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Predicting the Behavioural Intention of Jordanian Healthcare Professionals to Use Blockchain-Based EHR Systems: An Empirical Study

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Abstract. Despite facing economic challenges, Jordan has a competitive position among Arab countries in terms of adopting emerging technologies, which is seen as an opportunity to reduce healthcare costs in a developing country like Jordan. TAM is the study's underlying theory, which has been expanded to include perceived privacy, perceived security, and perceived trust. The current study aims to predict the behavioural intention of Jordanian healthcare professionals to use blockchain-based electronic health record systems. Furthermore, the purpose of this study is to investigate the mechanism by which perceived privacy and perceived security influence healthcare professionals' behavioural intention to use blockchain technology in Jordan. This study proposed perceived usefulness, perceived ease of use, and perceived trust as mediators. The quantitative approach was used to collect data from 389 Jordanian healthcare professionals working in the public sector via cross-sectional surveys. The data was analysed with Smart-PLS and IBM-SPSS. Except for the influence of perceived security on perceived usefulness, all of the supposed relationships were supported in this study. Furthermore, all suggested mediating relationships were supported, with the exception of the mediation role of perceived usefulness between the influence of perceived security on behavioural intention. The study's results could be helpful in developing future policies. Furthermore, the Jordanian healthcare sector could use these findings to develop strategies that encourage the adoption of secure and decentralised digital platforms, such as blockchain technology.

Keywords: Blockchain, TAM, EHR, perceived privacy, perceived security, perceived trust, developing countries, Jordan

1. Introduction

Despite having the lowest real GDP growth among Arab nations due to various economic challenges (World Bank, 2023), Jordan's healthcare expenditures have risen to be among the highest among other countries, accounting for 9.3% of the country's GDP (MedXJordan, 2023). As a developing country, taking firm steps towards managing and reducing the escalating costs of healthcare would be beneficial. One of the most significant solutions suggested in the literature to reduce healthcare costs is to expand the implementation of health information technologies (Ahlan & Ahmad, 2014; Alsharo et al., 2021; Davis et al., 2007). Several studies in developing countries have shown that emerging technologies play an important role in improving both individual and organisational performance (Aldholay et al., 2018; Isaac et al., 2017, 2018, 2019). Despite Jordan's economic challenges (World Bank, 2023), it has the advantage of ranking 59th globally and 7th among 11 Arab countries in terms of use of emerging technologies (see Fig. 1). Furthermore, according to the Network Readiness Index (2022), future technologies are regarded as the most important Jordanian opportunities for improving economic performance, with Jordan ranking 42nd out of 131 countries in terms of future technology in the world (see Fig. 2). This demonstrates Jordan's strong interest in adopting emerging technologies and relying more on information technology in all fields.

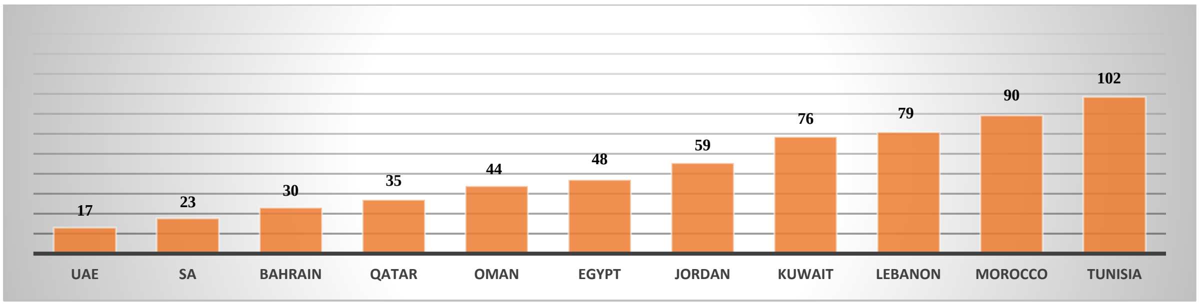

Fig. 1: Adopting Emerging Technologies: Jordan vs. Arab countries
(The Network Readiness Index, 2022).

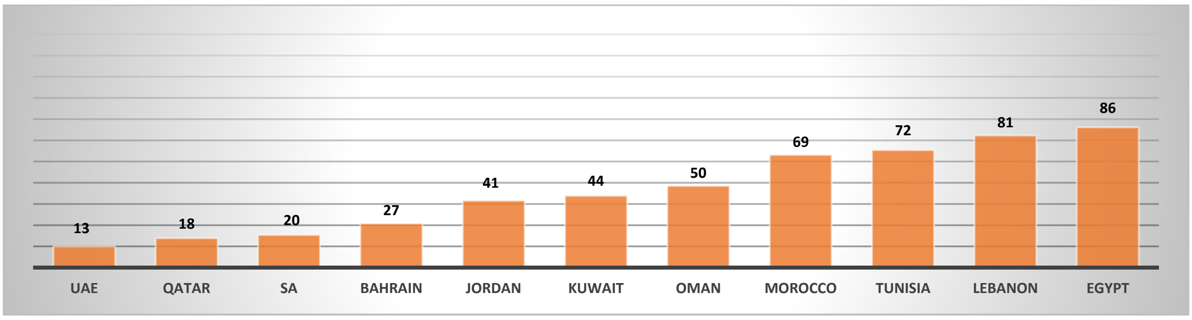

Fig. 2: Future Technologies: Jordan vs. Arab countries
(The Network Readiness Index, 2022).

Blockchain Technology (BT) has recently gotten a lot of attention from different industries because it is seen as a potential game changer for business operations (Hashimy et al., 2023). Nakamoto (2008) introduced blockchain, which provides a secure and transparent way to conduct business. Blockchain enables a decentralised system in which untrusted parties can communicate in a transparent manner without the need for a trusted third party (Christidis & Devetsikiotis, 2016). Moreover, the transparency provided by distributed ledger technology reduces the need for central parties and increases the reliability of operations (Ghosh, 2019).

The healthcare sector has undergone significant changes in the last few years (Čerkauskienė & Meidute-kavaliauskiene, 2023). According to Haleem et al. (2021), using blockchain applications in the medical sector can effectively detect significant and potentially hazardous errors. This results in enhanced medical data with improved performance, security, and transparency within the healthcare system. As a result, medical institutions benefit from this technology because it allows for better understanding and analysis of medical records (Haleem et al., 2021).

Consequently, in Jordan, as a developing country, the implementation of a blockchain-based electronic health record (EHR) system may have a significant impact on service quality and the national and health economy. However, before implementing any emerging technology, it is crucial to understand the level of acceptance among users. Therefore, the objective of this study is to investigate the behavioural intention of Jordanian healthcare professionals to use a blockchain-based electronic health record system in the public sector.

