"ARTIFICIAL INTELLIGENCE AND ITS APPLICATIONS IN NURSING HEALTH CARE AND LABORATORY IN SAUDI ARABIA".

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ABSTRACT
Practically every area of science and technology, including healthcare, is currently undergoing a huge paradigm shift as a result of artificial intelligence (AI). In order to develop AI-based healthcare systes, Therefore, this study aimed to study aimed to explore the artificial intelligence and its applications in nursing healthcare and laboratory in Saudi arabia, The descriptive study was used, a theorethical framework based on UTAUT is proposed in this study whoch theorizes that four constructs play a significant role as direct determinants of user acceptance and usage behaviour: performance expectancy, effort expectancy, social influence, A quantitative study is conducted using questionnaire to artificial intelligence and its applications in nursing healthcare centers and laboratory in Saudi arabia, the results of this study may be provide the developers of AI-based healthcare systems in Saudi Arabia in Saudi Arabia.

Keywords: Artificial Intelligence, Health Care Systems, Health Centers, Saudi Arabia.

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1-1 Introduction

The combination of rising technologies like artificial intelligence and healthcare is one of the hottest topics today, artificial Intelligence is defined as the ability of machines to mimic human intelligence and perform tasks that would normally require human cognition. Integrating artificial intelligence with healthcare has the potential to change the way healthcare is delivered and managed to become a comprehensive, effective and integrated health system, as artificial intelligence can help analyze large amounts of data, identify patterns, and even make predictions of future patient outcomes.

In light of the development of global health systems, and with the acceleration and increase in the use of artificial intelligence in health care, and research and health organizations racing to adopt artificial intelligence technology to improve the patient experience and help address some of the pressing problems facing health care today, and in order to obtain a deeper understanding of the impact of these emerging technologies. to patients, healthcare professionals and wider society (Ministry of health Saudi Arabia, 2021). To ensure the continued development of health care services in the Kingdom of Saudi Arabia and to focus efforts in this sector to face the challenges related to health services by raising their quality and efficiency, we can discuss the following topics: Excerpts from the current health care situation; A closer look at ways to use artificial intelligence technology in health care; potential future impact; Challenges in implementation and adoption of emerging technologies in health care (Abu-Shanab, 2019).

The Kingdom Vision (2030) plan, launched by the Saudi government in 2016, includes a comprehensive strategy to transform the healthcare system. The plan aims to create a more patient-centered health care system. It also emphasizes the importance of preventive health care, health education, and reducing health care costs. The program includes several goals, such as increasing the number of health care providers, enhancing health care infrastructure, and applying new health care technologies. It also aims to make the Kingdom one of the most efficient countries in the field of health care (Alhashmi & Salloum, 2019).

AI in healthcare is an important part of Vision 2030, the Saudi Data and Artificial Intelligence Authority (SDAIA) was created for this purpose, and other entities including the National Healthcare Command and Control Center (NHCCC). According to the 2023 Artificial Intelligence Index report issued by Stanford University, Saudi Arabia has the second largest amount of knowledge and awareness of the benefits of artificial intelligence among countries.

According to the results of this recent index, the Kingdom of Saudi Arabia ranked highly among the most "efficient" countries in the health sector, occupying second place directly after Singapore, recording 44.17 points, and surpassing the overall average of the index in the group of 16 countries, by a difference of 17 points, as this represents Points: Rates of countries' spending on the health care sector versus the returns achieved in the health sector. As part of the Kingdom Vision 2030 strategy, the first World Summit on Artificial Intelligence was held in September 2020 under the patronage of His Royal Highness Prince Mohammed bin Salman bin Abdulaziz, Crown Prince, Deputy Prime Minister and Minister of Defense. The summit included 30 sessions attended by 60 speakers, including ministers, leaders of global entities, academics, investors and businessmen from 20 countries (Alijerin & Arfat, 2022).

