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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. 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 that 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 behaviors of Middle Eastern users.

Keywords: *intelligence, Health, computer, engineering, management*

Introduction

The utilization of AI-based healthcare systems in Jordan is characterized by streamline healthcare operations. However, its adoption in Jordan has been slower compared to more (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.

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Fig 1: Five Main Components of Emotional Intelligence

Source: (Daniel Goleman, 1995)

Emotional intelligence in healthcare

The importance of EI in healthcare settings can be demonstrated, given its enormous contribution

Theoretical framework of Unified Theory of Acceptance and Use of Technolo

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 modesargued that encapsulation principles can lead to explanations of how people and society influence technology

Methodology

The UTAUT model consists of six main constructs, Facilitating Conditions (FC), and the new factors of Emotional Intelligence (EMI) (Patil, 2020).

Firstly, 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.

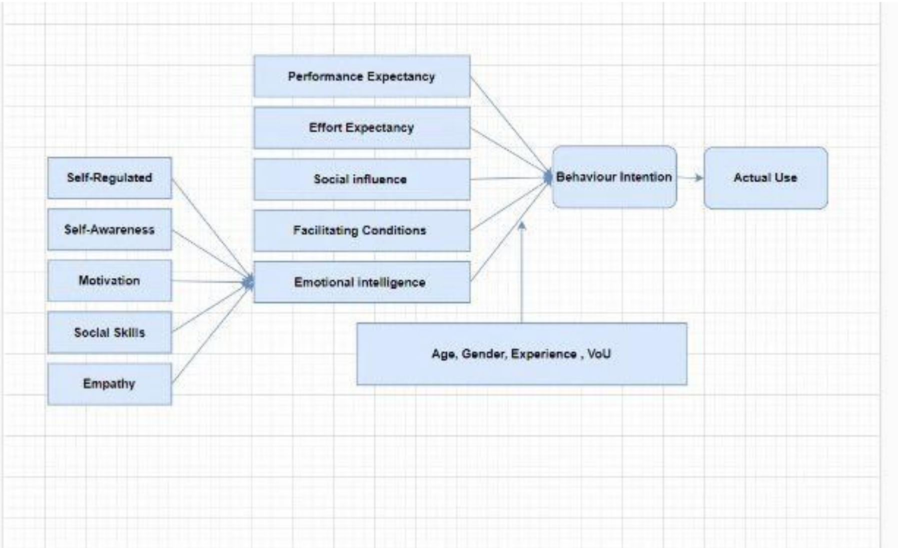

Fig 2: The Proposed Theoretical Framework

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 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 completed for the analysis.

Instrument of the Study

This study uses a questionnaire to survey physicians and patients in Jordan who use AI-based healthcare facilities. It aims to understand their views on the use of AI-based care structures and the factors influencing their use. This study uses convenience sampling to collect data from selected respondents, focusing on current and former clients of AI-based medical facilities in Jordan to improve model representativeness and reduce model error (Bornstein et al., 2017). The study uses a convenience sampling approach with a web-based questionnaire survey to collect data on respondents' intention to use AI-based healthcare systems. The survey is shared on social media and used as a valid data collection tool (Regmi et al., 2016).

Data Analysis

The proposed using partial least squares (PLS) and structural Composite reliability coefficients were used to verify measurement reliability (Hair et al., 2016; Boomsma & Hoogland, 2001)

Demographic Distribution

Table 1 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.

Table 1: 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 (Table 2) 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.

Table 2: Gender distribution

		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 distribution of respondents by level of experience (Table 3), 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.

Table 3: Distribution of respondents by level of 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	

The data in the table above shows the distribution of respondents according to four age groups (Table 5), 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 respondents' demographic features and compare various age groups in later studies.

Table 4: Distribution of respondents according to 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	

Mean and Standard Deviation of the Study Variables

Table 5 displays mean values, medians

Table 5: The descriptive statistics

	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

Analysis of Mediation

Mediating effect hypotheses test results Table 6.

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 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, 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 explored different moderating variables in relation to EI and its impact on various outcomes. However, as shown in the table 8 below, not all these hypotheses were supported, with some p-values indicating non-significant relationships between the variables.

Table 7:

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

Discussion

This study uses the Unified Theory of Acceptance and Use of Technology (UTAUT) to understand the adoption of AI services technology. It considers behavioral intention, performance expectancy, effort expectancy, social influence, and enabling conditions. It also incorporates e-emotional Intelligence as an independent variable. The study provides a comprehensive

Conclusion

The findings 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 involve. 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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