Because of BT's significant advancement and widespread adoption in many industries, several researchers have attempted to understand users' attitudes towards accepting this technology. The Technology Acceptance Model (TAM) is one of the most effective theories and models for understanding, explaining, and predicting the ways individuals accept and use emerging technologies. It has been widely confirmed by numerous empirical studies across contexts and times as a reliable predictor of information system (IS) adoption and usage. Such as:

- North American (Fussell & Truong, 2021; Presley & Presley, 2009):
- South American (Jan & Contreras, 2011; Singh et al., 2006):
- Europe (Tarhini et al., 2013; Ferri et al., 2021):
- Asia (Çelik & Yilmaz, 2011; Teo & Zhou, 2014):
- Sub-Saharan Africa (Cudjoe et al., 2015):
- Oceania (Ryan & Rao, 2008; Revels et al., 2010):
- The Middle East and North Africa (Alsuwaidan & Almegren, 2020; Isaac et al., 2018).

In addition to that, TAM has been demonstrated to be a vigorous model for investigating the usage and acceptance of blockchain technology across various sectors and contexts, such as; Korea (Albayati et al., 2020), Saudi Arabia (AlSuwaidan & Almegren, 2020), Indonesia (Atmoko et al., 2021; Saputra & Darma, 2022; Wahyuni et al., 2021), India (Adnan et al., 2022; Singh et al., 2019), Jordan (Altamimi et al., 2022), United Kingdom (Chowdhury et al., 2022), China (Esfahbodi et al., 2022; Wang et al., 2022), Italy (Ferri et al., 2021; Prisco et al., 2022; Sciarelli et al., 2022), Taiwan (Lian et al., 2020; Nuryyev et al., 2020), Thailand (Namahoot & Rattanawiboonsom, 2022), Spain (Palos-Sanchez et al., 2021), Malaysia (Ullah et al., 2021, 2022). Appendix A represents a summary of previous studies that used the TAM model to examine the acceptance of blockchain technology.

Because the TAM model does not account for all of the factors that influence technology intention, Davis (1989) suggested investigating the influence of external constructs on the TAM constructs, namely perceived usefulness (PU) and perceived ease of use (PEOU). As a result, most studies in the literature have been adapted to fit the specific context and people's characteristics in each country of study (Ala'a & Ramayah, 2023). This is because technological theories and models cannot be applied universally across all contexts (Straub et al., 1997). Furthermore, there are differences in the outcomes of factors that influence technology adoption across research studies (Sun & Zhang, 2006). As a result, it is critical to adapt these theories to the specific circumstances of each country.

Jordanians are known for their high levels of uncertainty avoidance, which makes them reluctant to take risks in the workplace (Hofstede-Insights, 2023; Hoftede et al., 2010). Consequently, perceived security (PSEC), perceived privacy (PRV), and perceived trust (PTR) are factors that may influence the behavioural intention of Jordanian healthcare professionals toward the adoption of a blockchain-based EHR system. Furthermore, Toufaily et al. (2021) discovered that when it comes to adopting BT, individuals prioritise security. Furthermore, perceived security was found to be a motivator for users' acceptance of technology (Almaiah et al., 2019). Security and privacy have been identified as critical issues in the protection of electronic health systems (Abdekhoda et al., 2019). Besides, Kabir (2021) emphasised that trust in technology is established when people believe that adequate security measures are in place.

Consequently, the current study aims to extend the TAM model by incorporating perceived security (PSEC), perceived privacy (PRV), and perceived trust (PTR) to predict the behavioural intention of healthcare professionals to use a blockchain-based EHR system in Jordan. The modified model, which is based on Davis' (1989) original TAM, retains the critical constructs of PU, PEOU, and behavioural intention (BINT). Furthermore, despite the fact that the original TAM included the attitude construct, the final model of this research did not include it because it was found to not fully mediate the impact of PEOU and PU on intention (Davis et al., 1989).

Before adopting a new technology, it is essential to consider the users' willingness to use it, as their behaviour intention plays a significant role in determining their acceptance. In addition, security and privacy were identified as crucial factors in the implementation of blockchain technology. Therefore, it is essential to investigate how PRV and PSEC influence behaviour intention. The current study investigates whether PU, PEOU, and PTR as mediators could impact the influence of PRV and PSEC on behavioural intention. The theoretical contribution is displayed in Table 1.

Table 1: Theoretical Contribution

	Independent variables		Mediators			Dependent variable
	PRV	PSEC	PTR	PU	PEOU	BINT
TAM (Davis, 1989)	gap	gap	gap	✓	✓	✓
Proposed model for closing the gaps	✓	✓	✓	✓	✓	✓

This study seeks to address the following research questions:

1. What are the influences of perceived privacy and perceived security on perceived usefulness, perceived ease of use, and perceived trust among the public sector in Jordan?
2. What are the influences of perceived usefulness, perceived ease of use, and perceived trust on the intention to use a blockchain-based EHR system among the public sector in Jordan?
3. Do perceived usefulness, perceived ease of use, and perceived trust mediate the impact of perceived privacy and perceived security on the intention to use a blockchain-based EHR system among the public sector in Jordan?

In this research, if the findings support the hypothesis that the proposed constructs significantly affect the behavioural intention of healthcare professionals in Jordan to use a blockchain-based EHR system significantly, the researchers will make further recommendations on the factors that affect the acceptance of blockchain in developing countries. This research could be extremely useful to other sectors interested in a blockchain platform.

2. Literature Review

2.1. Perceived Usefulness

Perceived usefulness (PU) is the degree to which people believe that using a system will improve their work performance (Davis et al., 1989). By reviewing the prior literature, Almekhlafi and Al-Shaibany (2021) discovered that PU is a critical factor when adopting BT systems. Many studies have confirmed that PU has a positive effect on the behavioural intention to use technology (Abu-Shanab et al., 2012; Almajali et al., 2022; Chowdhury et al., 2022; Dirsehan, 2020; Dhagarra et al. (2020); Gao & Li, 2021; Liu & Ye, 2021; Kamble et al., 2018; Kelly & Palaniappan, 2022; Nuryyev et al., 2020; Roca et al., 2009; Ullah et al., 2020). Billanes and Enevoldsen (2022), Muhamad et al. (2020) and Chi and Tsai

(2017) discovered no relationship between PU and BINT. As a result, the following hypothesis is proposed:

H1: Perceived usefulness positively predicts the behavioural intention to use blockchain.

2.2. Perceived Ease of Use

Perceived ease of use (PEOU) refers to how easy a user believes it is to use a system (Davis et al., 1989). Almekhlafi and Al-Shaibany (2021) found, by reviewing the previous literature, that PEOU is a vital factor in the adoption of BT systems. Several research studies have shown that PEOU plays a significant influence on BINT to use systems (Abu-Shanab et al., 2012; Almajali et al., 2022; Billanes & Enevoldsen, 2022; Chowdhury et al., 2022; Gao & Li, 2021; Kelly & Palaniappan, 2022; Liu & Ye, 2021; Nuryyev et al., 2020). However, Dhagarra et al. (2020), Muhamad et al. (2020) and Roca et al. (2009) found that PEOU had no influence on BINT of users to use systems. As a result, the following hypothesis is formalised:

H2: Perceived ease of use positively predicts behavioural intention to use blockchain.

