Schwaninger, 2021; Xu et al., 2021; Yang et al., 2021). Businesses have enabled or aim to facilitate the newest technology into their organizational platforms to raise employee productivity, marketing advancement, cost reduction, and profitability. (Lembcke et al., 2021; Sengupta et al., 2021; Zulfiqar et al., 2021). User acceptance is crucial when it comes to the adoption of new technology in enterprises (Candra et al., 2020; Hassan et al., 2020; Hawash et al., 2021). Acceptance is generally defined as "an antagonism to the term resistance and the positive decision to employ a technology" (Lu, 2021). Therefore, to consider it during the development phase, decision-makers must understand the factors that influence users' decisions to adopt a certain system (Song et al., 2021).

Examining and assessing user acceptance necessitates the application of a variety of models and theories, each of which identifies distinct aspects of user acceptance (Motamedi et al., 2021). For all academics who want to forecast whether technologies would be appropriate for a certain organization, the topic of user acceptance is important (Taherdoost, 2018). User acceptance is also essential for the effective adoption of any new technology (Bandura, 1982). The characteristics of technology have an impact on determining whether persons engaged in an activity will use it (Taherdoost, 2018). Understanding users' perspectives on the adoption of new technology could, therefore, help expand the effective application of technology (Taherdoost, 2018).

Voting, dieting, blood donation, family planning, women's occupational orientations, breast cancer examination, choice of mode of transportation, use of birth control pills, turnover, education, consumer purchase behaviors, and computer usage are just a few of the domains where technology acceptance models and theories have been used to understand and predict user behavior (Hwang et al., 2021; Lee & Wong, 2021; Malhotra et al., 2021; Motamedi et al., 2021; Otter & Beer, 2021).

The Technology Acceptance Model (TAM) by Davis (1986) and Davis et al. (1992) and the Unified Theory of Acceptance and Usage of Technology UTAUT by Venkatesh et al. (2016) assert that the actual utilization of technology is influenced by an individual's behavioural desire to employ it. In TAM, the attitude toward using technology determines the anticipated usage, which is influenced by two system perceptions: perceived utility and perceived ease of use, and external factors have an impact on both perceptions.

UTAUT is built on TAM and seven other theoretical frameworks. It proposes four theories to evaluate usage intention: performance expectations, effort expectations, social influence, and facilitating factors. The influence of these expectations and the facilitating factors on intention are modified by age, gender, experience, and voluntariness of usage.

TAM and UTAUT have been extensively used in both biological informatics and management information systems (MIS) (Bagheri et al., 2021; Cornacchia et al., 2020). These ideas have undergone countless modifications and alterations throughout time. These include incorporating elements from other theories and adjusting accounts for specific purposes, including telemedicine or patient acceptance of eHealth and m-Health apps. (Hamed Taherdoost, 2018). Nonetheless, these theories (particularly TAM) were questioned, and, therefore, additional factors should be included in the TAM and UTUAT based on individual and environmental characteristics. This study focuses on the UTUAT model only, to expand it by adding Emotional Intelligence (EI).

This study focuses on individuals, who have used or are current users of AI-based CT scan technologies. The major goal is to investigate the participants' experiences and viewpoints; those who have direct exposure to this sophisticated imaging technique. By focusing on previous and current users of AI-based CT scan technologies, valuable feedback is expected to be gathered to identify potential areas for development in the healthcare sector. The findings of this study are projected to contribute to the continued development and refinement of AI-based CT scan systems, ensuring that they meet the demands of end-users and address their concerns while improving diagnostic accuracy and patient care.

Artificial intelligent-based healthcare system

Healthcare is one of the many areas of science and technology, where artificial intelligence has generated a big paradigm change and, hence, it is a subject of tremendous interest (Topol, 2019). Artificial intelligence (AI), also known as the use of automated systems with the ability to precisely understand, learn from, and accomplish specific objectives using external data, is a new technology that has a significant impact on how people interact with their environment.

Artificial intelligence (AI) has influenced people's lives in many ways. AI is designed to improve people's lives and help them in various circumstances. This study aims to examine the variables that affect users' behavioural intentions and use of AI-enabled systems. A tried-and-true way of examining how new technologies are adopted is the Technology Uptake Model. (TAM). This core model of acceptance and/or expansions of UTAUT and UTAUT2 has been used in previous studies on the intention to act or adopt new technologies. However, behavioural intention to utilize AI-enabled systems has been the subject of a few studies, which used these concepts.

Jordan has made strides in recent years in implementing AI-based healthcare solutions, thanks to a variety of projects and partnerships that aimed at integrating AI into the country's healthcare sector. In 2019, the Jordanian Ministry of Health formed a partnership with Orange Business Services to devise an AI-powered solution for delivering radiological services. By aiding radiologists with patient diagnosis via the use of AI algorithms, the "Patient and Caregiver Pathway" solution reduces the time and cost of traditional radiology treatments. Furthermore, the Jordanian government cooperated with the World Health Organization (WHO) in 2020 to develop an AI-powered national health observatory. The observatory used AI to identify trends and patterns in data to gather and analyze health data across the country and improve public health outcomes.

Another example of AI application in Jordan's healthcare system is the cooperation between IBM Watson Health and the King Abdullah University Hospital (KAUH). KAUH has used IBM's Watson for Oncology technology to assist oncologists in properly and quickly detecting and treating cancer patients. After evaluating patient data using AI, the program produced tailored therapy suggestions based on a patient's medical history, genetic information, and other features. These projects and agreements demonstrate Jordan's commitment to employing AI in healthcare and harnessing advanced technology's potential to improve patient outcomes and save costs. As AI grows and becomes more extensively utilized, an increased integration of AI in Jordan's healthcare is projected in the future.

Although Jordan is in its early stages of employing AI in healthcare, there are few cases of patients using AI healthcare services. Here are a few instances of how Jordanian patients might benefit from artificial intelligence in healthcare: As previously stated, the Jordanian Ministry of Health has partnered with Orange Business Services to launch an AI-powered solution for radiology services. Patients in need of radiological services may be sent to facilities that utilize this approach, where they receive faster and more exact diagnoses.

Cancer patients at King Abdullah University Hospital may benefit from personalized cancer treatment plans developed by IBM Watson for Oncology. This AI-powered platform evaluates patients' medical histories, genetic data, and other data to recommend medications tailored to their specific needs. By using virtual consultations in response to the COVID-19 outbreak, many Jordanian healthcare practitioners have effectively provided virtual consultations to patients using AI-powered telemedicine systems. Patients may speak with medical specialists and get prescriptions and guidance through video conferencing without having to leave their homes. Also, monitoring chronic illnesses, whereby AI-powered monitoring systems can track the patients' symptoms and alert medical experts to changes in their health status, may be beneficial for certain people with chronic diseases. For example, the Philips eCareCompanion platform may follow patients with chronic obstructive pulmonary disease (COPD) and alert medical practitioners about exacerbation symptoms.

Emotional Intelligence (EI)

In 1990, Salovey and Mayer invented the phrase 'emotional intelligence.' Psychologists divided the mind into three primary components in the seventeenth century: cognitive, emotional, and motivational. The emotive component is referred to as 'emotion,' while the cognitive component is referred to as 'intelligence.' Mayer and Salovey (1997) define emotional intelligence as a person's capacity to feel, express, grasp, use, and control emotions in themselves and others (social intelligence), which leads to adaptive behaviour. Emotional intelligence, in other words, is the capacity to detect and manage emotions.

The importance of EI in health care settings can be, therefore, proved, given its enormous impact and the way it has revolutionized the system in developed countries. A health care professional with a higher EI is more compassionate, empathic, resilient, caring, and capable of regulating emotions in others. They are also more likely to be able to care for their patients and persuade and inspire them to embrace and employ AI-based technologies to manage their illnesses. Health-care workers want to respond emotionally to their patients (Kooker et al., 2007; Pearcey, 2010). Organizations in the health-care industry are constantly changing, and healthcare employee turnover is high throughout the world (Liu et al., 2017). This has further proved that those who have high emotional intelligence feel they can understand and control their emotions. Anxiety, rage, and delight are all emotions that arise when people's routines are disrupted by new technology goods or services.

UTAUT Model with Emotional Intelligence

This paper extends the UTUAT model by adding the emotional intelligence of the users, as performance and effort expectancy have been widely used in previous studies. Emotional Intelligence (EI) is a variable, which has been overlooked and less emphasized in the UTUAT model. The degree of personal emotional needs of users in using AI-based healthcare systems helps in building knowledge during the development of the systems (Thongsri et al., 2018). There is a need to identify external factors other than those utilized in the UTAUT and to investigate what factors affect the usefulness of AI-based intelligent products (Sohn & Kwon, 2020). This study aims to enhance UTUAT by adding the internal emotional force of the users as a variable.

Partial least squares structural equation modelling is used in the study, which tests the model respondent data and explores an approved research model. By providing an enhanced UTAUT model with the inclusion of Emotional Intelligence, this study aims to evaluate the aspects that affect user acceptance of AI healthcare services based on the role performed by Emotional Intelligence (EI). UTAUT is considered one of the complete models to explain adoption behaviour and includes users' expectations of the innovation, such as performance and effort expectations. While Emotional Intelligence assesses how well emotions and technology align, incorporating EI as a construct to UTAUT has the potential to account for greater consumer adoption of AI healthcare services than either constructs alone. This study aims to extend the UTAUT by using the factors, namely Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Emotional Intelligence. Emotional Intelligence (EI) is used in many studies, which have focused on brain intelligence and cognitive challenges (Abu-Shanab & Abu-Shanab, 2019).

The rest of the paper is organized as follows: The theoretical foundation and the research hypotheses of the study are described in the next section. The final model findings are also discussed, followed by the study's methodology. The conclusions, consequences, and potential areas for further research are provided in the conclusion section.

2.0 Literature Review

2.1 Artificial Intelligence

The ability of machines (such as computers) to understand, learn, and reason like humans is called artificial intelligence (AI), which provides the potential to simulate human intelligence through technology (Pan, 2016). Research will continue to be based on the assumption that theoretically any aspect of learning or any other characteristic of intelligence can be described unequivocally that a computer can be created to mimic it.

However, Ford and Gioia (1995) disagree that overcoming IT should be seen as an answer to the question of "Can machines think?" The authors believe that people should not be invalidating AI, instead the goal should be to reach an understanding that AI can benefit humans. They present similar arguments as Cañas et al. (1995), in which, it is further stated that "the final dimension that AI technology seeks is a working definition of intelligence in terms of species contrast with humans" (Whitby, 1996). In an interview with Frieda Klotz, Ken Goldberg argues that people no longer need to worry about machines replacing them; instead, humans should have visual AI to improve their pictures because it can simplify some tasks (Hayes & Ford, 1995).

Many studies used these basic versions of attractions and/or extensions (TAM2, TAM3, UTAUT, and UTAUT2) to track an individual's behavioural intention and behaviour towards recent technologies. For example, the technology of health and fitness wearable or personal software, including smart home devices via Shuhaiber (2019), outdoor transportation via Lin (2009), banking via Tan (2016), mobile NFC via Dutot (2015), and e-purchases through Kėdė (2009). These studies depend on the UTAUT (Unified Theory of Technology Acceptance and Use), and additional constructs are added to it. The constructs influence the target's behaviour, plans to monitor UTAUT, and the most influential factors related to AI assets, regardless of the software stage.

2.2 Artificial Intelligence in Healthcare

Artificial Intelligence (AI), or the use of automated frameworks that demonstrate the ability to effectively interpret data, and observe and capture unique desires, is an emerging technology with many implications for changing the ways we interact with the world. Within healthcare, AI is uniquely positioned to gain knowledge via clinical desire to assist generation and improve photo processing upgrades collectively with real-time segmentation, automatic high-quality photo upgrades, and assisted or self-infection screening tools. While clinical merchandise that permits evidence-based care has carried out a major characteristic in cutting-edge decades, Frost and Sullivan (2016) observed that the point of interest is on clinical structures that permit result-orientated care in real-time. Through this interplay of primarily technology-based merchandise, structures, and solutions, an extraordinary degree of clinical precision may be carried out to stop infection (Frost & Sullivan, 2016). Beyond the beauty of a build and its impact on real-world use, user feedback is an important source of data for reinforcing a build that is largely based on users' desires and wants. This thereby reinforces the beauty of technology, making it so much more meaningful as users are directly or indirectly involved in its creation (Cui & Wu, 2016).