During this 2020 Global AI Summit, the Kingdom signed strategic agreements with IBM, Alibaba, Huawei and other companies to develop a global framework that supports international cooperation in the field of artificial intelligence. SDAIA also announced a partnership with the World Bank to strengthen local economies in developing countries after that, many meetings and conferences followed, the most important of which was the Riyadh International Summit for Medical Biotechnology in Riyadh, September 2021. The Kingdom of Saudi Arabia hosted the summit as one of the events accompanying its presidency of the G20. The Riyadh Global AI in Healthcare Summit was also held in Riyadh in March 2022. Leading AI scientists, executives and business leaders from around the world gathered to discuss the latest AI research and technologies and to explore the potential of AI, machine learning and deep learning in healthcare. Aramco also established Prosperity Ventures, a global venture fund to invest in emerging technologies (Alijerin & Arfat, 2022).

1.2 Using Technology in healthcare Center:

Technology has been developing over time, and at present, the progress of its development is continuously flourishing. Technologies change all the time, typically in a sequence of replacements of older technologies by newer technologies (Sprenger & Schwaninger, 2021) . The usefulness of AI-powered tools in the newest medical technology is acknowledged by the healthcare ecosystem.

In Saudi Arabia, where the use of new technology is acquiring a sizable market, AI has the potential to significantly enhance a number of procedures in healthcare operations and delivery. For example, the cost reductions that AI may bring to the healthcare system are a major motivator for AI deployment. so Saudi Arabia is suffering from a scarcity of healthcare practitioners, particularly Nursing, as the demand for healthcare services grows. Likewise, Saudi Arabia healthcare institutions are struggling to keep up with the latest technology innovations and patients' high expectations in terms of service and outcomes that they have grown to expect from healthcare services (Alijerin & Arfat, 2022).

Despite of the enormous importance of AI application and adoption in the health care system as it has been proven effective in advanced countries, the Saudi Arabiai populace is sceptic about its adoption with a slow-paced movement. However, some studies observe a potential market in AI-based healthcare systems that is capable of reducing cost and is effective in healthcare management. The significance of the Unified Theory of Technology Acceptance and Use (UTAUT) model cannot be overemphasized in examining the impact of technology acceptance and use of technology in the modern healthcare system (Barrane & Karuranga, 2018).

While in the process, there exist limitations in enhancing the efficacy of the model in recent times as a failure to address the aspect of behavioural attitude toward the acceptance of AI in the healthcare environment. Emotional intelligence can play a significant role in facilitating acceptance of users and customers of AI base systems. In essence, behavioural attitude and emotion significantly determine the success rate in the healthcare ecosystem (Frost & Sullivan, 2016).

1.3Artificial intelligent-based healthcare system

Artificial Intelligence (AI) is now generating a major paradigm change in practically every field of science and technology, including healthcare, and is thus a hot issue (Shaban, & Buckeridge, 2018).). Artificial intelligence—or the usage of computerized structures that can understand, learn, and extract precise information from the outside data—is a rising development with many implications for the way human beings engage with their surroundings The heightened hazard that it may bring underscores the need for the healthcare quarter to cautiously manipulate AI innovation and adoption.

Artificial intelligence (AI) is rapidly penetrating people's lives in many ways. Artificial Intelligence aims to make people's lives easier and help people in different situations. Gaze explores the factors that influence the behavior and the use of AI-enabled devices. The Technology Adoption Model (TAM) is a well-used method in Next Generation Popularity research. Many studios utilized UTAUT and UTAUT2 to find the use of new technologies among users. Few scientists are using these thoughts to target behavior using artificial intelligence devices (Sohn & Kwon, 2020).

Artificial Intelligence (AI)—or the use of automated frameworks that demonstrate the ability to effectively interpret data, observe and capture unique desires—is an emerging technology with many implications for changing the way we interact with the world. Within healthcare, AI is uniquely positioned to gain knowledge via clinical desire 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 permit evidence-based care have carried out a major characteristic in cutting-edge decades. Frost and Sullivan (2016) see the point of interest nowadays 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 for stopping infection withinside the future (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 a technology, making it so much more meaningful as users are directly or indirectly involved in its creation (Cui & Wu, 2016).

1.4 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., 2013). Empirically analyzing user adoption by statistical age in an organizational context, researchers find that UTAUTas shown in figure 1 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), Motovational Model (MM), and Social Cognitive Theory (SCT). Various existing studies utilized combination of different theories to find the acceptance and use of intelligent healthcare systems among users (Keikhosrokiani, 2023; Keikhosrokiani et al., 2022; Keikhosrokiani, & 2019).