2.3. Perceived Trust

According to Khazaei (2020), in the context of blockchain adoption, "perceived trust" refers to the confidence that users have in accepting a transformative technology. Trust is essential because without it, very few digital transactions would take place (Uche et al., 2021). Multiple studies have supported the positive impact of PTR on the intention to use systems (Almajali et al., 2022; Almarashdeh et al., 2021; Billanes & Enevoldsen, 2022; Dhagarra et al., 2020; Dirsehan, 2020; Gao & Li, 2021; Kabir et al., 2021, 2022; Khazaei, 2020; Latifa & Zakaria, 2020; Liu & Ye, 2021; Roca et al., 2009, Yaseen et al., 2022). However, Abu-Shanab et al. (2012), Ayedh et al. (2020) and Queiroz and Wamba (2019) found no relationship between PTR and BINT. Thus, the following hypothesis is proposed:

H3: Perceived trust positively predicts the intention to use Blockchain.

2.4. Perceived Privacy

Perceived privacy (PRV) refers to an organisation's rights and responsibilities regarding collecting, using, and sharing user information (Asadi et al., 2017). Haleem et al. (2021) stated that BT improves privacy in healthcare applications. Kumar et al. (2022) and Asadi et al. (2017) determined that PRV affects PU, PEOU, and PTR through their respective research studies. Al-Okaily et al. (2022) discovered that in the Jordanian context, privacy has a significant effect on mobile payment system trust. According to Maqableh et al., (2021) the relationship between privacy and trust was not confirmed among Jordanian Facebook users. Gao and Li (2021), Nelloh et al. (2019), Normalini and Ramayah (2017), Ponte et al. (2015) and Roca et al (2009) all discovered no relationship between privacy and trust. In addition, Belanche-Gracia et al. (2015) found that privacy had no impact on PU. As a result of this, the following hypotheses have been proposed:

H4: Perceived privacy positively influences perceived usefulness.

H5: Perceived privacy positively influences perceived ease of use.

H6: Perceived privacy positively influences perceived trust.

2.5. Perceived Security

Perceived security (PSEC) is defined as the level at which the use of BT advances the management of EHR systems (Cimperman et al., 2016). When conducting online transactions, a sense of security can increase users' trust (Ooi et al., 2021). Kumar et al. (2022) and Asadi et al. (2017) discovered that PSEC significantly affects PU, PEOU, and PTR. Lai (2017) found that PSEC significantly affects PU and

PEOU. Belanche-Gracia et al. (2015) found that security had an influence on PU. Moreover, PSEC has also been shown to influence trust by Al-Okaily et al. (2022), Gao and Li (2021), Khazaei (2020), Maqableh et al., (2021), Nelloh et al. (2019), Normalini and Ramayah (2017), Ooi et al. (2021), Ponte et al. (2015), and Roca et al (2009). Furthermore, Dutot (2015) discovered that while security had a strong impact on PEOU, there was no relationship between security and PU. The following hypothesis is based on these findings:

H7: Perceived security positively influences perceived usefulness.

H8: Perceived security positively influences perceived ease of use.

H9: Perceived security positively influences perceived trust.

2.6. Mediating Relations

This research investigated the mediating role of PU in the relationship between PRV and BINT, based on the direct and validated effect of PRV on PU (Kumar et al., 2022; Asadi et al., 2017) and the effect of PU on BINT (Nuryyev et al., 2020; Ullah et al., 2020). Furthermore, the mediating role of PEOU in the relationship between PRV and BINT was examined, based on the direct and validated effect of PRV on PEOU (Kumar et al., 2022; Asadi et al., 2017) and the effect of PEOU on BINT (Almajali et al., 2022; Kelly & Palaniappan, 2022). Finally, the mediating role of PTR in the relationship between PRV and BINT was studied, based on the direct and validated effect of PRV on PTR (Kumar et al., 2022; Asadi et al., 2017) and the effect of PTR on BINT (Almarashdeh et al., 2021; Gao & Li, 2021). Therefore, the following hypotheses are suggested:

H10: Perceived privacy has an indirect effect on behavioural intention via perceived usefulness.

H11: Perceived privacy has an indirect effect on behavioural intention via perceived ease of use.

H12: Perceived privacy has an indirect effect on behavioural intention via perceived trust.

This research also investigated the mediating role of PU in the relationship between PSEC and BINT, based on the direct and validated effect of PSEC on PU (Kumar et al., 2022; Asadi et al., 2017; Lai, 2017) and the effect of PU on BINT (Nuryyev et al., 2020; Ullah et al., 2020). Furthermore, the mediating role of PEOU in the relationship between PSEC and BINT was examined based on the direct and validated effect of PSEC on PEOU (Kumar et al., 2022; Asadi et al., 2017; Lai, 2017) and the effect of PEOU on BINT (Chowdhury et al., 2022; Kelly & Palaniappan, 2022). Finally, the mediating effect of PTR on the relationship between PSEC and BINT was studied, based on the direct and validated effect of PSEC on PTR (Kumar et al., 2022; Asadi et al., 2017) and the effect of PTR on BINT (Almarashdeh et al., 2021; Gao & Li, 2021). Therefore, the following hypotheses are proposed:

H13: Perceived security has an indirect effect on behavioural intention via perceived usefulness.

H14: Perceived security has an indirect effect on behavioural intention via perceived ease of use.

H15: Perceived security has an indirect effect on behavioural intention via perceived trust.

2.7. Behavioural Intention to Use Blockchain

Behavioural intention (BINT) is defined as the individuals' desire to take action in order to perform a certain behaviour (Fishbein & Ajzen, 1975). According to Davis (1989) and Davis et al. (1989), the BINT has an impact on a person's actual behaviour and determines whether they will embrace a new system. BINT was also considered by Chatterjee et al. (2021) as a reliable measure of an individual's perceived value. The evaluation of individuals' technology acceptance during the early stages using BINT is vital, as it helps individuals determine if they will accept or reject a technology, thus reducing the chances of unsuccessful implementation of technology (Davis et al., 1989).

3. Research Methods

3.1. Overview of the Proposed Research Model

An analysis of previous TAM-related studies was performed to establish the expected constructs of the research model and their relationships. Fig. 3 depicts the proposed model.