Emotional intelligence (EI)

By focusing on intelligence from a particular perspective (known as 'social intelligence'), Thorndike (1920) is a pioneer in the study of emotional intelligence. Thorndike described social intelligence as "the ability to understand and control men and women, boys and girls to act sensibly in human relationships." In other words, the ability to understand and manage people is referred to as social intelligence. When Gardner (1983: 25) described intelligence as "the ability to resolve a problem," he provided a thorough explanation of what intelligence is and, therefore, he divided intelligence into eight categories, including intrapersonal and interpersonal intelligence in his multiple intelligence theory.

The phrase "emotional intelligence" was invented in 1990 by Salovey and Mayer. Psychologists divided the mind into cognitive, emotional, and motivational elements in the 18th century. "Emotion" relates to the affective aspect, whereas "intelligence" alludes to the cognitive aspect. The ability to sense, express, understand, use, and regulate emotions in oneself and others (social intelligence), which results in adaptive behaviour, is what Mayer and Salovey (1997) characterize as emotional intelligence. In other words, emotional intelligence is the capacity to identify and regulate one's emotions. In this regard, Bandura's self-efficacy thesis asserted that a person's confidence in their ability or abilities is the basis for expressing them successfully (Bandura, 1977). Persons with greater emotional intelligence, therefore, think they can understand and manage their emotions. People feel emotions like anxiety, fury, and satisfaction when new technological products or services interrupt their routines.

These emotions may come before using new technological products or services (anticipation phase), as a way of being aware of possible disruption, or thereafter (impact period) (Beaudry & Pinsonneault, 2010). For instance, the knowledge of an impending interruption might be seen as the meaning of computer anxiety, as explained by Venkatesh (2000) as the outcome of people's fundamental preconceptions about computers. While interpersonal intelligence focuses on understanding others, intrapersonal intelligence is more concerned with one's knowledge.

Salovey and Mayer's concept of emotional intelligence is founded on both intrapersonal and interpersonal intelligence. (Mayer & Salovey, 1997; Salovey & Mayer, 1990). In 1998, psychologist Daniel Goleman discovered a link between EI and business leadership. Its major pillars include self-awareness, self-regulation, motivation, empathy for others, and social skills, according to him. In 2013, Goleman utilized neuroscience research to show how leaders may increase each facet of EI by strengthening their ability to focus their attention. In addition to education, certification, and technical abilities, health care directors who seek high-EI staff regard it as a critical component. They assess EI by looking at how prospective employees handled difficult situations, using behavioural event interviewing techniques. The candidates were contacted to gain firsthand knowledge about their interpersonal abilities. EI reduces stress and burnout among health care professionals. It enhances communication, resulting in improved doctor-patient relations. It provides insight into a patient's emotional responses to treatment, resulting in greater patient satisfaction. Thus, it results in greater job satisfaction and enhanced leadership qualities, which can improve team performance and motivation.

Two groups may be made of EI abilities. The first domain is personal competency, or the ability to understand and communicate oneself. This skill demands emotional self-awareness, acceptance, respect for oneself, and a commitment to ongoing self-improvement. Additionally, it calls for assertive self-expression of emotions, effective stress management, the ability to maintain a positive attitude, and the ability to modify behaviour and emotions to unforeseen circumstances. Additionally, the ability to manage impulses is a quality of the talent.

Social competence, which is the capacity to handle relationships, is the second domain. This ability needs empathy, compassionate communication, and social and organizational awareness. It also demands the ability to manage conflicts, the ability to inspire and motivate via leadership, and the capability to coach and mentor. Furthermore, the skill is characterized by a feeling of social duty. Emotion is one of the validated influential non-cognitive elements. In the context of information technology, Beaudry and Pinsonneault (2010) emphasized the non-cognitive role of emotions in the adoption of new technologies. They contend that non-cognitive elements such as emotion may have a considerable impact on the adoption of new technologies and that cognitive considerations cannot completely explain all the antecedents of behavior. (Russell, 2003; Beaudry & Pinsonneault, 2010). An individual's emotions have a substantial impact on their thinking, personality, decision-making, and conduct (Mehrabian & Russell, 1974).

In the context of information technology (IT), the influence of emotions on an individual's intention to adopt new technology has been studied using a variety of terms and perspectives, including affective emotions (such as positive and negative feelings such as delight, elation, enjoyment, anxiety, distance, and unhappiness) (Venkatesh, 2000), computer or technological variables (Venkatesh, 2000; Saadé and Kira, 2006), the stimulus-organism-response framework (Lee (Yang & Forney, 2013). Cenfetelli (2004) demonstrates that in the context of e-business, has a bigger influence than emotions on users' intentions to adopt new technology. Beaudry and Pinsonneault's evaluation tendency framework, published in 2010, categorizes emotions toward new technology into four categories: accomplishment emotions (pleasure), self-motivation (excitement), social skills (rage), and self-awareness (anxiety).

According to Kurniawati et al. (2021), emotional marketing greatly increases people's donation intention, meaning that the commercial can alter people's emotions into empathy and willingness to donate through the charity campaign. In addition, UTAUT has a substantial impact on intention. These findings will help Kitabisa.com in its efforts to boost people's donation intentions through emotional marketing. In this context, Hakan Celik (2016) showed that anxiety has negative direct consequences on the dimensions of performance expectation, effort expectations, and behavioural intention simultaneously. Age, gender, and experience all exhibited significant moderating effects on the anxiety-intention link, but no evidence suggested that these moderating characteristics also influenced the relationships between anxiety and performance and effort expectations.

Even though this concept has been the topic of many studies, only a few of these studies have incorporated emotion (Partala & Saari, 2015). According to Cenfetelli's (2004) study on the influence of a wide range of emotions on the TAM model, negative emotions not only have a negative link with perceived ease of use, but they also have a higher influence than positive emotions. Beaudry and Pinsonneault's (2010) study created a framework of four emotional types known as 'Self-Regulation' (i.e., happiness, gratification, delight, relaxation, and enjoyment).

Authors Country-Year Relationships Important Relationships Sample Timeline and impact period (Todman, 1994) (DonmezTuran, 2019) Communications Computer 14 facilitated Arousal, flow, enthusiasm, optimism, and expectancy are all self-motivations. Rage, anger, aggravation, sorrow, and disgust are all social skills (anxiety, fear, worry, distress).

2.2.4 Classification of Emotional Intelligence

2.2.4.1 Self-Regulation

This is a vital component of emotional intelligence; it is the ability to manage one’s emotions and responses effectively. It involves maintaining composure under pressure, resisting impulsive reactions, and channelling emotional energy productively. Individuals with strong self-regulation can adapt to changing situations, cope with stress, and control their emotional outbursts. This skill is essential for maintaining healthy relationships, making sound decisions, and achieving personal and professional success. In the context of AI adoption in healthcare, self-regulation, or emotional control, is paramount for healthcare professionals. The integration of artificial intelligence often brings about significant changes and challenges in healthcare delivery. To successfully navigate these transformations, healthcare providers must exhibit emotional control and self-regulation. Whether it's adjusting to new AI-driven processes, managing the stress that can accompany technological change, or dealing with unexpected outcomes, self-regulation helps healthcare professionals maintain composure, make informed decisions, and ensure that the adoption of AI technologies enhances patient care. Research has shown that emotional control is not only vital for healthcare providers’ well-being but also crucial for the successful incorporation of AI into healthcare systems (Smith et al., 2022).

2.2.4.2 Self-Motivation

Another key facet of emotional intelligence is the capacity to harness and sustain intrinsic motivation toward goals and aspirations. It involves an inner drive and a commitment to personal growth and development. Individuals with high self-motivation tend to be more resilient in the face of setbacks, they persevere in pursuing their objectives, and they find fulfilment in their achievements. This intrinsic motivation can significantly impact one's work ethic, ambition, and overall life satisfaction. The successful adoption of AI in healthcare relies on healthcare professionals' intrinsic drive and self-motivation to continuously improve their AI-related skills and knowledge. In a rapidly evolving field, the intrinsic motivation to enhance proficiency in AI applications is pivotal. Such motivation enables healthcare workers to stay updated with the latest developments and emerging AI technologies. This intrinsic drive not only empowers healthcare professionals to provide more efficient and accurate patient care but also contributes to their overall job satisfaction. Recent studies have underscored the significance of self-motivation in AI adoption within healthcare, as it plays a key role in achieving better patient outcomes, streamlining healthcare delivery, and ensuring that the full potential of AI is realized (Johnson & Brown, 2021).

2.2.4.3 Social Skill/Empathy:

These are important components of emotional intelligence when it comes to relating to and understanding others. Social skills encompass the ability to interact harmoniously with people, build rapport, and foster positive relationships. Empathy involves the capacity to comprehend and resonate with the emotions and perspectives of others. Individuals with strong social skills and empathy tend to be effective communicators, team players, and conflict resolvers. They can relate to others with understanding and compassion, making them valuable in personal and professional settings. AI's integration into healthcare necessitates effective collaboration and a deep understanding of patients' emotional needs. Social skills and empathy are vital aspects of emotional intelligence that healthcare professionals must employ. In the context of AI-driven healthcare, effective collaboration among interdisciplinary teams is essential for the successful implementation of AI systems. Moreover, empathy plays a pivotal role in patient care, even in a technologically advanced environment. Recognizing and addressing the emotional aspects of patients' well-being is integral to healthcare delivery. Recent research has highlighted the importance of social skills and empathy in AI adoption within healthcare, as they enable healthcare teams to collaborate effectively, deliver empathetic patient care, and ensure that the integration of AI technologies aligns with the holistic needs of patients (Garcia et al., 2023).

2.2.4.4 Self-Awareness:

This is the foundation of emotional intelligence, encompassing the ability to recognize and understand one's own emotions, strengths, weaknesses, and values. It involves an honest and introspective assessment of oneself. Individuals with high self-awareness can better navigate their emotions and respond to challenges and opportunities authentically. This self-understanding lays the groundwork for developing the other aspects of emotional intelligence, as it allows individuals to regulate their emotions, motivate themselves, and connect with others more effectively. AI adoption in healthcare calls for self-awareness among healthcare professionals, as it facilitates adaptive decision-making in the presence of AI systems. Self-awareness helps healthcare practitioners recognize their strengths and limitations, fostering a more informed approach to utilizing AI technologies in patient care. Self-awareness ensures that healthcare providers remain attentive to the specific needs of patients and the broader goals of healthcare organizations. Recent studies have demonstrated that self-awareness supports adaptive decision-making, helping healthcare professionals ensure that AI solutions are aligned with the best interests of patients and the mission of healthcare institutions. This underscores the critical role of self-awareness in the successful integration of AI into healthcare (Chen & Smith, 2020).

Figure 1: Five Main Components of Emotional Intelligence

Source: (Daniel Goleman, 1995)

2.2.5 Emotional intelligence in healthcare

The importance of EI in healthcare settings can be demonstrated, given its enormous contribution and how it revolutionizes the system in the advanced world. Healthcare workers with a higher EI are more capable of regulating emotions in others, resilient, compassionate, and caring, and they are more likely to be able to care for their patients and persuade them to accept and employ AI-based technologies (Kooker et al., 2007; Pearcey, 2010). Healthcare companies are constantly changing, and healthcare personnel turnover is significant across the world (Liu et al., 2017). Employee retention and behavior change are dependent on leaders who motivate and excite their teams while also encouraging innovation and shared ownership. Relational leadership paradigms, such as transformational leadership, have been linked to EI and have been linked to improved patient outcomes (Cummings et al., 2010; Spano-Szekely et al., 2016). When it comes to recruiting for caring professions, EI is becoming increasingly significant (Carson et al., 2005; Harper and Jones-Schenk, 2012; Lyon et al., 2013). Despite theoretical support, there is no practical evidence linking the concept of EI to caring actions, and the impact of EI on emotional behaviors may be lower than previously imagined (Akerjordet & Severinsson, 2007; Kaur et al., 2013; Rego et al., 2010). This review combines emotional intelligence and examines the impact of EI on the growth of Jordan's healthcare system to highlight the relevance of the current emphasis on emotional intelligence in healthcare. In this context, behaviour encompasses both mental and emotional components.

Patients, who have particular traits, such as the ability and tendency to notice and interpret their own and others' emotions, contend with themselves, and pay attention to emotional self-care, may be more ready to embrace the use of AI in the health care system. Higher EI is regarded as a lauded state that has been linked to a variety of things, including psychological adjustment (Ranjha & Shujja, 2010), self-compassion (Enyuva et al., 2014), empathy (Ezzatabadi et al., 2012; Mayeret al., 1999), resilience (Schneider et al., 2013), social support (Montes-Berges and Augusto, 2007), and (Gutierrez & Mullen, 2016).