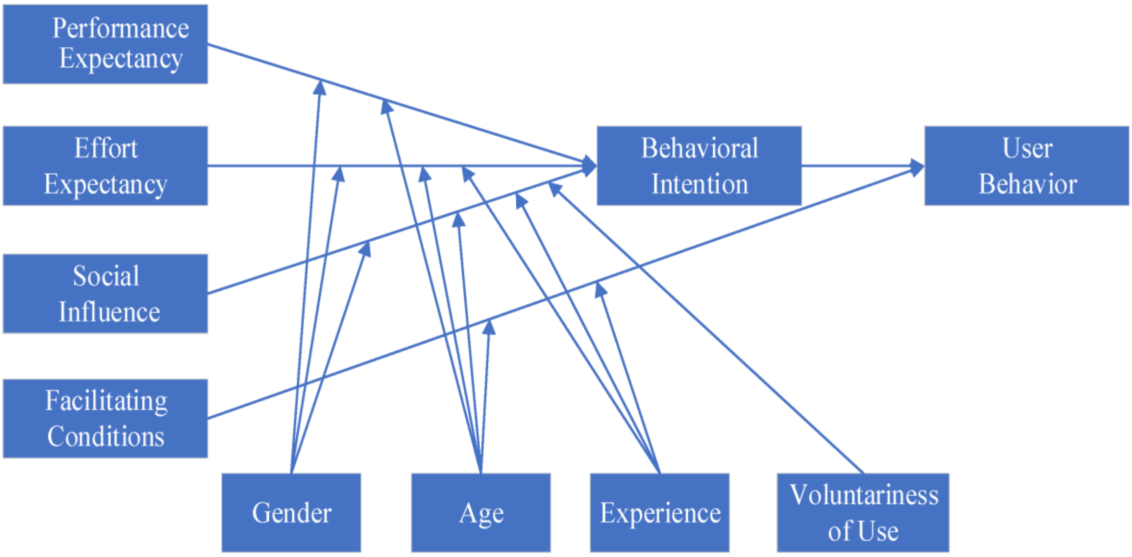

Figure 1: Original UTAUT Model (Venkatesh et al., 2013).

2.1Methodology

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 behavioral 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) (Pan, 2016).

Firstly, the current study will explore the literature published on Technology Acceptance Model and highlight the issues that have been extensively neglected in past research. This will help future studies acknowledge the gaps in TAM. But still, some factors have not yet been studied as much. Also, factors which have not been considered significant in past studies will be highlighted in the current study.

In the context of IT, Beaudry & Pinsonneault (2010) emphasize 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 (Rosli, & Keikhosrokiani, 2022; Beaudry & Pinsonneault, 2010). Figure 2 illustrates the proposed theorethical framework which integrated emotional intelligence into the original UTAUT..