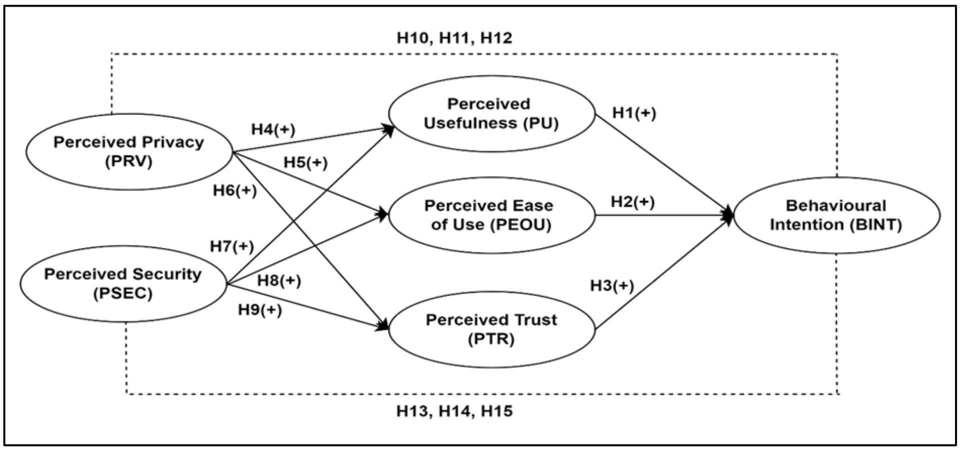

Fig. 3: The proposed model

3.2. Development of Instruments

The objective of the researchers in this study was to ensure conciseness in their survey by precisely defining the constructs and measuring the elements. Furthermore, to avoid confusion or intricacies, they incorporated the definitions of each variable throughout the survey as procedural controls. The aim was to avoid the possibility of Common-Method Bias (CMB) through the use of a self-administered survey, which could potentially affect the results and lead to incorrect conclusions (Baumgartner & Steenkamp, 2001; Kock et al., 2021; MacKenzie & Podsakoff, 2012). Researchers evaluated the constructs using a seven-point Likert scale. In addition, a process of pre-testing was conducted by three management information systems specialists and three healthcare professionals from Jordan to eliminate any measurement or language uncertainty. The questionnaire was pilot-tested for internal consistency before being distributed to 50 Jordanian healthcare professionals, who returned 42 valid and complete responses. All constructs demonstrated acceptable reliability and validity, as the individual Cronbach alpha values for all constructs exceeded the recommended value of 0.70, and the factor analyses for all constructs exceeded the recommended value of 0.40.

3.2. Data Collection

From June to September 2022, data was collected using a self-administered paper questionnaire that was distributed in person. The target sample consisted of Jordanian public sector healthcare professionals who directly use the Health Information System (HAKEEM) in hospitals and medical centres. The current study's population included 5,159 physicians, 802 pharmacists, 11,331 nurses, and 829 dentists (Ministry of Health [MoH], 2018, p. 33, as cited in Aljaafreh, 2020). A power analysis was performed to determine the minimum sample size for the structural equation model (SEM) of this study, as is common among researchers using second generation multivariate data analysis techniques like PLS-SEM (Memon et al., 2020), and the result was a minimum sample size of 138. The researchers used a simple random sampling technique and distributed 450 questionnaires, of which 389 were analysed, yielding an 86.4% response rate. The analysis excluded 61 questionnaires, 35 of which were discarded as straight-line responses and 26 of which were invalid due to incomplete responses. Table 2 shows the demographics of the participants.

4. Data Analysis and Results

To analyse the data, the partial least squares (PLS) method was used, which was implemented using the SmartPLS 4 software (Ringle et al., 2022). SEM was used in this research including both structural and measurement models, in a two-step process as described by Hair et al. (2021). The researchers began by analysing the descriptive data from the study, and then assessed the validity and reliability of the assessment of the measurements using the measurement model to clarify the measurement of each construct. Finally, they examined the relationships between the constructs using the structural model assessment to determine the relationship between variables (Hair et al., 2021).

4.1. Common-Method Bias

To detect CMB as ex-post statistical controls, the researchers in this study used both the Harman single-factor test (Podsakoff & Organ, 1986) and the marker variable (MV) technique (Lindell & Whitney, 2001). They conducted a principal component factor analysis, and the results showed that the first factor accounted for 22.99%, falling short of the 50% limit set by Podsakoff et al (2003). In addition, the marker variable (attitude towards the colour blue) (Miller & Simmering, 2022) had no effect on the dependent or independent variables. When the MV was included, the correlations and R-square values of the variables remained unchanged. Therefore, it was determined that the CMB was not a significant concern in this study.

Table 2: Demographic Information

Demographic Item	Categories	Frequency	Percent
Gender	1. Male	156	40.1
	2. Female	233	59.9
Age	1. Less than 30 years	74	19.0
	2. 31 – 50 years	231	59.4
	3. More than 50 years	84	21.6
Career	1. Physician	131	33.7
	2. Nurse	167	42.9
	3. Pharmacist	51	13.1
	4. Dentists	40	10.3
Experience	1. Less than 5 years	71	18.3
	2. 5–10 years	116	29.8
	3. 11-15 years	125	32.1
	4. More than 15 years	77	19.8
Region	1. Amman	132	33.9
	2. Irbid	130	33.4
	3. Aqaba	127	32.6

4.2. Data Outliers and Data Normality

The Z-score was used to identify outliers in this study. According to Tabachnick and Fidell (2013), the standard absolute value for identifying outliers is 3.29. As shown in Table 5, every value was below this threshold. The research used the statistical methods of skewness and kurtosis, where the absolute value of skewness should not exceed 3 and the Kurtosis should be less than 10 (Kline, 2011). According to Table 5, all values fell within the recommended range.

4.3. Descriptive Analysis

In this study, the researchers calculated the mean along with the standard deviation to show the participants' responses and views regarding each survey question. According to Sekaran and Bougie (2016), the mean represents the central tendency of the data, and the standard deviation measures its dispersion and shows the spread of the data. A small standard deviation demonstrates that the values are close to the mean, while a large deviation proposes the opposite (Sekaran & Bougie, 2016). The study used the following formula to evaluate each measurement and variable: (highest point on the Likert scale - the lowest point in the Likert scale)/the number of levels used = (7 - 1)/7 = 0.85. Based on this calculation, scores between 1 and 1.85 are categorised as "extremely low", scores between 1.86 and 2.71 are categorised as "very low", scores between 2.72 and 3.57 are categorised as "low", scores between 3.58 and 4.43 are categorised as "moderate", scores between 4.44 and 5.29 are categorised as "high", scores between 5.30 and 6.15 are categorised as "very high", and scores between 6.16 and 7 are categorised as "extremely high".

Tables 3 and 4 present the findings, which rank variables and items based on their mean values. Table 3 shows that all research variables have a "moderate" level, with the highest means belonging to the "perceived usefulness" and "privacy" constructs. This indicates that healthcare professionals value the system and keep the data secure.