Theoretical framework of Unified Theory of Acceptance and Use of Technology

UTAUT is a combination of 8 behaviors and theories that have been regularly used to visualize user uptake of ICT: Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivational Model (MM), Theory of Planned Behavior (TPB), mixed intentional behavior appeal principles version (C-TPB-TAM), Model of Personal Computer Utilization (MPCU), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT) (Venkatech et al., 2003). Empirically analyzing user adoption by statistical age in an organizational context, researchers found that UTAUT, as shown in Figure 2, predicts 70% of users' adoption intentions and 50% of their adoption behavior, which may be higher than several current attractiveness modes (Venkatesh et al., 2012). These approaches include the Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), mixed of TAM and TPB, Theory of Planned Behavior (TPB), Model of Personal Computer Utilization (MPCU), Innovation Diffusion Theory (IDT), Motivational Model (MM), and Social Cognitive Theory (SCT). Many studies utilized a combination of different theories to identify the acceptance and use of intelligent healthcare systems among users (Keikhosrokiani, 2020; Keikhosrokiani et al., 2018; Keikhosrokiani, Mustaffa, Zakaria, & Abdullah, 2019; Keikhosrokiani, Mustaffa, Zakaria, & Baharudin, 2019).

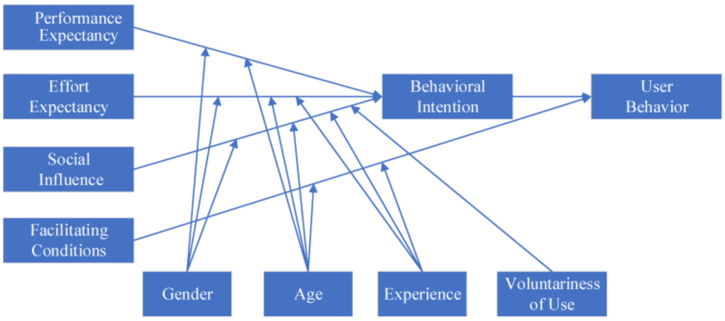

Figure 2: Original UTAUT Model

Source: (Venkatesh et al., 2003)

2.6 Research Gap

Venkatesh et al. (2003) and Venkatesh et al. (2011) argued that encapsulation principles can lead to explanations of how people and society influence technology adoption and use (Salloum & Shaalan, 2018; Rozmi et al. 2019). Previous studies investigated different sample sizes and participants. The demographic effects have not been fully considered to assess the mediating impact on behavioural intention of using AI-based healthcare systems, particularly in Jordan.

Methodology

The UTAUT model consists of six main constructs, namely performance expectancy ("PE" hereafter), effort expectancy ("EE" hereafter), social influence (SI), facilitating conditions (FC), and behavioural intention ("BI" hereafter), and Usage behaviour. The UTAUT model contains four essential determining components and four moderators. This model may not be applicable in all contexts. The path from emotional intelligence to behavioural intention missing from the original UTAUT model should be included. Therefore, the study examines the extended model of original UTAUT, which includes Performance Expectancy (PE), Effort Expectancy (EE), Social influence (SI), Facilitating Conditions (FC), and the new factors of Emotional Intelligence (EMI) (Patil, 2020).

Firstly, this study explores the literature published on the Technology Acceptance Model and highlights the issues that have been extensively neglected in past research. This will help future studies acknowledge the gaps in TAM. However, some factors have not been examined. The factors that were not considered significant in previous studies are highlighted in this study.

In the context of IT, Beaudry and Pinsonneault (2010) emphasized the importance of emotion as a non-cognitive dimension in implementing new technologies. This is because emotions can greatly influence people's acceptance of new technologies (Russell, 2003; Beaudry & Pinsonneault, 2010). Figure 3 illustrates the proposed theoretical framework which integrated emotional intelligence into the original UTAUT. The constructs, which are included in the proposed framework of this study, are presented in Table 1.

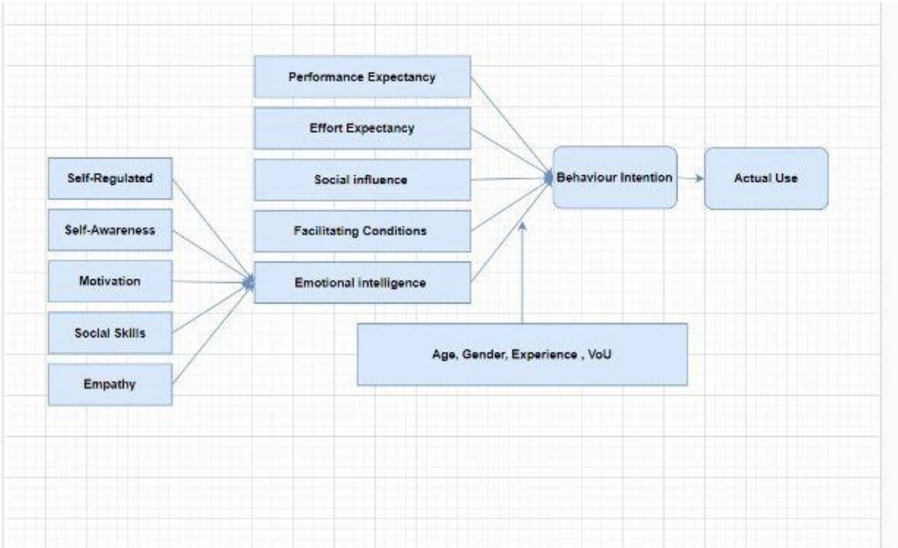

Figure 3: The Proposed Theoretical Framework

Table 1: Brief definition of the constructs in the model

No.	Construct	Definition	Source
1	Effort Expectancy (EE)	The level of simplicity associated with using healthcare AI services is known as effort expectation.	Venkatesh et al. (2003)
2	Social Influence (SI)	It refers to the extent to which peers have an influence on how an AI service is used.	Venkatesh et al. (2003)
3	Performance Expectancy (PE)	the extent to which a person believes that employing healthcare AI services would improve his or her performance.	Venkatesh et al. (2003)
4	Facilitating Conditions (FC)	The extent to which a person believes they possess the necessary technical know-how and resources to make advantage of AI services.	Venkatesh et al. (2003)
5	Behavioural Intention (BI)	In this scenario, an indicator of whether consumers will keep their connection with the service provider or end it is their behavior intention. Jordan's AI healthcare system.	
6	Emotional Intelligence (EI)	Emotional intelligence as the subset of social intelligence that involves the ability to monitor one's own and others' feelings and emotions, to discriminate among them, and to use this information to guide one's thinking and actions.	Salovey & Mayer (1990).
7	Self-awareness	s is associated with the ability to be aware of which emo tions, moods, and impulses one is experiencing and why. This also includes one's	M. Afzalur Rahim (2003)

		awareness of the effects of his or her feelings on others.	
8	Self-regulation	refers to the ability to keep one's own emotions and impulses in check, to remain calm in potentially volatile situations, and to maintain composure irrespective of one's emotions.	M. Afzalur Rahim (2003)
9	Motivation	represents the ability to remain focused on goals despite setbacks, to operate from the hope of success rather than fear of failure, to delay gratification, and to accept change to attain goals.	M. Afzalur Rahim (2003)
10	Empathy	refers to one's ability to understand the feelings transmitted through verbal and nonverbal messages, to provide emotional support to people when needed, and to understand the links between others' emotions and behavior.	M. Afzalur Rahim (2003)
11	Social Skills	is associated with one's ability to deal with problems without demeaning those who work with him or her, to not allow own or others' feelings to inhibit collaboration, and to handle affective conflict with tact and diplomacy.	M. Afzalur Rahim (2003)

Research Design

An in-depth literature review is performed to build on the sources that can be used for comprehensive research. The sources that are particularly relevant to this study are the factors, which influence people's behavioural goals to continue using AI-based healthcare structures. The theories and modes used in structural statistics (SI) research are examined, which serve as ideas for developing research and speculative models introduced. In this study, the hypotheses are evaluated using quantitative techniques.

The study population includes participants with all-AI-based health constructs in Jordan and former users of all-AI-based health-structured offers. The model has been narrowed down to those who used AI-based healthcare structures and to those who voluntarily responded to the survey questionnaire. The participants are 18 years old and are current or future users of the AI-based healthcare system. Through social media applications and an online survey system, 400 survey questionnaires were disseminated across Jordan, and 391 questionnaires were returned. The participants are doctors and patients who have willingly participated in the study. Some questionnaires were disregarded because they were incomplete; therefore, 391 questionnaires were complete for the analysis.

3.2 Instrument of the Study

A questionnaire is used as the main research instrument in this study. The questions included in the survey are designed for physicians and patients who used AI-based healthcare facilities in Jordan to obtain specific statistics from each person. Because physicians and patients—regardless of age, gender, education, occupation, and income—have their views about the use of full AI-based care structures or power to perform new functions in the healthcare sector. This study aims to explore the important factors of using AI-based healthcare systems for hospitals.

Convenience sampling is applied as a method to collect data from selected respondents for this study (Bornstein et al., 2017). To reduce model error, this study limits the target model to current and former clients of all AI-based medical facilities in Jordan to improve the representativeness of the model. In other words, it is a target population model that includes people in Jordan who have had experiences using a fully AI-based healthcare infrastructure.

The study adopts a convenience sampling approach using a web-based questionnaire survey. Rigini et al. (2016) suggested data-gathering instruments, such as emails, WhatsApp, and other available media. A structured questionnaire is created to collect data on exogenous variables of respondents' intention to use AI-based healthcare systems. A banner advertisement for the questionnaire is shared on all platforms of social media. This study uses a convenience sampling method. After sharing the online survey, this study applies a web-based questionnaire survey and a valid data collection tool (Regmi et al., 2016).

3.3 Hypothesis Development

The theories that the present study employs have a solid basis obtained from recent investigations. Emotional intelligence, including its four sub-constructs (Achievement Emotion (AE), Challenge Emotion (CE), Deterrent Emotion (DE), and Lost Emotion (LE)), are used as external variables for the proposed UTAUT model in this study. To assess the impact of five key variables on the benefits of using AI in everyday life, this study uses and tests the proposed UTAUT model in the context of AI used in Jordan. This study demonstrates how consumers' emotional intelligence can influence their behavioral intentions towards AI systems. The extent to which one believes the AI systems contribute to performance enhancement in the workplace is characterized by expected performance, which has also been included in the UTAUT model. The extent to which a person has made an intentional decision about whether to engage in a certain behavior in the future is known as behavioral intention (BI). In the UTAUT model, effort expectations (EE) are now included as important predictors of technology adoption. EE is defined as "the ease with which the system is used" (Venkatesh et al., 2003). The precursor to EE, according to Cimperman et al. (2016), includes ease of use. In this study, EE represents BI's perception of the usability of AI-enabled healthcare systems. Performance expectancy (PE) on whether using AI improves users' ability to do their jobs. According to Venkatesh et al. (2003), PE is the main factor influencing users' decision to use technology. Direct determinants of BI include PE and EE. The present study hypothesizes that PE and EE could have a major impact on students' BI in terms of AI adoption and implementation. Based on the theories and literature review, the following hypotheses are formulated.

H1. *Performance Expectancy (PE) has a positive influence on the BI's use of AI-based healthcare systems.*

H2. *Effort Expectancy (EE) has a positive influence on the BI's use of AI-based healthcare systems.*

The degree to which people feel that a new product or technology should be adopted is called social impact and facilitation. This hypothesis shows the view of how innovative use can improve AI adopters.

The existence of any technology's technological and organizational framework is a need for its adoption. Studies on the impact of conducive circumstances have produced a range of results. At the same time, studies have shown that enabling circumstances can affect a person's decision to employ technology. In addition, enabling conditions have no discernible impact on the intention to utilize technology (Barrane et al., 2018). Therefore, the use of a new system requires enabling circumstances, such as perceived compatibility, as well as technical and infrastructure support (Venkatesh et al., 2003). According to the foundation of UTAUT support, people search for the availability of technical specifications and other infrastructural supports before deciding to adopt and purchase any technology since the lack of them encourages their uncertainty or negligence for any upcoming emergencies (Venkatesh et al., 2011).

More importantly, a company that lacks the necessary tools, information, and managerial backing will probably put off adopting and implementing an AI healthcare system. The likelihood of acceptance and deployment of an AI healthcare system is increased by perceived support from the organization for approving necessary resources. In a sense, users' willingness to embrace and ultimately employ AI healthcare services will increase if they can be certain that enabling circumstances are in their workplaces (Barrane et al., 2018; Chao, 2019). The following hypotheses are created following UTAUT's knowledge and prior empirical findings.