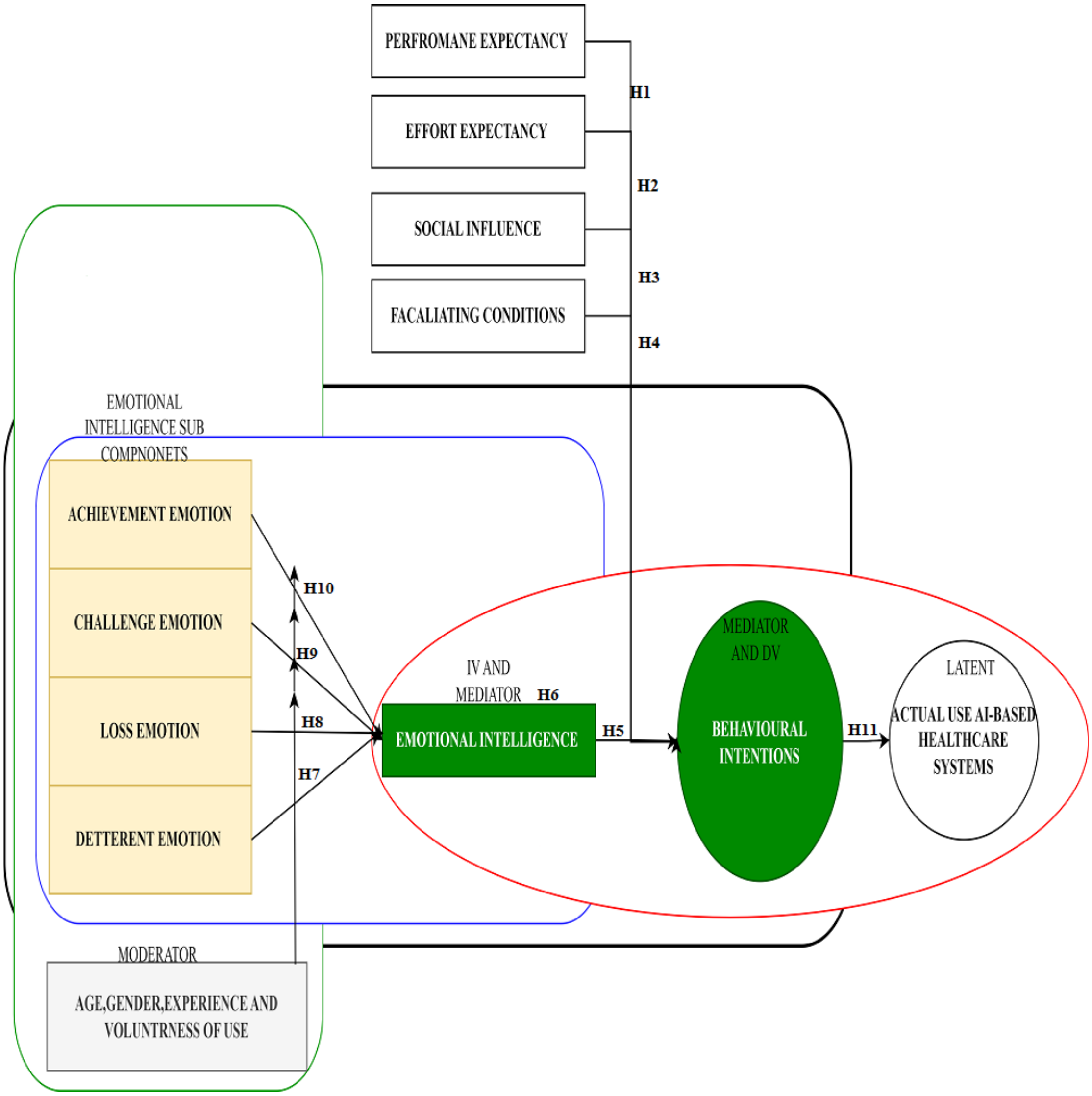

Figure 2 A proposed structural model

Lost Emotion (LE) Bagozzi (1992), Lazarus (1991)

2.2 Research Design

At the discovery stage, an in-depth literature review is performed to build on the sources that can be used for a comprehensive research. The sources that are particularly relevant to current research are those that discuss factors influencing people's behavioral goals to continue using AI-based healthcare structures. In addition, at this level of discovery, theories and modes used in structural statistics (SI) research are examined, which serve as ideas for developing research and speculative models that will be introduced.

The specific target audience is people with all-AI-based health constructs in Saudi Arabia, and former users of all-AI-based health-structured offers. The model has been narrowed down to those who use a purely AI-based healthcare structure and to those who voluntarily respond to the survey questionnaire. The research study's inclusion requirements for Saudi Arabiaians are that the participants are at least 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 have been disseminated throughout Saudi Arabia. 391 questionnaires are returned out of the 400 doctors and patients who have accepted the offer to take part in the study. Some of the submissions are disregarded after review because they are unclear. As a result, 391 questions have been submitted by respondents that either doctors or patients.

2.3 Instrument of the research

A questionnaire was 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 Saudi Arabia to obtain specific statistics from each person. Because physicians and patients—

regardless of age, gender, education, occupation, and income—have their own 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 towards using AI-based healthcare systems for healthcare centers and in Lbooratory.

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 Saudi Arabia to improve the representativeness of the model. In other words, it is a target population model that includes people in Saudi Arabia who have had experiences using a fully AI-based healthcare infrastructure, in this study used convenience sampling method. After sharing the online survey, this study applies a web-based questionnaire survey and a valid data collection tool.