Table 4 presents the mean, standard deviation, level and order scores of the participants' responses to each construct. The results show that healthcare professionals believe that the system will be secure for the transmission of confidential information. They also believe that the system will protect their data and improve their efficiency. They also view the system as trustworthy and reliable. Furthermore, the participants predict that it will become a regular part of their work.

Table 3: The overall Mean and Standard Deviation for the Constructs

Type of Variable	Variables	Mean	SD	Level	Order
Independent	Perceived Security (PSEC)	4.149	1.756	Moderate	5
	Perceived Privacy (PRV)	4.26	1.754	Moderate	2
Mediating variables	Perceived Usefulness (PU)	4.309	1.707	Moderate	1
	Perceived Ease of Use (PEOU)	4.233	1.659	Moderate	3
	Perceived Trust (PTR)	4.225	1.668	Moderate	4
Dependent	Behavioural Intention (BINT)	4.246	1.718	Moderate	-

Table 4: Zscore, Skewness, Kurtosis, Mean and standard deviation of measurements

Items	Min-Zscore	Max-Zscore	Skewness	Kurtosis	Mean	SD	Level	Order
			Statistic	Statistic				
PSEC1	-1.575	1.435	-.124	-1.245	4.401	1.90	Moderate	3
PSEC2	-1.634	1.454	-.098	-1.189	4.414	1.88	Moderate	1
PSEC3	-1.554	1.388	-.083	-1.303	4.409	1.95	Moderate	2
PSEC4	-1.635	1.518	-.116	-1.140	4.347	1.86	Moderate	4
PRV1	-1.716	1.470	-.079	-1.168	4.231	1.88	Moderate	2
PRV2	-1.688	1.392	-.204	-1.138	4.288	1.94	Moderate	1
PU1	-1.653	1.431	-.184	-1.147	4.254	1.93	Moderate	5
PU2	-1.696	1.406	-.164	-1.169	4.321	1.91	Moderate	3
PU3	-1.750	1.358	-.245	-1.127	4.414	1.91	Moderate	2
PU4	-1.795	1.360	-.213	-1.121	4.44	1.89	High	1
PU5	-1.666	1.405	-.165	-1.163	4.301	1.93	Moderate	4
PEOU1	-1.665	1.359	-.264	-1.137	4.303	1.98	Moderate	1
PEOU2	-1.700	1.412	-.181	-1.106	4.278	1.92	Moderate	2
PEOU3	-1.599	1.426	-.117	-1.244	4.172	1.98	Moderate	4
PEOU4	-1.658	1.491	-.133	-1.101	4.159	1.90	Moderate	5
PEOU5	-1.641	1.386	-.175	-1.174	4.252	1.97	Moderate	3
PTR1	-1.699	1.377	-.224	-1.125	4.314	1.94	Moderate	1
PTR2	-1.668	1.429	-.154	-1.154	4.231	1.93	Moderate	3
PTR3	-1.588	1.472	-.048	-1.223	4.113	1.95	Moderate	4
PTR4	-1.610	1.370	-.204	-1.199	4.242	2.01	Moderate	2
BINT1	-1.692	1.432	-.086	-1.235	4.465	1.91	High	2
BINT2	-1.680	1.467	-.113	-1.156	4.401	1.89	Moderate	3
BINT3	-1.721	1.422	-.192	-1.057	4.476	1.89	High	1

4.4. Assessment of Measurement Model

The internal consistency of the measurement items was evaluated using the Cronbach alpha. Scores above 0.9 are considered excellent, scores between 0.7 and 0.8 are acceptable, scores greater than 0.8

are good, and scores less than 0.7 are regarded low (Abu-Taieh et al., 2022). According to Table 4, the individual Cronbach's alpha scores for all constructs in the study ranged from 0.808 to 0.929, which is higher than the minimum recommended threshold of 0.7 (Hair et al., 2021). This indicates that the constructs in the study are reliable. Composite reliability (CR) scores in the study were also high, ranging from 0.911 to 0.949 and exceeding the recommended minimum value of 0.7 (Hair et al., 2021). These results suggest that CR is met, as shown in Table 5, and that the Cronbach Alpha scores and CR values are accurate.

The factor loading test was used to determine the reliability of the indicators in this study. An indicator's factor loading must be greater than 0.7 in order to be considered significant. This means that a construct with a high factor loading indicates that the indicators are consistent with the construct definition (Hair et al., 2021). Table 5 shows that the factor loading of the indicators in this study was greater than 0.7, meeting all of the research model's criteria.

The researchers evaluated convergent validity using the extracted average variance (AVE) method. Table 5 demonstrates that the AVE values were greater than 0.5, ranging from 0.720 to 0.839. This shows that the criteria for convergence validity are met by the measures.

Table 5: Loadings, Cronbach's alpha (α), internal consistency, CR and AVE

Measurement Item	**Loading (>0.5)**	**α (> 0.7)**	**Internal consistency**	**CR (> 0.7)**	**AVE (>0.5)**
PU1: Accomplish tasks quickly	0.892	0.929	Excellent	0.946	0.779
PU2: Effectiveness	0.885				
PU3: Performance	0.860				
PU4: Makes job easy	0.888				
PU5: Useful	0.889				
PEOU1: Easy to learn	0.817	0.902	Excellent	0.928	0.720
PEOU2: Understandable	0.874				
PEOU3: Flexible	0.851				
PEOU4: Relevant	0.868				
PEOU5: Easy to use	0.831				
PTR1: Trustworthy	0.848	0.871	Good	0.911	0.720
PTR2: Transparent	0.878				
PTR3: Confidential	0.832				
PTR4: Reliable	0.834				
PSEC1: Feel secure	0.882	0.928	Excellent	0.949	0.822
PSEC2: Secure means	0.916				
PSEC3: Safe	0.926				
PSEC4: Safe way	0.902				
PRV1: Secure	0.919	0.808	Good	0.913	0.839
PRV2: Keep data safe	0.913				
BINT1: Predict usage	0.911	0.891	Good	0.931	0.818
BINT2: Favourable	0.929				
BINT3: Intention to use	0.873				

This study assessed the discriminant validity of the measurements using three different criteria: cross-loadings, Fornell-Larcker, and the MonoTrait (HTMT) ratio. As shown in Table 6, the model met the requirements by the results, where the factor loadings of an indicator among the constructs were greater than the cross-loading values with other variables.

Table 7 shows the results of the Fornell-Larcker test. The table reveals that the extracted square root of the average variance (AVE) is higher than the correlations among the model constructs. This demonstrates that each construct is more closely related to its specific indicators than to other constructs in the model (Hair et al., 2021), suggesting a high level of discriminant validity. Table 8 also illustrates that the HTMT (hypothesis test measurement model) values in the study were below 0.85, indicating that the discriminant validity is satisfactory. If the HTMT value exceeds 0.85, the discriminant validity is not satisfactory (Kline, 2010).