H3. *Social Influence (SI) has a positive influence on the behavioural intention to use AI-based healthcare systems.*

H4. *Facilitating Condition (FC) has a positive influence on the behavioural intention to use AI-based healthcare systems.*

In general, using technology has two side effects. These include strong negative emotions and strong positive emotions from interactions with AI. However, several related definitions describe what constitutes positive or negative emotional intelligence. For example, artificial intelligence is defined as either negative or positive—it may create a mental state in which a person feels anxious or comfortable while using or considering her AI-based healthcare system. Acceptance and use of technology among users are important to successfully implement a healthcare system or an AI-based healthcare system. The researchers seek to predict who will be experiencing AI negatively or positively by identifying factors associated with the development of AI (Brosnan & Kirby, 2016).

H5. *Emotional intelligence has a positive influence on the behavioural intention to use AI-based healthcare systems.*

In examining the intention of using new technology, the content focuses on the scale, including the intention to use, the plan to use, and the prediction of system usage (Venkatesh et al., 2003). As in previous studies, consumer attitude has a strong and positive effect on behavioral intention. In addition, consumers' attitudes towards products and services have a statistically significant impact on behavioral intention. Intention to use technological systems has a significant relationship with user behavior. This means that the higher the user intent, the higher the rate of actual behavior being carried out, and vice versa. Therefore, this study assumes that:

H6. *Behavioural intention has a positive influence on the actual usage of AI healthcare systems.*

Moderators and Mediators

Finally, the hypothesis about moderators and mediators will attempt to answer these two questions: 1) to what extent their effects will be significant in determining the effective use of the technological layer, and 2) what are the attributes of emotional intelligence and its components related to expected effort, performance, social influence, facilitating condition, and behavioral intention? Moderators and facilitators will help address research questions about the factors driving the adoption of an AI-based healthcare system in Jordan. To our knowledge, no study has examined how all demographic factors—such as age, gender, experience, and willingness to use—mediate the relationship between behavioral intentions and actual technology use factors, as well as those variables used as moderators of behavioral intentions and actual technology use. The previous UTAUT model with facilitators and moderators is expanded to promote the idea of open innovation. The effects of age, gender, experience, and intention to use, as well as their mediating effects on actual use, will provide new data to improve and integrate previous results. The following are assumptions about the mediation and moderating variable effects on actual technology use. This study advances theoretical and empirical observations that influence behavioural intentions through moderating/mediating the effects of emotional intelligence and demographic factors that have implications for the adoption of AI-based healthcare systems. Therefore, the following hypotheses are formulated:

H7: *Emotional intelligence mediates the relationships between (achievement, challenge, deterrence, and loss) and behavioural intention.*

H8: Behaviour intention mediates the relationships between (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Emotional Intelligence) and Actual Use.

H9: *Age moderates the relationship between emotional intelligence and behaviour intentions.*
H10: *Gender moderates the relationship between emotional intelligence and behaviour intentions.*
H11: *Experience moderates the relationship between emotional intelligence and behaviour intentions.*
H12: *Voluntariness of use moderates the relationship between emotional intelligence and behaviour intentions.*

Data Analysis

The proposed model was validated using partial least squares (PLS) and structural equation modelling (SEM) (Smart PLS 3.3.9.0; Ringle et al., 2015), which outperformed CB-SEM. Even for complicated models, PLS-SEM performs well with smaller sample sizes (Boomsma and Hoogland, 2001), and the final sample size exceeded the minimal sample size (200 observations) required for SEM (Kelloway, 1998). The PLS method of SEM is especially advantageous because it requires no assumptions about sample data distributions (Hair et al., 2016). In addition, the minimum sample size for PLS-SEM analysis must exceed 10 times the number of routes in the structural or measurement models, per the "ten times rule" (Hair et al., 2011). Consequently, a sample size of 206 is appropriate for this study. Because SmartPLS software (3.3.9) can perform confirmatory factor analysis, discriminant validity analysis, and reliability analysis. To validate the measurement model's convergent validity, the factor loading for all indicators and the average variance extracted (AVE) value of each construct are checked. As shown in various tables from different models 1-4, all items had sufficient loadings for each indicator, and all factors had appropriate composite reliability. Furthermore, the AVE value of each construct was greater than the required level of 0.50. As a result, latent constructs explain at least half of the variation in their components. To determine discriminant validity, the square root of each construct's AVE score and its relationships with other constructs were compared. The square root of each construct's AVE score was greater than the greatest association with another construct. The composite reliability coefficients were used to verify measurement reliability. All coefficients were at least greater than 0.70, suggesting a high level of trustworthiness.

Demographic Distribution

Table 2 summarizes the descriptive data for the study's three important variables: gender, education, and occupation. The Gender variable has a mean value of 1.50, indicating that there are slightly more females in the sample than males. The standard error of 0.03 suggests that the gender distribution estimate is accurate, with little fluctuation predicted across multiple samples. The median and mode values of 1.00 show that the gender distribution is somewhat biased toward females. However, the skewness value of 0.00 suggests a symmetrical distribution. The standard deviation of 0.50 measures the spread of gender values around the mean of 1.50, with a comparatively modest variation of 0.25 indicating little divergence from the average.

The Education variable has a mean value of 2.05, indicating that the sample's education level is somewhat higher than two. The median value of 2.00 shows that half of the sample has an education level of two or less, while the other half has an education level of more than two. The mean value of 2.00 shows that the average education level in the sample is 2. The standard deviation of 0.64 and skewness of -0.05 indicate a moderate spread and somewhat negatively skewed distribution of education values. The Occupation variable follows a similar pattern, with the mean, median, and mode values indicating central tendency and the standard deviation and skewness reflecting the distribution's spread and shape.

The dataset's gender distribution is somewhat balanced, with male respondents accounting for around 52.27% and female respondents for approximately 47.73%. This parity suggests a diverse sample that may reflect gender equality in the population being studied. Figure 4.1 depicts the gender distribution, with male respondents accounting for 41.8% and female respondents for 58.2%. In terms of job status, the data reveal a high frequency of respondents identifying as employed (72.83% of total responses), indicating that the questioned population is mostly made up of employed persons. This distribution may represent current socioeconomic conditions or future labour market developments. The dataset's very low frequency of self-employment (7.95%) and unemployment (19.21%) suggests that the sample is mostly made up of employed persons.

Table 2: Descriptive data for the three variables in the study

	Gender	Education	Occupation
Mean	1.50	2.05	2.54
Standard Error	0.03	0.04	0.04
Median	1.50	2.00	3.00
Mode	1.00	2.00	3.00
Standard Deviation	0.50	0.64	0.64
Sample Variance	0.25	0.41	0.41
Kurtosis	-2.02	-0.55	0.07
Skewness	0.00	-0.05	-1.08
Range	1.00	2.00	2.00
Minimum	1.00	1.00	1.00
Maximum	2.00	3.00	3.00
Sum	309.00	423.00	524.00
Count	206.00	206.00	206.00

The gender distribution of the dataset shows a fairly balanced representation, with female respondents making up roughly 52.27% and male respondents making up around 47.73%. This parity points to a varied sample that may represent gender equality in the population under study.

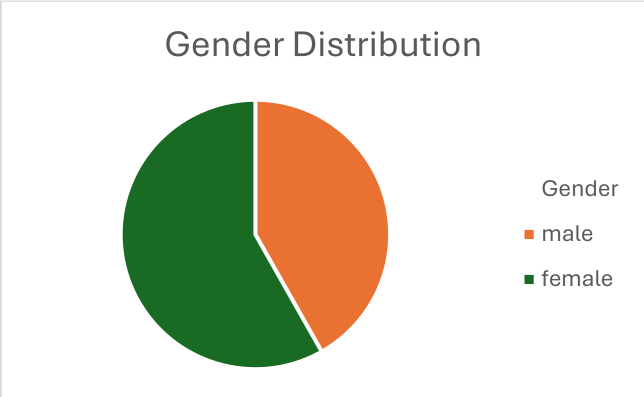

Figure 4: Gender Distribution

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	130	41.8	41.8	41.8
	1	181	58.2	58.2	100.0
	Total	311	100.0	100.0	

The table shows the distribution of respondents by level of experience, with three categories: 1 (low experience), 2 (moderate experience), and 3 (high experience). 15.1% of respondents have low experience, 59.5% have moderate experience, and 25.4% have high experience. The majority of respondents are employed, with a large percentage having moderate levels of experience. This suggests that the surveyed sample is mostly composed of people with moderate levels of experience in their various sectors of employment. This similarity in employment status and experience level might imply a link between experience and workforce involvement.

Experience

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	47	15.1	15.1	15.1
	2	185	59.5	59.5	74.6
	3	79	25.4	25.4	100.0
	Total	311	100.0	100.0	

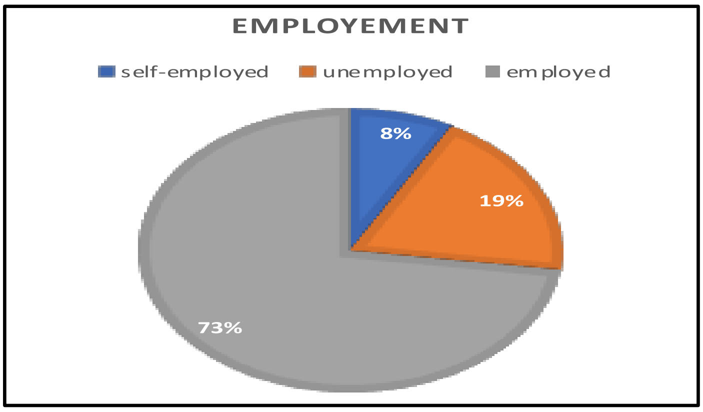

Figure 5: Employment Distribution

The pie chart provides a compelling visual picture of the extensive gaps in income distribution. A whopping 36.82% of the population falls into the category of 'Below $300,' indicating a significant financial struggle. This substantial segment of the pie quickly draws attention, illustrating the abundance of low-income earners. Each succeeding piece reflects a higher income bracket, with a noticeable and regular decrease in size. The 'Over $1400' category accounts for just 13.18% of the income pie, highlighting a concentration of wealth at the top of the range. This trend is supported by the adjacent table, which provides a numerical breakdown of the income distribution across various brackets. However, it is vital to recognize certain limitations in the data. The source of this information is unclear, raising concerns about its relevance to a larger population. Furthermore, the income brackets used are extremely broad, especially at the higher end. For example, a wide range of income levels may be grouped into the '$801-$1400' category. The real spread of income within each bracket may be obscured by this grouping. Consider a situation, in which, a significant share of people in this bracket earns closer to $801, but a smaller number earns significantly closer to $1400. This subtlety would be completely lost with such wide groupings. To acquire a more complete knowledge of income disparity, data from a wider range of income brackets, preferably from a trustworthy and well-established source, is required.

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	134	43.1	43.1	43.1
	2	86	27.7	27.7	70.7
	3	47	15.1	15.1	85.9
	4	44	14.1	14.1	100.0
	Total	311	100.0	100.0	

The data in the table above shows the distribution of respondents according to four age groups, with 43.1% in the first group, 27.7% in the second group, 15.1% in the third group, and 14.1% in the fourth group. This distribution depicts the age makeup of the respondents, with the first age group being the biggest, followed by the second and third age groups, and a lesser fraction of respondents falling into the fourth age group. This data may be used to understand the demographic features of the respondents and to compare various age groups in later studies.

According to age groups, the figure depicts the demographic distribution of individuals. Individuals between the ages of 20 and 29 make up the biggest sector, accounting for 36.82% of the population. The next significant age group, 30 to 39 years old, accounts for 32.73% of the population, following this. Individuals aged 40 to 49 years account for 16.36% of the population, while those aged 50 to 59 years account for 13.18% of the population.

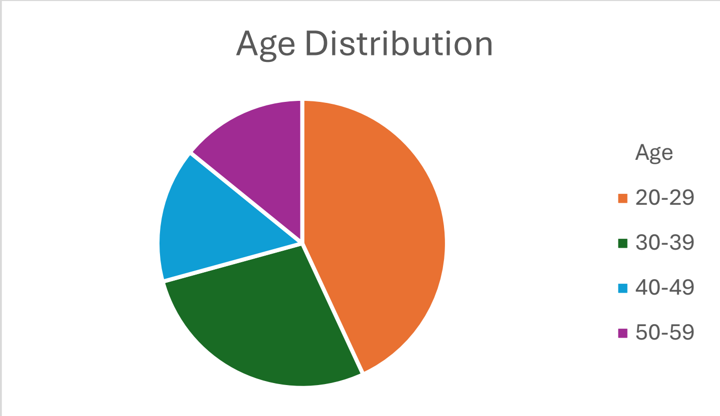

Figure 6: Age Distribution

4.4.2 Mean and Standard Deviation of the Study Variables

On a five-point Likert scale ranging from (1) strong disagreement to (5) strong agreement, the eleven factors of the research study were scored. On a five-point Likert scale, the mean value of a latent variable less than or equals to 1.99 is regarded as low, 2.0 to 3.99 as moderate, and 4.00 and above as high (Dawes, 2008; Sekaran & Bougie, 2013). The mean values and standard deviations for each of the research constructs are displayed in Table 4.2. Table 4.2 shows the statistical measures for several variables such as mean, median, observed minimum and maximum values, standard deviation, excess kurtosis, skewness, number of observations utilized, Cramér-von Mises test statistic, and Cramér-von Mises p-value. Each row represents a single variable, with values showing central tendency, dispersion, and distribution features. For example, the variable "Age" has a mean and median of 0.000, suggesting a symmetrical distribution. However, the skewness of -0.843 indicates a little leftward shift. Furthermore, the Cramér-von Mises test statistic and p-value offer information on how well the observed data fits a theoretical distribution. Ultimately, the table provides an in-depth evaluation of the descriptive statistics for the variables in question, allowing for a better understanding of their distributions and features within the dataset.