3.1 Analysis of the result

The research begins with the descriptive and frequency analysis result using SPSS, which provides the demographic profile of the respondents and organizations. The validity and reliability of the measurement model are then reported. The suggested model is tested using partial least squares (PLS) and structural equation modelling (SEM) (Ringle et al., 2015). According to the ten times rule, the minimal sample size for PLS-SEM analysis must be greater than 10 times the routes in the structural or measurement models (Hair et al., 2013). As a result, a sample size of 391 is appropriate for this investigation.

Each construct's AVE value is higher than the required level of 0.50. As a result, latent constructs account for at least 50% of the variation in their components. The square root of each construct's AVE score and its relationships with other constructs are compared to determine discriminant validity. The square root of the AVE score for each structure is greater than the highest association with any other structures. Composite reliability coefficients are used to check the reliability of the measurements. All coefficients are at least greater than 0.70, indicating a high degree of confidence.

The study has achieved the necessary response rate base on the target set. All respondents are assuring the confidentiality of the information they provide for research purposes. The response rate of 20% to 30% (Cherry & Fraedrich, 2002; Hair et al., 2011) is deemed promising although the study is able to achieve above that rate. A discovery by Baruch and Holtom (2008) on meta-analyses of 1607 articles published in 17 academic publications between 2000 and 2005 has found that the average organizational response rate observed in a survey performed is 30.5 percent. The participants have provided 430 replies over the internet. 39 of the 430 submitted replies are discarded due to missing or inaccurate information. As a result, the model is evaluated using 391 validated responses for formal analysis as shown in Table1.

Table 1. Profile of the respondent

Variable	**Category**	**Frequency**	**Percentage**
Gender	Female	158	40.40
	Male	233	59.59
Age	19-25	87	24.80
	26-32	118	31.50
	33-39	94	24.60
	Above 40 years	105	19.20
Education	High School	51	13.00
	Bachelor	194	49.60
	Postgraduate	146	37.30
Occupation	Student	91	23.30
	Employed	203	51.90
	Unemployed	63	16.10
	Self-Employed	34	8.70

The factors in the study are all rated on a five-point Likert scale: moving progressively from (1) strongly disagree to (5) strongly agree. A latent variable mean value less than or equal to 1.99 is considered low, 2.00 to 3.99 is moderate, and 4.00 or higher is high on the five-point Likert scale (Dawes, 2008; Sekaran & Bougie, 2013). The mean and standard deviation of all studied structures are shown in Table 2.

Table 2. Summary statistics

Variable	Description	Mean	Std. Error	Std. Deviation
PE	Performance Expectancy	3.731	0.044	0.870
EE	Effort expectancy	3.732	0.044	0.869
SI	Social Influence	3.821	0.042	0.831
FC	Facilitating conditions	3.844	0.047	0.921
EQ	Emotional Intelligence	3.835	0.046	0.911
AE	Achievement emotion	4.034	0.035	0.695
CE	Challenge emotion	3.891	0.042	0.831
LE	Loss emotion	3.891	0.041	0.814
DE	Deterrent emotion	3.944	0.044	0.869
BI	Behavioural Intention	3.935	0.046	0.906
UAI	Actual Use	3.968	0.035	0.701

3.2 Discussion of result

The study result sohwed Once people start to notice that their productiveness is increased by taking part in an AI fitness primarily on device, they are more inclined to accept and utilize such a technology. The result also shows that perceived effort has a significant impact on the applied goal prediction. This position is consistent with previous studies (Kollmann & Kayser, 2010), confirming that these works are extensive.

The results reveal the condition of the healthcare system of Saudi Arabia, which seeks to address the original research objectives and identify significant variables, that affect the acceptability of AI. By advancing our knowledge of artificial intelligence and paving the way for implementing AI-based technologies in Saudi Arabia's healthcare system.

3.3 Conclusion:

More importantly, according to the results of this study, artificial intelligence has a significant impact on consumers' attitudes to use AI healthcare facilities in Saudi Arabia, and may be this study makes improvement and enhancement of previous research about AI-based healthcare. In addition, by raising awareness and focusing on this topic, the study has contributed to the AI in healthcare centers in Saudi Arabia as it has received little attention so far—the study reveals its uniqueness by highlighting the contribution of emotional intelligence to health care. Finally, the study wants to emphasize on healthcare systems that have already made significant breakthroughs in several healthcare fields, including diagnosis and treatment. AI-based healthcare as suggested in this study will boost the overall health services and result in a healthier of people that benefits from it.

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