Table 6: The results of the discriminant validity test using the cross-loading

	BINT	PEOU	PRV	PU	PSEC	PTR
BINT1	**0.911**	0.164	0.194	0.172	0.068	0.168
BINT2	**0.929**	0.157	0.225	0.192	0.102	0.195
BINT3	**0.873**	0.170	0.157	0.071	0.055	0.113
PEOU1	0.161	**0.817**	0.221	0.217	0.109	0.143
PEOU2	0.132	**0.874**	0.206	0.173	0.113	0.193
PEOU3	0.132	**0.851**	0.196	0.123	0.172	0.187
PEOU4	0.179	**0.868**	0.148	0.138	0.194	0.183
PEOU5	0.154	**0.831**	0.200	0.100	0.182	0.196
PRV1	0.224	0.255	**0.919**	0.154	0.233	0.260
PRV2	0.171	0.163	**0.913**	0.207	0.210	0.277
PU1	0.163	0.174	**0.174**	0.892	0.085	0.118
PU2	0.121	0.121	0.190	**0.885**	0.134	0.146
PU3	0.143	0.203	0.147	**0.860**	0.093	0.149
PU4	0.173	0.155	0.167	**0.888**	0.079	0.126
PU5	0.148	0.131	0.187	**0.889**	0.097	0.099
PSEC1	0.107	0.182	0.183	0.092	**0.882**	0.270
PSEC2	0.074	0.149	0.218	0.109	**0.916**	0.261
PSEC3	0.045	0.152	0.222	0.085	**0.926**	0.263
PSEC4	0.083	0.179	0.257	0.116	**0.902**	0.237
PTR1	0.162	0.171	0.245	0.117	0.295	**0.848**
PTR2	0.191	0.172	0.252	0.127	0.228	**0.878**
PTR3	0.129	0.155	0.197	0.113	0.198	**0.832**
PTR4	0.129	0.220	0.290	0.130	0.233	**0.834**

Table 7: Results of the discriminant validity assessment using the Fornell-Larcker criterion

	Factor	1 BINT	2 PEOU	3 PRV	4 PSEC	5 PTR	6 PU
1	BINT	**0.905**					
2	PEOU	0.179	**0.848**				
3	PRV	0.216	0.229	**0.916**			
4	PSEC	0.086	0.183	0.242	**0.907**		
5	PTR	0.181	0.213	0.293	0.285	**0.848**	
6	PU	0.169	0.176	0.197	0.111	0.144	**0.883**

Table 8: Results of the discriminant validity test using the HTMT

	Factor	1 BINT	2 PEOU	3 PRV	4 PSEC	5 PTR	6 PU
1	BINT						
2	PEOU	0.201					
3	PRV	0.249	0.267				
4	PSEC	0.090	0.198	0.280			
5	PTR	0.197	0.238	0.346	0.312		

6	PU	0.176	0.195	0.227	0.119	0.160	[redacted]

4.5. Structural Model Assessment

In this study, the structural model was evaluated using various statistical measures such as Beta (β), R^2, t-values, F^2, and Q^2. The bootstrapping method with 5000 resampling was also used for the assessment (Hair et al., 2017).

4.5.1. Test of Hypotheses

The evaluation results of the structural model are shown in Figure 4 and Table 9. PU, PEOU and PTR could predict BINT. Accordingly, H1 (ß = 0.128, t = 2.456, $p < 0.01$), H2 (ß = 0.128, t = 2.371, $p < 0.01$) and H3 (ß = 0.136, t = 2.658, $p < 0.01$) were supported adequately. Furthermore, PRV could predict PU, PEOU and PTR. Therefore, H4 (ß = 0.180, t = 3.368, $p < 0.001$), H5 (ß = 0.196, t = 3.915, $p < 0.001$) and H6 (ß = 0.238, t = 4.527, $p < 0.001$) were accepted. Furthermore, PSEC could predict PEOU and PTR. Hence, H8 (ß = 0.135, t = 2.594, $p < 0.01$) and H9 (ß = 0.227, t = 4.407, $p < 0.001$) were supported. But PSEC had no influence on PU. Consequently, H7 (ß = 0.067, t = 1.302, $p > 0.05$) was not supported. It is important to note that the path coefficient values revealed that perceived privacy has a greater impact on perceived trust than other constructs.

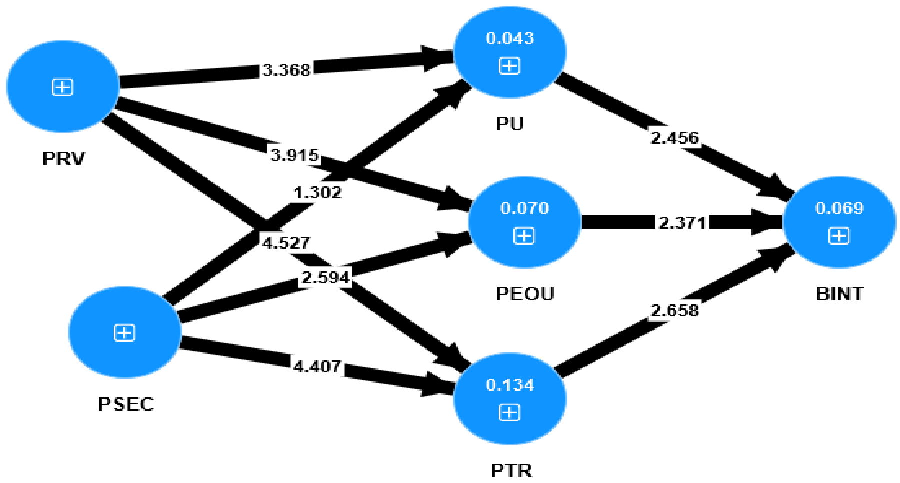

Fig. 4: Results of the PLS algorithm

4.5.2. Effect Size f²

Cohen (1988) classified the effect size f^2 of exogenous constructs into four categories: no effect (if $f^2 < 0.02$), small (if $0.02 < f^2 < 0.15$), medium (if $0.15 < f^2 < 0.35$), and large (if $f^2 > 0.35$). Table 9 shows the results for the effect size f^2 of exogenous latent constructs.

4.5.3. Variance Inflation Factor (VIF)

When the variation inflation factor (VIF) exceeds 10 (Bowerman & O'connell, 1990), it can cause problems. According to Hair et al. (2021), multicollinearity exists when the maximum VIF value exceeds 5. Hair et al. (2019) also proposed that the best VIF values are less than 3. The results of the multicollinearity assessment using the VIF are shown in Table 9. In this study, the VIF values are less than 3 and 5, indicating that the exogenous latent constructs do not exhibit significant multicollinearity.