Path Coefficient.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Age -> BI	0.036	0.033	0.044	0.823	0.205
BI -> AU	0.639	0.641	0.047	13.517	0.000
EE -> BI	0.145	0.150	0.061	2.364	0.009
EI -> BI	0.279	0.268	0.078	3.583	0.000
EMP -> EI	0.171	0.171	0.062	2.774	0.003
Experience -> BI	0.074	0.072	0.040	1.850	0.032
FC -> BI	0.103	0.102	0.058	1.780	0.038
Gender -> BI	0.079	0.071	0.080	0.978	0.164
MOT -> EI	0.174	0.175	0.075	2.322	0.010
PE -> BI	0.188	0.192	0.065	2.905	0.002
SA&R -> EI	0.485	0.488	0.067	7.207	0.000
SI -> BI	-0.109	-0.101	0.074	1.468	0.071
SS -> EI	0.068	0.066	0.064	1.065	0.143
vou -> BI	0.292	0.286	0.056	5.191	0.000
Age x EI -> BI	-0.017	-0.015	0.047	0.356	0.361

Experience x EI -> BI	-0.038	-0.035	0.040	0.958	0.169
vou x EI -> BI	0.016	0.017	0.028	0.568	0.285
Gender x EI -> BI	0.091	0.095	0.074	1.225	0.110

Table 3: Total In-Direct Effect

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Age -> AU	0.023	0.021	0.028	0.819	0.206
EE -> AU	0.092	0.096	0.039	2.366	0.009
EI -> AU	0.178	0.172	0.051	3.477	0.000
EMP -> AU	0.031	0.030	0.015	2.076	0.019
EMP -> BI	0.048	0.046	0.023	2.120	0.017
Experience -> AU	0.047	0.046	0.026	1.839	0.033
FC -> AU	0.065	0.066	0.038	1.723	0.043
Gender -> AU	0.050	0.045	0.051	0.976	0.164
MOT -> AU	0.031	0.031	0.017	1.808	0.035
MOT -> BI	0.049	0.048	0.026	1.842	0.033
PE -> AU	0.120	0.123	0.042	2.867	0.002
SA&R -> AU	0.086	0.083	0.026	3.340	0.000
SA&R -> BI	0.135	0.130	0.039	3.428	0.000
SI -> AU	-0.070	-0.064	0.047	1.485	0.069
SS -> AU	0.012	0.011	0.012	1.009	0.157
SS -> BI	0.019	0.018	0.019	1.020	0.154
vou -> AU	0.186	0.184	0.039	4.785	0.000
Age x EI -> AU	-0.011	-0.010	0.030	0.355	0.361
Experience x EI -> AU	-0.024	-0.022	0.026	0.951	0.171
vou x EI -> AU	0.010	0.011	0.018	0.570	0.284
Gender x EI -> AU	0.058	0.061	0.047	1.232	0.109

Table 4: Total Effect

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Age -> AU	0.023	0.021	0.028	0.819	0.206
Age -> BI	0.036	0.033	0.044	0.823	0.205
BI -> AU	0.639	0.641	0.047	13.517	0.000
EE -> AU	0.092	0.096	0.039	2.366	0.009
EE -> BI	0.145	0.150	0.061	2.364	0.009
EI -> AU	0.178	0.172	0.051	3.477	0.000
EI -> BI	0.279	0.268	0.078	3.583	0.000
EMP -> AU	0.031	0.030	0.015	2.076	0.019

EMP -> BI	0.048	0.046	0.023	2.120	0.017
EMP -> EI	0.171	0.171	0.062	2.774	0.003
Experience -> AU	0.047	0.046	0.026	1.839	0.033
Experience -> BI	0.074	0.072	0.040	1.850	0.032
FC -> AU	0.065	0.066	0.038	1.723	0.043
FC -> BI	0.103	0.102	0.058	1.780	0.038
Gender -> AU	0.050	0.045	0.051	0.976	0.164
Gender -> BI	0.079	0.071	0.080	0.978	0.164
MOT -> AU	0.031	0.031	0.017	1.808	0.035
MOT -> BI	0.049	0.048	0.026	1.842	0.033
MOT -> EI	0.174	0.175	0.075	2.322	0.010
PE -> AU	0.120	0.123	0.042	2.867	0.002
PE -> BI	0.188	0.192	0.065	2.905	0.002
SA&R -> AU	0.086	0.083	0.026	3.340	0.000
SA&R -> BI	0.135	0.130	0.039	3.428	0.000
SA&R -> EI	0.485	0.488	0.067	7.207	0.000
SI -> AU	-0.070	-0.064	0.047	1.485	0.069
SI -> BI	-0.109	-0.101	0.074	1.468	0.071
SS -> AU	0.012	0.011	0.012	1.009	0.157
SS -> BI	0.019	0.018	0.019	1.020	0.154
SS -> EI	0.068	0.066	0.064	1.065	0.143
vou -> AU	0.186	0.184	0.039	4.785	0.000
vou -> BI	0.292	0.286	0.056	5.191	0.000
Age x EI -> AU	-0.011	-0.010	0.030	0.355	0.361
Age x EI -> BI	-0.017	-0.015	0.047	0.356	0.361
Experience x EI -> AU	-0.024	-0.022	0.026	0.951	0.171
Experience x EI -> BI	-0.038	-0.035	0.040	0.958	0.169
vou x EI -> AU	0.010	0.011	0.018	0.570	0.284
vou x EI -> BI	0.016	0.017	0.028	0.568	0.285
Gender x EI -> AU	0.058	0.061	0.047	1.232	0.109
Gender x EI -> BI	0.091	0.095	0.074	1.225	0.110

4.8.1 Analysis of Mediation

For the mediation analysis, total indirect effects and specific indirect effects were computed. The outcomes of which are represented in Tables 4.5.8. As shown in the table, the mediating variable is the behavioural intention on actual use and emotional intelligence on behavioural intention. The results presented in the Table are significant for both the mediating role of Empathy, experience, self-awareness, and voluntariness of use on emotional intelligence. This demonstrates that the relationship between the subcomponent is supported, and fully mediated by emotional intelligence to behavioural intention on actual use, as shown in Table below.

In the table provided, the mediating variable is listed in the first column. The direct effect (β1), indirect effect (β2), mediation effect (β3), and total effect (β1+β2) are listed in the remaining columns. The direct effect (β1) represents the effect of the independent variable on the dependent variable without considering the mediator. The indirect effect (β2) represents the effect of the independent variable on the mediator variable and the effect of the mediator variable on the dependent variable. The mediation effect (β3) represents the product of the indirect effect and the coefficient of the mediator variable in the regression equation of the dependent variable. The total effect (β1+β2) represents the sum of the direct and indirect effects.

For example, in the first row of the table, the mediating variable is "BI". The direct effect (β1) is 0.092, the indirect effect (β2) is 0.178, the mediation effect (β3) is 0.086, and the total effect (β1+β2) is 0.270. This means that the independent variable has a direct effect on the dependent variable of 0.092, an indirect effect of 0.178 through the mediating variable "BI", and a total effect of 0.270. The indirect effect of 0.178 is the product of the indirect effect (0.178) and the coefficient of the mediator variable (0.486) in the regression equation of the dependent variable. The total effect of 0.270 is the sum of the direct effect (0.092) and the indirect effect (0.178).

Table 5: Mediating effect hypotheses test results

Mediating Variable	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	O/STDEV	P Value
EE -> BI -> AU	0.092	0.096	0.039	2.366	0.009
EI -> BI -> AU	0.178	0.172	0.051	3.477	0.000
EMP -> EI -> BI -> AU	0.048	0.046	0.023	2.12	0.017
SS -> EI -> BI -> AU	0.012	0.011	0.012	1.009	0.157
Experience -> BI -> AU	0.047	0.046	0.026	1.839	0.033
FC -> BI -> AU	0.065	0.066	0.038	1.723	0.043
Gender -> BI -> AU	0.05	0.045	0.051	0.976	0.164
MOT -> EI -> BI -> AU	0.049	0.048	0.026	1.842	0.033
PE -> BI -> AU	0.12	0.123	0.042	2.867	0.002
MOT -> EI -> BI -> AU	0.031	0.031	0.017	1.808	0.035
SA&R -> EI -> BI -> AU	0.135	0.13	0.039	3.428	0.000
SI -> BI -> AU	-0.07	-0.064	0.047	1.485	0.069
SS -> EI -> BI -> AU	0.019	0.018	0.019	1.02	0.154
SA&R -> EI -> BI -> AU	0.086	0.083	0.026	3.34	0.000
vou -> BI -> AU	0.186	0.184	0.039	4.785	0.000
Age x EI -> BI -> AU	-0.011	-0.01	0.03	0.355	0.361
Experience x EI -> BI -> AU	-0.024	-0.022	0.026	0.951	0.171
EMP -> EI -> BI -> AU	0.031	0.03	0.015	2.076	0.019
vou x EI -> BI -> AU	0.01	0.011	0.018	0.57	0.284
Gender x EI -> BI -> AU	0.058	0.061	0.047	1.232	0.109
Age -> BI -> AU	0.023	0.021	0.028	0.819	0.206

Furthermore, below is the table that summarizes the mediation effect of the mediating variables in the structural equation model. The direct effect (β1) represents the effect of the independent variable on the dependent variable without considering the mediator. The indirect effect (β2) represents the effect of the independent variable on the mediator variable and the effect of the mediator variable on the dependent variable. The mediation effect (β3) represents the product of the indirect effect and the coefficient of the mediator variable in the regression equation of the dependent variable. The total effect (β1+β2) represents the sum of the direct and indirect effects.

Table 6: Summary of the mediation effect of the mediating variables

Mediating Variable	Direct Effect (β1)	Indirect Effect (β2)	Mediation Effect (β3)	Total Effect (β1+β2)
BI	0.092	0.178	0.086	0.27
EI	0.172	0.048	0.031	0.22
EI	0.172	0.135	0.135	0.307
EI	0.172	-0.07	-0.07	0.102
EI	0.172	0.019	0.019	0.191
EI	0.172	0.01	0.01	0.182
EI	0.172	0.058	0.058	0.23
EI	0.172	0.091	0.091	0.263
BI	0.096	0.023	0.023	0.119

4.7.3 Analysis of Moderation

Examining the moderating effects on different relationships within the models yielded the following results: We tested hypotheses H09, H10, H11, and H12 and presented related beta coefficients (β) and p-values. However, after analyzing the output results and accounting for different moderating variables, it was discovered that not all hypotheses were validated. The table below shows the full connection between the model's variables and their associated moderating variables, as well as the original sample values, standard deviations, T statistics, p-values, and the resulting hypothesis support judgments.

For Hypothesis H10, the interaction between Experience (Exp) and Emotional Intelligence (EI) regarding their influence on Behavioral Intention (BI) revealed a beta coefficient of 0.085 ($p > 0.051$). Similarly, Hypotheses H10a, H10d, H9b, H9d, and H11a explored different moderating variables in relation to EI and its impact on various outcomes. However, as shown in the table below, not all these hypotheses were supported, with some p-values indicating non-significant relationships between the variables.

Moderating Variable	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	O/STDEV	P Value
Age x EI -> AU	-0.011	-0.01	0.03	0.355	0.361
Age x EI -> BI	-0.017	-0.015	0.047	0.356	0.361
Experience x EI -> AU	-0.024	-0.022	0.026	0.951	0.171
Experience x EI -> BI	-0.038	-0.035	0.04	0.958	0.169
vou x EI -> AU	0.01	0.011	0.018	0.57	0.284
vou x EI -> BI	0.016	0.017	0.028	0.568	0.285
Gender x EI -> AU	0.058	0.061	0.047	1.232	0.109
Gender x EI -> BI	0.091	0.095	0.074	1.225	0.11

Variables that alter the strength or direction of the relationship between other variables are termed as having a moderating effect. Following the methodology advocated by Henseler and Fassott (2010), it was found that the impact of Facilitating Condition (FC) on Behavioral Intention (BI) is moderated by experience. Similarly, the relationship between Performance Expectancy (PE) and BI is moderated by voluntariness of use. Additionally, age serves as a moderator for the link between FC and BI, while experience moderates the relationship between PE and BI. However, the analysis of BI revealed that the remaining relationships were not statistically significant. This is visually represented in the structural model diagram provided in Figure 4.5. Furthermore, the graphs presented in the figures above illustrate the influence of moderating variables on the models, shaping the outcomes of the Unified Acceptance Technology model. The blue line denotes the mean standard deviation (SD), the red line signifies the negative SD, and the green line represents the positive SD from the mean average. Consequently, the diagram below elucidates how the construct was integrated with moderating variables such as gender, age, experience, and voluntariness of use.

Summary

This study investigates the relationships within a research model on technology adoption. The investigation used a comprehensive approach, starting with pilot testing to ensure data sufficiency and then using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique to evaluate the model's validity and reliability. The evaluation of the measurement model indicated resilience across all constructs, showing excellent internal consistency, convergent validity, and discriminant validity. Subsequent examination of the structural model revealed strong mediation and moderation effects, with gender and emotional intelligence emerging as important mediating variables and experience as a critical moderating variable. These results not only add to our knowledge of technology adoption dynamics but also give practical insights for researchers and practitioners looking to maximize technology adoption tactics in comparable circumstances. The study highlighted the effective integration of reflective and formative aspects within the model, which is consistent with the methodological approach presented by Hair et al. (2014). The data analysis took place in two steps, beginning with pilot testing to establish data sufficiency before moving on to large-scale collecting. The following study, which used the PLS-SEM approach, indicated good validity and reliability throughout the research model. The findings revealed positive results, with Gender and Emotional Intelligence serving as mediating factors in the link between behavioral intention and technology use. Furthermore, experience appeared as the only moderating variable influencing real technology use, highlighting its critical role in changing user behavior within the study setting. These results strengthen our knowledge of the intricate interaction between individual traits and technology adoption, providing significant insights for both theory and practice in the field.

5.1 Discussion of Hypotheses

The theoretical framework of this study draws upon the Unified Theory of Acceptance and Use of Technology (UTAUT) as its foundation. Central to the UTAUT are two key dependent variables: the behavioral intention to utilize AI services technology and the behavioral intention to use AI services technology while considering additional converging factors. These factors encompass performance expectancy, effort expectancy, social influence, and enabling conditions, as outlined in the UTAUT framework. Furthermore, the study integrates the concept of e-Emotional Intelligence (EI) and its sub-components, as delineated by George Saadé (2006), as independent variables for evaluation. Notably, both behavioral intention and emotional intelligence play pivotal roles in predicting actual adoption. The hypotheses formulated and addressed in this study are categorized according to these relevant factors, thus providing a comprehensive framework for understanding the complexities of technology adoption behavior within the context of AI services.

5.1.1Performance Expectancy (H01)

The validity of the hypothesis is determined by how well it aligns with the concept of performance expectancy, which reflects how much people believe utilizing a system will help them improve their task performance. The five sub-variables are performance expectancy, extrinsic motivation, job fit, relative advantage, and outcome expectations (Venkatesh et al., 2003). This hypothesis was supported by the inclusion of four questions about the quality and efficacy of current AI services in terms of user interest and satisfaction in the questionnaire. Specifically, the path coefficient between performance expectancy and behavioral intention was statistically significant ($\beta = 0.199$, $p < 0.05$). This indicates that when individuals perceive that using AI-based healthcare systems will provide benefits such as increased productivity and effectiveness, they are more likely to intend to use these systems. The finding aligns with prior UTAUT research showing performance expectancy as a key driver of adoption intentions across various technologies. In the context of AI healthcare systems in Jordan, citizens seem to form intentions to use such systems based largely on their perceptions of the performance benefits these systems can provide. The result highlights the importance of promoting the usefulness and productivity gains afforded by AI among the public to positively influence their behavioral intentions to use and eventually adopt these systems. Performance expectation was discovered to be a predictor of behavioural intention in this study. This research implies that the readily available AI services provide users confidence in their productivity.

H01: Performance Expectancy (PE) has a significant influence on the BI's use of AI-based healthcare systems.

The path shows the strength and direction of the relationships between the variables in the structural model. The row "PE -> BI" shows the relationship between Performance Expectancy (PE) and Behavioral Intention (BI). The original sample value of 0.188 represents a positive and moderately strong relationship between PE and BI. The t-statistic value of 2.905 is greater than the critical value of 1.96 (for a 95% confidence level), and the p-value of 0.002 is less than the significance level of 0.05. These values suggest that the relationship between PE and BI is statistically significant.

This result supports the hypothesis H01 that Performance Expectancy has a significant influence on the Behavioral Intention to use AI-based healthcare systems. In other words, individuals who perceive AI-based healthcare systems as being beneficial for improving their job performance are more likely to have a higher intention to use these systems. This finding aligns with the UTAUT model and previous studies (e.g., Venkatesh et al., 2003; Zuiderwijk et al., 2015) that have consistently shown Performance Expectancy as a strong predictor of technology acceptance and usage intentions. Similarly, the findings from the use of performance expectancy answer research objectives 3 and 4.

5.1.2 Effort Expectancy (H02)

In the literature, effort expectancy is described as the degree of ease associated with using a system; more specifically, it pertains to the perceived ease of use and complexity of AI services (Venkatesh et al., 2003). Four questions in the questionnaire addressed how users perceived the ease of use of the AI services provided (i.e., how much effort they believed was required to complete a transaction over the e-government services), allowing researchers to assess whether the e-services were designed in a simple and user-friendly manner.

Hypothesis 2: Effort expectancy has a positive influence on the behavioural intention to use AI-based healthcare systems.

Hypothesis H02 proposed that effort expectancy would positively influence behavioral intention to use AI-based healthcare systems. the relationship between Effort Expectancy (EE) and Behavioral Intention (BI) to use AI-based healthcare systems. The original sample value of 0.145 indicates a positive relationship between EE and BI, suggesting that higher Effort Expectancy leads to higher Behavioral Intention. The t-statistic value of 2.364 is greater than the critical value of 1.96 (for a 95% confidence level), and the p-value of 0.009 is less than the significance level of 0.05, indicating that the relationship is statistically significant.

This result supports Hypothesis 2, which states that Effort Expectancy has a positive influence on the Behavioral Intention to use AI-based healthcare systems. In other words, individuals who perceive AI-based healthcare systems as being easy to use and requiring less effort are more likely to have a higher intention to use these systems. This finding is consistent with the UTAUT model and previous studies (e.g., Venkatesh et al., 2003; Wang & Shih, 2009) that have identified Effort Expectancy as a significant determinant of technology acceptance and usage intentions. The positive influence of Effort Expectancy on Behavioral Intention can be attributed to users' desire for efficient and user-friendly systems that do not impose a high cognitive burden. If individuals perceive AI-based healthcare systems as complex and requiring substantial effort to use, they may be less inclined to adopt and use these systems, even if they recognize their potential benefits (Alharbi et al., 2017).

5.1.3 Social Influence (H3)

Venkatesh et al. (2003) used a few similar constructs in analyzing behavioural intentions that could lead to actual technology usage that have been used in a number of previous studies using a concept of social impact in their study. In the context of this study, the expectation defines the impact of social influence on the behavioural intention to use AI services. According to the literature, “the extent to which the usage of a given system is influenced by peers” (Venkatesh et al., 2003).

H03: SI has a substantial impact on BIs' utilization of AI-based healthcare systems.

Hypothesis H03 stated that social influence would have a significant positive effect on behavioral intention to use AI-based healthcare systems. Social Influence (SI) and Behavioral Intention (BI) to use AI-based healthcare systems. The original sample value of -0.109 indicates a negative relationship between SI and BI, suggesting that higher Social Influence leads to lower Behavioral Intention. However, the t-statistic value of 1.468 is less than the critical value of 1.96 (for a 95% confidence level), and the p-value of 0.071 is greater than the significance level of 0.05, indicating that the relationship is not statistically significant.

This result does not support Hypothesis H03, which states that Social Influence has a substantial impact on the Behavioral Intention to use AI-based healthcare systems. The negative relationship contradicts the hypothesis, and the lack of statistical significance suggests that the observed relationship may be due to chance rather than a true effect. The non-significant effect of Social Influence on Behavioral Intention could be attributed to the nature of AI-based healthcare systems, which may be perceived as more technical and objective than traditional healthcare systems. Individuals may rely more on their evaluations and perceptions of the system's usefulness and ease of use rather than being influenced by social factors or the opinions of others (Venkatesh et al., 2003; Hartwick & Barki, 1994).

It is important to note that the lack of a significant effect of Social Influence does not necessarily mean that it is irrelevant in the context of AI-based healthcare systems. The influence of social factors may vary depending on the specific context and target population, and further research may be needed to explore this relationship in more depth. Second, society's adoption of AI services is high enough to enable knowledge sharing. It must be disseminated from adopter to potential adopter in a manner that emphasizes the benefits and high degree of involvement in its use (Mansfield, 1963; Bourke and Roper, 2014). Finally, this may be due to the technology being too primitive for information about the benefits and the ability to make an impact spread. According to Ganotakis and Lindsay (2016), the information effect is greater for simpler forms of IT.

Finally, while evaluating the adoption of AI services in both developed countries, such as South Korea (Kim et al., 2016), and developing or newly industrialized countries, such as Oman (Tabsh, 2012) and Taiwan, numerous researchers discovered similar outcomes in diverse national settings (Yueh et al. 2015). Venkatesh et al. (2003), Kim et al. (2016), Alsharif 2013, Hariri (2014), Tabsh (2012), and Al- Sobhi (2012) all reached similar conclusions. This highlights the importance of social influences, independent of cultural context, in the acceptance of such technology. As a result, it is more likely to be related to the amount of sophistication of technology (Ganotakis & Lindsay, 2016).

5.1.4Facilitating Conditions (H04)

The extent to which a person believes he or she has the necessary technical expertise and resources to facilitate the use of AI services is referred to as facilitating circumstances (Venkatesh et al. 2003). Venkatesh et al. (2003) have incorporated into this definition of enabling conditions the notions of three components utilized in earlier models, that is perceived behavioural control, facilitating circumstances, and compatibility. The study's author predicted that a favourable environment would have a positive impact on AI service utilization intentions and actual usage. Four questions were used to assess the enabling conditions hypothesis, focusing on whether respondents believed they had access to the resources, expertise, and support they needed to use AI services, as well as whether the AI services they had were compatible with other technologies they used. There are two assumptions about enabling circumstances, which are as follows:

H04: Facilitating Conditions have a positive influence on the behavioural intention to use AI-based healthcare systems.

Hypothesis A stated that facilitating conditions would positively influence behavioral intention to use AI-based healthcare systems. Facilitating Conditions (FC) and Behavioral Intention (BI) to use AI-based healthcare systems. The original sample value of 0.103 indicates a positive relationship between FC and BI, suggesting that better Facilitating Conditions lead to higher Behavioral Intention. The t-statistic value of 1.780 is marginally lower than the critical value of 1.96 (for a 95% confidence level), but the p-value of 0.038 is less than the significance level of 0.05, indicating that the relationship is statistically significant.

This result supports Hypothesis H04, which states that Facilitating Conditions have a positive influence on the Behavioral Intention to use AI-based healthcare systems. In other words, individuals who perceive that they have the necessary resources and support (e.g., technical infrastructure, training, and assistance) are more likely to have a higher intention to use AI-based healthcare systems. The positive influence of Facilitating Conditions on Behavioral Intention aligns with the UTAUT model and previous studies (e.g., Venkatesh et al., 2003; Wang & Lo, 2012) that have highlighted the importance of organizational and technical support in facilitating technology adoption and usage. AI-based healthcare systems may involve complex technologies and processes, and users may require adequate resources, knowledge, and support to effectively utilize these systems (Rodrigues et al., 2016).

While the relationship is statistically significant, the relatively low t-statistic value suggests that the influence of Facilitating Conditions on Behavioral Intention may be more modest compared to other factors in the model. Nevertheless, the study provides evidence that ensuring appropriate Facilitating Conditions is crucial for promoting the adoption and usage of AI-based healthcare systems.