4.5.4. Mediation Analysis

The researchers adopted the method proposed by Preacher and Hayes (2008) to analyse the effects of mediation, which is known to have higher statistical power than the Sobel test (Isaac et al., 2019). They followed the steps outlined by Preacher and Hayes and then used bootstrapping to estimate the sample distribution of all indirect effects with a resample size of 2,000. The effects of PSEC and PRV on behavioural intention via PU, PEOU, and PTR were investigated using the bootstrapping methods described by Preacher and Hayes (2008). Table 10 shows the results of this analysis, which were obtained through bootstrapping. The indirect effect of PRV on BINT through PU, with a β value of 0.023, is significant with a t-value of 1.751. The 95% Boot CI: [LL = 0.007, UL = 0.050] for the β value of 0.023, indicates that the trend does not intersect with zero between the values, demonstrating the presence of mediation. As a result, it was concluded that PU plays a significant role as a mediator between PRV and BINT, thus supporting hypothesis H10.

Furthermore, the indirect effect of PRV on BINT through PEOU, with a β value of 0.025, is significant with a t-value of 1.899. The 95% Boot CI: [LL = 0.007, UL = 0.051] for the β value of 0.025, indicates that the trend does not intersect with zero between the values, which demonstrates the presence of mediation. As a result, it was concluded that PEOU plays an important role as a mediator between PRV and BINT, thereby supporting hypothesis H11. Additionally, the indirect effect of PRV on BINT through PTR, with a β value of 0.032, is significant with a t-value of 2.004. The 95% Boot CI: [LL = 0.012, UL = 0.065] for the β value of 0.032, indicates that the trend does not intersect with zero between the values, which demonstrates the presence of mediation. Hence, it was concluded that PTR plays a significant role as a mediator between PRV and BINT, thereby supporting hypothesis H12.

The p-value for the indirect effect of PSEC on BINT through PU is greater than 0.05, indicating an insubstantial relationship, which implies the absence of a mediating effect. Therefore, hypothesis H13 is not supported by the results of this study. On the contrary, the indirect effect of PSEC on BINT through PEOU, with a β value of 0.017, is significant with a t-value of 1.795. The 95% Boot CI: [LL = 0.005, UL = 0.037] for the β value of 0.017, indicates that the trend does not intersect with zero between the values, demonstrating the presence of mediation. Hence, it was concluded that PEOU has a significant role as a mediator between PSEC and BINT, thereby supporting hypothesis H14. Furthermore, the indirect effect of PSEC on BINT through PTR, with a β value of 0.031, is significant with a t-value of 2.198. The 95% Boot CI: [LL = 0.011, UL = 0.057] for the β value of 0.031, indicates that the trend does not intersect with zero between the values, which demonstrates the presence of mediation. Therefore, it was concluded that PTR plays a significant role as a mediator between PSEC and BINT, thereby supporting hypothesis H15.

4.5.5. Coefficient of Determination R^2: The Variance Explained

According to Table 11, PU, PEOU, and PTR accounted for 6.9% of the variation in BINT. Furthermore, PRV and PSEC explained 4.3%, 7%, and 13.4% of the variation in PU, PEOU, and PTR, respectively.

4.5.6. Predictive Relevance Q^2

If Q^2 is greater than zero, the proposed model has predictive relevance for a specific endogenous latent construct (Fornell & Cha, 1994; Hair et al., 2017). As shown in Table 12, all Q^2 values in the study exceeded zero, indicating that the predictive relevance was satisfactory. The predictive significance of a specific endogenous latent construct can be calculated using values of 0.35, 0.15, and 0.02, which represent large, medium, and small predictive relevance, respectively (Hair et al., 2017). Table 12 shows that all of the variables in the study had a small predictive relevance.

Table 9: Results of the structural path analysis

Hypothesis	Relationship	Std Beta	Std Error	t-value	p-value	BCILL	BCIUL	Decision	f^2		VIF <3.3
									Value	Effect	
H1	PU → BINT	0.128	0.052	2.456	P<.01	0.034	0.206	Supported	0.02	Small	1.045
H2	PEOU → BINT	0.128	0.054	2.371	P<.01	0.039	0.214	Supported	0.02	Small	1.072
H3	PTR → BINT	0.136	0.051	2.658	P<.01	0.050	0.218	Supported	0.02	Small	1.060
H4	PRV → PU	0.180	0.054	3.368	P<.001	0.088	0.264	Supported	0.03	Small	1.062
H5	PRV → PEOU	0.196	0.050	3.915	P<.001	0.110	0.275	Supported	0.04	Small	1.062
H6	PRV → PTR	0.238	0.053	4.527	P<.001	0.143	0.319	Supported	0.06	Small	1.062
H7	PSEC → PU	0.067	0.051	1.302	P>.05	-0.020	0.149	Not Supported	0.00	No effect	1.062
H8	PSEC → PEOU	0.135	0.052	2.594	P<.01	0.046	0.219	Supported	0.02	Small	1.062
H9	PSEC → PTR	0.227	0.052	4.407	P<.001	0.140	0.310	Supported	0.06	Small	1.062

Table 10: Results of mediation analysis

Hypothesis	Relationship	Std Beta	Std Error	T-value	p-value	BCILL	BCIUL	Decision
H10	PRV -> PU -> BINT	0.023	0.013	1.751	P<.05	0.007	0.050	Supported
H11	PRV -> PEOU -> BINT	0.025	0.013	1.899	P<.05	0.007	0.051	Supported
H12	PRV -> PTR -> BINT	0.032	0.016	2.004	P<.05	0.012	0.065	Supported
H13	PSEC -> PU -> BINT	0.009	0.008	1.068	P>.05	0.000	0.026	Not-Supported
H14	PSEC -> PEOU -> BINT	0.017	0.010	1.795	P<.05	0.005	0.037	Supported
H15	PSEC -> PTR -> BINT	0.031	0.014	2.198	P<.05	0.011	0.057	Supported

Table 11: Coefficient of determination results R^2

Exogenous construct	Endogenous construct	R^2	(Cohen, 1988)	(Chin, 1998)	(Falk & Miller, 1992)
PU, PEOU, and PTR	BINT	0.069	Small	Un-acceptable	Acceptable
PRV and PSEC	PU	0.043	Small	Un-acceptable	Acceptable
PRV and PSEC	PEOU	0.070	Small	Un-acceptable	Acceptable
PRV and PSEC	PTR	0.134	Medium	Un-acceptable	Acceptable

Table 12: Predictive relevance Q^2

Exogenous construct	Endogenous construct	Q^2	(Fornell & Cha, 1994)	(Hair et al., 2017)
PU, PEOU, and PTR	BINT	0.031	Predictive relevance	Small
PRV and PSEC	PU	0.031	Predictive relevance	Small
PRV and PSEC	PEOU	0.058	Predictive relevance	Small
PRV and PSEC	PTR	0.122	Predictive relevance	Small