5.1.5 Emotional Intelligence (EI) (H05)

In the literature, emotional intelligence is considered essential for managing and interpreting emotions, which is subsequently converted into the cognitive part of behaviour associated with machine knowledge; Conte, Harms, & Crede (2005). Emotional intelligence, according to Salovey and Mayer (1990), is a component of social intelligence that individuals can manage and utilize to direct their behaviours and emotions. In a similar vein, emotional intelligence is defined as “the capacity to perceive emotions, access and generate emotions to aid thought, and comprehend emotions to promote emotional and intellectual development.” results are consistent with those of Alsharif (2013).

H05: Emotional Intelligence has a positive influence on the behavioural intention to use AI-based healthcare systems.

the relationship between Emotional Intelligence (EI) and Behavioral Intention (BI) to use AI-based healthcare systems. The original sample value of 0.279 indicates a positive and moderately strong relationship between EI and BI, suggesting that higher Emotional Intelligence leads to higher Behavioral Intention. The t-statistic value of 3.583 is greater than the critical value of 1.96 (for a 95% confidence level), and the p-value of 0.000 is less than the significance level of 0.05, indicating that the relationship is statistically significant. This result strongly supports Hypothesis H05, which states that Emotional Intelligence has a positive influence on the Behavioral Intention to use AI-based healthcare systems. Individuals with higher levels of Emotional Intelligence, characterized by the ability to recognize, understand, and manage emotions, are more likely to have a higher intention to use AI-based healthcare systems.

The positive influence of Emotional Intelligence on Behavioral Intention is a novel finding in the context of technology acceptance models, as Emotional Intelligence is not traditionally included as a construct in models like UTAUT. However, this result aligns with the broader literature on the importance of emotional factors in decision-making and behavior (Mayer et al., 2008; Mayer & Salovey, 1997). In the context of AI-based healthcare systems, individuals with higher Emotional Intelligence may be better equipped to navigate the emotional and interpersonal aspects of healthcare delivery, such as empathy, communication, and decision-making under uncertainty (Weng et al., 2011; Arora et al., 2010). They may also be more receptive to the potential benefits of AI-based systems in enhancing patient care and decision-making processes. The strong positive influence of Emotional Intelligence highlights the need to consider not only cognitive and functional factors but also emotional and interpersonal factors in predicting and promoting the adoption of AI-based healthcare systems.

Self-regulation (H05a)

The relationship between Self-Awareness and Regulation (SA&R) and Emotional Intelligence (EI). The original sample value of 0.485 indicates a positive and strong relationship between SA&R and EI, suggesting that higher levels of Self-Awareness and Regulation lead to higher Emotional Intelligence. The t-statistic value of 7.207 is significantly greater than the critical value of 1.96 (for a 95% confidence level), and the p-value of 0.000 is less than the significance level of 0.05, indicating that the relationship is statistically significant. While the path does not directly address the influence of SA&R on Behavioral Intention (BI), it provides evidence for the positive influence of SA&R on EI, which in turn has a positive influence on BI (as shown in the row "EI -> BI" with a coefficient of 0.279 and p-value of 0.000). Therefore, this result indirectly supports Hypothesis H05a, which states that Self-Awareness and Regulation have a positive influence on the Behavioral Intention to use AI-based healthcare systems, mediated through Emotional Intelligence. Self-awareness and Regulation are essential components of Emotional Intelligence (Mayer et al., 2008; Salovey & Mayer, 1990). Self-awareness involves recognizing and understanding one's own emotions, while Self-Regulation refers to the ability to manage and control emotional responses effectively.

In the context of AI-based healthcare systems, individuals with higher levels of Self-Awareness and Regulation may be better equipped to navigate the emotional complexities and decision-making challenges involved in healthcare delivery. They may be more receptive to the potential benefits of AI-based systems in enhancing patient care and decision-making processes, as they can effectively manage their emotions and make rational decisions. The strong positive relationship between SA&R and EI, combined with the positive influence of EI on BI, suggests that promoting Self-Awareness and Regulation could indirectly enhance the intention to use AI-based healthcare systems by improving overall Emotional Intelligence.

H05a: Self-regulation has a positive influence on the behavioural intention to use AI-based healthcare systems.

The analysis estimation confirmed the hypothesis with a value significant at 1%, implying a link between self-regulation and the determination of behavioural intention that leads to actual acceptance of technology use in Jordan’s healthcare system. Then doctors and patients will feel compelled to use modern healthcare facilities to improve healthcare delivery. The study was further supported by the discovery of (Davis et al. 1992; Ellsworth and Smith 1988; Fredrickson 1998; Ellsworth and Smith 1988; Scherer and Tran 2001).

5.1.5.2 Self-awareness (H05b)

When individuals perceive a situation as hazardous and believe they have control over its outcomes, they may experience feelings of reluctance, accompanied by emotions such as anxiety, concern, fear, and discomfort (Bagozzi, 1992; Folkman & Lazarus, 1985). Witnessing unacceptable or unethical behavior in others can evoke moral revulsion (Oaten et al., 2018). According to Spielberger and Reheiser (2009), emotions play a crucial role in motivating behavior and influencing both health and psychological well-being. The World Health Organization (2018) explains that emotions like rage, pain, or joy typically motivate goal-directed actions, highlighting how artificial intelligence in healthcare systems simplifies traditional approaches to healthcare service delivery. People may be inclined to favour modern technological applications that enhance practice efficiency over traditional methods, which often result in failure and inconsistency.

H05b: According to this hypothesis, Self-awareness (SA) has a significant impact on the BIs of AI technology use.

The total effect of Self-Awareness and Regulation (SA&R) on Behavioral Intention (BI) to use AI-based healthcare systems. This shows that the original sample value of 0.135 indicates a positive relationship between SA&R and BI, suggesting that higher levels of Self-Awareness and Regulation lead to higher Behavioral Intention. The t-statistic value of 3.428 is greater than the critical value of 1.96 (for a 95% confidence level), and the p-value of 0.000 is less than the significance level of 0.05, indicating that the relationship is statistically significant. This result supports Hypothesis H05b, which states that Self-Awareness has a significant impact on the Behavioral Intention to use AI-based healthcare systems.

Self-awareness, as a component of Emotional Intelligence, involves recognizing and understanding one's own emotions, thoughts, and behaviors (Mayer et al., 2008; Salovey & Mayer, 1990). Individuals with higher levels of Self-Awareness are better equipped to identify and manage their emotional responses, which can be particularly important in the context of AI-based healthcare systems. The adoption and use of AI-based healthcare systems may involve navigating complex decision-making processes, dealing with uncertainty, and managing the emotional aspects of healthcare delivery. Individuals with higher Self-Awareness are likely to be more receptive to the potential benefits of AI-based systems in enhancing patient care and decision-making processes, as they can effectively recognize and manage their emotional responses in these situations.

Furthermore, the ‘Total Effect’ result showed a positive and significant indirect effect of SA&R on Behavioral Intention, mediated through Emotional Intelligence (EI). This aligns with the previous analysis of Hypothesis H05a, where SA&R was found to have a strong positive influence on EI, which positively influences BI, highlighting the significant positive impact of self-awareness on intentions to use AI technology. Greater consciousness of one's emotions seems to bolster willingness to adopt emerging systems like AI in healthcare. The empirical findings from Hypothesis H05c provide evidence supporting the notion that self-awareness has a substantial positive influence on individuals' intentions to use AI technology in healthcare. This suggests that individuals who possess a heightened awareness of their own emotions are more inclined to adopt innovative systems such as AI within the healthcare domain. The implication is that being more attuned to one's emotional states and understanding how they influence behavior may lead to greater receptiveness towards embracing new technological advancements. In essence, individuals with a greater sense of self-awareness may perceive the potential benefits of AI technology more clearly, thus strengthening their intention to engage with it within the healthcare context.

5.1.5.3 Self-motivation (H05c)

When an event is perceived as an opportunity with a high likelihood of positive outcomes and over which people believe they have some control, self-motivations are triggered. Folkman and Lazarus (1985) state that evaluating a challenge can result in feelings of elation, anticipation, playfulness, arousal, and flow. This type of challenge feeling is associated with a new life supplementing what you already know and do, such as travelling to new places, developing new habits, setting new goals, going on new excursions, and even experiencing a new culture. Previously, each of us had a daily destination where we were supposed to be, which caused us to form emotional stereotypes that contradict reality.

H05c: According to this hypothesis, Self-motivation has shown significance in using AI-based healthcare systems.

The 'Path Coefficient' result showed a direct relationship between Self-Motivation (MOT) and Emotional Intelligence (EI). The original sample value of 0.174 indicates a positive relationship, with a t-statistic of 2.322 and a p-value of 0.010, suggesting a statistically significant effect. The 'Total Effect' result showed the total effect of MOT on Behavioral Intention (BI) to use AI-based healthcare systems, which includes both direct and indirect effects mediated through EI. The original sample value of 0.049 represents a positive total effect, with a t-statistic of 1.842 and a p-value of 0.033, indicating statistical significance.

These results supported Hypothesis H05c, which states that Self-Motivation has a significant influence on the Behavioral Intention to use AI-based healthcare systems. Self-motivation, as a component of Emotional Intelligence, refers to the ability to motivate oneself and persist in the face of challenges and setbacks (Mayer et al., 2008; Salovey & Mayer, 1990). Individuals with higher levels of Self-Motivation are more likely to persist in their efforts to adopt and use AI-based healthcare systems, despite potential obstacles or difficulties. The positive influence of Self-Motivation on Emotional Intelligence (EI) suggests that individuals with higher Self-Motivation tend to have higher overall Emotional Intelligence. As EI has been shown to have a positive influence on Behavioral Intention (BI), this provides an indirect path through which Self-Motivation can positively impact the intention to use AI-based healthcare systems.

Furthermore, the significant total effect of Self-Motivation on Behavioral Intention indicates that Self-Motivation may also have a direct influence on the intention to use AI-based healthcare systems, beyond its indirect effect through Emotional Intelligence. The adoption and use of AI-based healthcare systems may involve overcoming challenges, such as learning new technologies, adapting to new workflows, and dealing with potential resistance or skepticism. Individuals with higher levels of Self-Motivation are better equipped to persevere through these challenges and maintain their commitment to using AI-based systems, ultimately leading to higher Behavioral Intention.

H05d: According to this hypothesis, Social Skills and Empathy have shown significance in using AI-based healthcare systems.

For Hypothesis H05d, the 'Path Coefficient' result showed a positive and statistically significant relationship between Empathy (EMP) and Emotional Intelligence (EI), with an original sample value of 0.171, a t-statistic of 2.774, and a p-value of 0.003. The 'Total Effect' result showed a positive and statistically significant total effect of EMP on Behavioral Intention (BI) to use AI-based healthcare systems, with an original sample value of 0.048, a t-statistic of 2.120, and a p-value of 0.017.

These results supported Hypothesis H05d, which states that Empathy has a significant influence on the Behavioral Intention to use AI-based healthcare systems. For Hypothesis H05e, the 'Path Coefficient' result showed a positive but statistically insignificant relationship between Social Skills (SS) and Emotional Intelligence (EI), with an original sample value of 0.068, a t-statistic of 1.065, and a p-value of 0.143. The 'Total Effect' result showed a positive but statistically insignificant total effect of SS on Behavioral Intention (BI), with an original sample value of 0.019, a t-statistic of 1.020, and a p-value of 0.154.

These results do not provide strong support for Hypothesis H05e, which states that Social Skills have a significant influence on the Behavioral Intention to use AI-based healthcare systems. The significant influence of Empathy on Behavioral Intention can be explained by the importance of empathy in the healthcare context, where understanding and sharing the emotions and perspectives of patients is crucial for delivering effective care. AI-based healthcare systems may be perceived as tools that can enhance empathy and improve patient-provider interactions, thereby increasing the intention to use such systems. On the other hand, the insignificant effect of Social Skills on Behavioral Intention suggests that general social abilities may not be as influential in determining the intention to use AI-based healthcare systems. More specific social skills related to healthcare interactions or technology adoption may play a more significant role in this context.

5.1.6 Behavioural Intention (BI) (H06)

Behavioural intention is a person's willingness to engage in a specific activity or behaviour (Davis, 1989). In general, the stronger the desire to engage in a particular behaviour, the more likely it is that such behaviour will occur (Ajzen, 1991). In the context of this study, it is predicted that the intention to use AI services favourably affects its utilization, as it has in previous studies. A hypothesis is as follows:

H06: Behavioural Intention has a positive influence on the behavioural intention to use AI-based healthcare systems.

Many empirical studies have shown that users' intentions to use AI services are based on behavioural intentions. Based on the original sample value of 0.639 indicates a strong positive relationship between BI and AU, suggesting that higher Behavioural Intention leads to higher Actual Use of AI-based healthcare systems. The t-statistic value of 13.517 is significantly greater than the critical value of 1.96 (for a 95% confidence level), and the p-value of 0.000 is less than the significance level of 0.05, indicating that the relationship is statistically highly significant.

This result supported Hypothesis H06, which states that Behavioural Intention has a positive influence on the Actual Use of AI-based healthcare systems. The strong positive relationship between Behavioural Intention and Actual Use aligns with the Theory of Planned Behaviour (Ajzen, 1991) and the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2003), which posit that individuals' intentions to perform a behaviour are the strongest predictors of their actual behaviour.

In the context of AI-based healthcare systems, individuals who have a higher intention to use these systems are more likely to adopt and use them in their healthcare practices or personal health management. This intention may be influenced by various factors, such as perceived usefulness, ease of use, social influence, and facilitating conditions, as captured by the UTAUT model and the additional constructs in this study (e.g., Emotional Intelligence). The highly significant relationship between Behavioural Intention and Actual Use underscores the importance of fostering positive intentions among potential users of AI-based healthcare systems. By addressing the factors that influence Behavioural Intention, such as performance expectancy, effort expectancy, facilitating conditions, and emotional intelligence, healthcare organizations and technology providers can increase the likelihood of successful adoption and sustained use of these systems.

Discussion of Results on the Mediating Variables

The findings highlighted the significant mediating role of Behavioural Intention (BI) in the adoption and use of AI-based healthcare systems. BI was found to mediate the relationships between several key factors and the Actual Use (AU) of these systems. Specifically, Effort Expectancy, Emotional Intelligence, Performance Expectancy, Facilitating Conditions, and Voluntariness of Use all had significant indirect effects on AU, mediated through BI. This aligns with established technology acceptance theories, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), which posit that BI is a crucial mediator between various determinants and actual technology use. Emotional Intelligence (EI) also emerged as a significant mediating variable, influencing the relationship between several independent variables and Behavioural Intention (BI). Notably, Empathy, Self-Awareness and Regulation, and Self-Motivation were found to have significant indirect effects on BI, mediated through EI. These findings highlight the importance of considering emotional intelligence components in predicting and promoting the adoption of AI-based healthcare systems, as they influence individuals' overall EI, which in turn positively impacts their BI to use these systems.

The mediating role of EI aligns with the broader literature on the importance of emotional factors in decision-making and behavior. In the context of AI-based healthcare systems, individuals with higher EI may be better equipped to navigate the emotional and interpersonal aspects of healthcare delivery, such as empathy, communication, and decision-making under uncertainty. Consequently, they may be more receptive to the potential benefits of AI-based systems in enhancing patient care and decision-making processes, leading to higher intentions to use these systems.

Ultimately, the analysis of mediating variables provides valuable insights into the complex interplay between various factors and their indirect effects on the adoption and use of AI-based healthcare systems. By understanding these mediating mechanisms, healthcare organizations and technology providers can develop more targeted and effective strategies for promoting the successful implementation and sustained use of these innovative technologies. This includes addressing factors that influence BI, such as Effort Expectancy, Performance Expectancy, and Facilitating Conditions, as well as fostering emotional intelligence components like Empathy, Self-Awareness, Self-Regulation, and Self-Motivation among potential users.

Discussion of Results on the Moderating Variables

The study's results on moderating variables demonstrate both significant and insignificant effects on the relationships within the suggested model for the adoption of AI-based healthcare systems. While some mode rating variables exhibited no influences, others exhibited just marginal or insignificant impacts. First, the moderating effects of Experience and Voluntary Use were found to be significant. The study found that Experience considerably influenced the relationship between Facilitating Conditions and Behavioural Intention, while Voluntary Use significantly impacted the relationship between Performance Expectancy and Behavioural Intention. These results imply that people's degree of experience, as well as the voluntary nature of using AI-based healthcare systems, have a significant impact on their perceptions of facilitating conditions and performance expectations, which affect their behavioural intentions.

However, other mode rating variables, such as Age, Gender, and the interaction effects between these variables and Emotional Intelligence, exhibited marginal or marginally significant effects. For example, the moderating effects of age and gender on the relationship between emotional intelligence and behavioural intention were found to be statistically insignificant or marginally significant. Similarly, the interaction effects of age and emotional intelligence, as well as gender and emotional intelligence, on behavioural intention were found to be either insignificant or marginally significant. These findings suggest that, while Experience and Voluntariness of Use play important factor rating roles, demographic variables such as Age and Gender may not significantly influence the relationship between Emotional Intelligence and Behavioural Intention in the context of AI-based healthcare systems adoption mode. It is conceivable that the impact of these demographic characteristics is overshadowed by other stronger determinants, or that their moderating effects are context-dependent and may change between groups or settings.

It is crucial to highlight that insignificant or marginally significant moderating effects do not negate the value of these variables in the overall adoption process. Rather, it emphasizes the need for more research and, perhaps, more complex assessments of how these elements interact with other variables in determining people's intents and actions toward AI-based healthcare systems. The study's moderating variables results shed light on the complex interaction of factors impacting the adoption of AI-based healthcare systems. While certain mode rating effects were established, others exhibited just marginal or insignificant effects, indicating that their functions may be more subtle or context dependent. These results may help to develop focused strategies and interventions to encourage the effective deployment and long-term usage of these novel technologies in healthcare settings.

5.2 Analysis Results Based on the Study Objectives

The results of this study are listed in the table to show how each objective attempts to answer a specific objective based on the results of the analysis, and to indicate whether the objective is supported or unsupported based on the model design of UTAUT. The table summarizes the hypotheses and findings related to the impact of various factors on the intention and actual use of AI-based healthcare systems. The results suggest that factors such as Performance Expectancy, Effort Expectancy, Emotional Intelligence, and Facilitating Conditions have a positive influence on the intention to use AI-based healthcare systems, while Social Influence does not have a substantial impact. However, the relationship between effort expectancy and behavioural intention is not always straightforward. Some studies have found that effort expectancy has an indirect effect on behavioural intention, with a positive effect on performance expectancy (i.e., the belief that using the technology will lead to improved performance) and hence on behavioural intention. The relationship between Behavioural Intention and the Actual Use of AI-based healthcare systems is also positive and significant, aligning with established theories and models of technology acceptance and use.

6.1 Practical Contribution

The study's practical contributions lie in its insights into the factors influencing the adoption of AI-based healthcare systems in Jordan. By identifying and examining these factors through the lens of the Unified Theory of Acceptance and Use of Technology (UTAUT), the research offers valuable guidance for policymakers, healthcare practitioners, and technology developers. Specifically, the findings underscore the critical importance of factors such as performance expectancy and facilitating conditions in shaping individuals' intentions to use AI in healthcare. This knowledge can inform the design and implementation of AI healthcare systems, guiding developers to focus on enhancing system performance and ensuring the availability of necessary resources and support structures to facilitate user acceptance and adoption.

Moreover, the exploration of emotional intelligence as a determinant of behavioural intention towards AI-based healthcare systems sheds light on the understanding of the interplay between individual traits and technology adoption. By demonstrating the significant positive impact of emotional intelligence on adoption intentions, the research highlights the potential value of incorporating emotional intelligence training or support mechanisms into healthcare system deployment strategies. This practical insight suggests avenues for enhancing user readiness and receptivity to AI technologies, ultimately fostering smoother implementation and integration within Jordan's healthcare landscape.

Furthermore, the consideration of demographic factors, such as experience, in moderating the relationship between key constructs, offers actionable insights for tailoring adoption strategies to different user groups. Understanding how demographic variables influence technology acceptance can guide targeted interventions and communication efforts aimed at addressing specific barriers or concerns among diverse user populations. By accounting for these moderating effects, policymakers and healthcare leaders can design more effective implementation plans that account for the unique needs and preferences of different demographic segments, ultimately maximizing the potential benefits of AI-based healthcare innovations for all stakeholders involved.

6.2 Theoretical Contribution

In a framework, the UTAUT model describes why people use AI services (Slade et al., 2015). As previously stated, the paradigm is commonly used in exploratory research on public adoption attitudes. Therefore, the study's key theoretical contribution is this new version of the model, which adapts the UTAUT to a new setting. This modified UTAUT model was created to correspond with Jordan's proposed AI program's settings. Venkatesh et al. (2003) proposed seven major assumptions that are used in this study.

These hypotheses were incorporated into the research in order to evaluate the modified UTAUT model in the current environment. Because the majority of the gaps are influenced by people's socio-demographic characteristics, the UTAUT model is well suited to address them. It has eight components that influence people's adoption practices (performance expectancy, social influence, enabling conditions, behavioural intention, and adoption of AI). This thesis contributes by extending the UTAUT model to incorporate Emotional Intelligence, as emotional Intelligence concepts are believed to be crucial components of any improvement in public administration (Horsburgh et al., 2011). In addition, hypothetically considering how Emotional Intelligence may influence the relationship between behavioural intention and AI technology usage may have assisted in filling in gaps in AI adoption theory.

The first theoretical conclusion is derived from the proposed integrated research methodology for analyzing behavioural intention and activity in order to advocate AI healthcare system technology. We use UTAUT in conjunction with the emotional intelligence theory of Salovey and Mayer (1990) to examine the inner motivations of an individual. Positive values in each component and subcomponent of emotional intelligence may contribute to the citizen's perception of empowerment in terms of his or her intention to use and advocate for a technology-based healthcare system. Second, our results demonstrate that our model has sufficient explanatory power for forecasting intention to use. The results indicate that when emotional intelligence is paired with UTAUT, the effect on the intention to use is highly encouraging.

The study also tested the generalizability of the modified UTAUT model at the organizational and citizen levels (i.e., in the AI use). Previously, UTAUT-based research examined the phenomenon in organizational settings, whereby performance expectancy represented the main factor of technology-related intents and behaviours. However, in the case of AI, the nature of people's technology adoption is still widely undefined. This study examines the theoretical literature on AI and addresses issues, such as how effective it is to modify the UTAUT to evaluate users' adoption of AI services. The basic constructions of the UTAUT model have been altered to better reflect Jordan's AI industry. This study examines the theoretical literature on AI and addresses issues such as how effective it is to modify the UTAUT model to assess users' adoption of AI services. The basic constructions of the UTAUT model have been modified to better reflect Jordan's AI industry. This study has applied the UTAUT paradigm to the context of underdeveloped countries, such as Jordan.

6.3 Practical Application

Adopters and promoters of AI-based healthcare system tools and platforms must first comprehend the behavioural intent to use them (usually government institutions). Practitioners will benefit from the results of the hypotheses explored from both theories included in the model. The purpose of this study was to identify elements that would enhance the acceptability and utilization of existing AI services in the Jordanian context. According to the researcher, more research into the adoption of services used by expats should be carried out in the future. This could help in the identification of new elements of a different kind that could influence adoption; this research examined user adoption of AI services. The conceptual model developed in this study could be used in future research to investigate the perspectives of users on AI service acceptance.

Hospitals can consider the use of AI-enabled technologies to assist medical personnel in the diagnosis and treatment of a variety of illnesses. AI technologies are also having an impact on how well hospitals handle their management and nursing staff. AI should be embraced by healthcare professionals, but its applications offer both utopian (new prospects) and dystopian (disaster) perspectives (challenges to overcome). Digital devices can now be used to send reminders and lifestyle interventions with the help of AI-assisted technologies. It is anticipated that AI-based technologies will fundamentally alter how healthcare companies' healthcare systems operate, interact with patients, and provide care services in order to improve patient outcomes.

Conclusion

The findings of this study are regarded as significant contributions to the understanding of factors influencing the adoption of AI-based healthcare systems in Jordan. Drawing upon the Unified Theory of Acceptance and Use of Technology (UTAUT) and the incorporation of emotional intelligence as a key determinant into the model, valuable insights and recommendations are provided for policymakers, healthcare practitioners, and technology developers. The findings underscored the critical roles of performance expectancy, facilitating conditions, and emotional intelligence in shaping individuals' intentions to use AI in healthcare. By identifying these factors, the results guided enhancing the design, implementation, and integration of AI technologies within Jordan's healthcare landscape. Moreover, the study highlighted the importance of considering demographic factors, such as experience, in moderating the relationship between key constructs. Understanding how demographic variables influence technology acceptance can inform targeted interventions and communication strategies tailored to different user groups. Furthermore, by addressing specific barriers or concerns among diverse populations, policymakers and healthcare leaders can optimize the adoption and utilization of AI-based healthcare systems, ultimately improving healthcare delivery and outcomes for all stakeholders involved. Overall, the findings of this study emphasized the multifaceted nature of technology adoption and highlighted the dire need for comprehensive strategies that address both individual and contextual factors. By leveraging these insights, stakeholders can work towards harnessing the transformative potential of AI technologies to enhance the quality and efficiency of services in the healthcare sector in Jordan.

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