5. Discussion

The researchers discovered that PU had a positive effect on BINT's use of BT. This result is consistent with previous literature findings (Abu-Shanab et al., 2012; Dirsehan (2020); Kamble et al., 2018; Nuryyev et al., 2020; Ullah et al., 2020). This influence was based on healthcare professionals believing that the blockchain-based EHR system could be a useful tool that would allow them to complete their tasks more quickly and improve their performance, thereby positively impacting their BINT. This result, however, contradicts the findings of Muhamad et al. (2020) and Chi and Tsai (2017), the researchers found no correlation between PU and the BINT. In addition, the researchers discovered that PEOU positively affected the BINT's use of BT. This result is consistent with previous findings reported by Abu-Shanab et al. (2012), Almajali et al. (2022), Billanes and Enevoldsen (2022), and Chowdhury et al (2022). This influence stemmed from the fact that the more healthcare professionals perceive the blockchain-based EHR system to be simple and adaptable, the more likely they are to use it. This result, however, contradicts the findings of Dhagarra et al. (2020), Muhamad et al. (2020) and Roca et al. (2009), the researchers discovered that PEOU had no positive influence on BINT's willingness to use information systems.

Furthermore, the findings of this study indicated that PTR had a positive effect on BINT. This impact was based on the fact that a more transparent, confidential, trustworthy, and reliable system increases healthcare professionals’ willingness to use it. Almajali et al. (2022), Almarashdeh et al. (2021), Billanes and Enevoldsen (2022), Liu and Ye (2021), and Yaseen et al. (2021) all agreed on this result. However, this finding contradicts the findings of a previous study by Abu-Shanab et al. (2012), Ayedh et al. (2020) and Queiroz and Wamba (2019), the researchers discovered that PTR had no effect on user BINT.

In addition, the researchers determined that PRV had a positive influence on PU. This influence was supported by Kumar et al. (2021) and Asadi et al. (2017). According to the findings, the better a system protects data, the more useful it is in improving the performance of healthcare professionals. However, this result contradicted the findings of Belanche-Gracia et al. (2015), who found no relationship between PRV and PU. This study also discovered that PRV had a positive effect on PEOU. This influence was based on the fact that the more secure a system is in protecting data, the more user-friendly it will be perceived. This result was supported by Kumar et al. (2022) and Asadi et al. (2017). Furthermore, the study found that PRV had a positive impact on PTR. This impact was also supported by Kumar et al. (2022), Asadi et al. (2017) and Al-Okaily et al. (2022). The impact was based on the fact that the more secure the system is in protecting data, the more it will be perceived as trustworthy, confidential, and reliable. This result was in contrast to previous findings (Maqableh et al., 2021; Normalini & Ramayah, 2017; Ponte et al., 2015; Roca et al., 2009), which did not report a significant relationship between PRV and PTR.

Moreover, this study found that PSEC had no impact on PU. This finding was in line with the results of Dutot (2015), who found no relationship between PSEC and PU. However, this result contradicts the findings of Asadi et al. (2017), Kumar et al. (2022) and Lai (2017), the researchers found a positive relationship between PSEC and PU. The proposed impact was based on the notion that the more secure and safe the system for transmitting information, the more useful it will be perceived by healthcare professionals. Besides, this study found that PSEC had a positive impact on PEOU, which was supported by previous studies such as Asadi et al. (2017), Kumar et al. (2022) and Lai (2017). This result suggests that the more secure the system is for transmitting information, the more comfortable healthcare professionals will feel while using it. Furthermore, PSEC positively impacted the PTR in this study. This finding is supported by studies conducted by Al-Okaily et al. (2022), Asadi et al. (2017), Maqableh et al. (2021) and Kumar et al. (2022). These results imply that people believe that a system will be more reliable and trustworthy if it provides secure and safe ways of transmitting information.

Finally, it was discovered that PU, PEOU, and PTR significantly mediate the relationship between PRV and the BINT to use blockchain-based EHR systems. This mediation is based on the fact that the more secure a system is in protecting data, the more useful, easy to use, flexible and trustworthy it will become, leading to an increase in the intention of healthcare professionals to use it. Additionally, PEOU and PTR significantly mediate the relationship between PSEC and BINT to use BT systems. This mediation occurs because when the system provides secure and safe methods for transmitting information, it becomes more useful, user-friendly, flexible, and trustworthy, thus increasing the healthcare professionals' intention to use it. However, in this study, PU did not mediate the relationship between PSEC and BINT to use blockchain-based EHR systems.

The earlier mentioned inconsistency in the findings could be attributed to the inconsistent effects of the factors examined in IS research on technology acceptance and usage (Sun & Zhang, 2006). Furthermore, as mentioned by Straub et al. (1997), theories and models cannot be applied equally in all situations and contexts. Therefore, the results were appropriate for the specific culture or context of each study (Ala’a & Ramayah, 2023).

6. Contributions

6.1. Theoretical Contributions

This study found strong evidence that the TAM model predicts the behavioural intention of healthcare professionals in Jordan to use blockchain-based EHR systems in the public sector. The findings of this study could add to the existing literature because the researchers extended the TAM model with perceived privacy, perceived security, and perceived trust to predict the BINT of Jordanian healthcare professionals to use the BT platform. Future research can use the proposed model to gain a better understanding of the behavioural intention to use BT. The extended TAM model has the potential to improve understanding and acceptance of BT while also assisting all efforts in Jordan to adopt BT. Moreover, the research model revealed strong evidence that perceived usefulness, perceived ease of use, and perceived trust mediated the relationship between perceived privacy and behavioural intention. While perceived usefulness had no mediation effect between perceived security and behavioural intention in this study.

Many studies have used the TAM model to understand technology acceptance in Jordan. Moreover, several studies have used the TAM to investigate the factors influencing the acceptance of new technologies, including BT, in various contexts. This study, however, extends the TAM model with perceived privacy, perceived security, and perceived trust in Jordan. This model was chosen based on the characteristics of Jordanians. This was done in an attempt to understand the factors that influence Jordanian healthcare professionals' behavioural intention to use a blockchain-based EHR system in the future.

6.2. Practical Contributions

All of the findings help healthcare professionals determine the factors that influence behavioural intention to use BT as a digital platform that may be used in the near future. These findings were deemed beneficial at both the organisational and individual levels. Furthermore, they emphasised the significance of information technology in the workplace. As a result, all of the information gleaned from these findings could be used to inform future policy decisions. The government can use these findings as it develops strategies to encourage people to use secure, decentralised digital platforms like BT. Furthermore, this study was deemed well-timed and was carried out at the appropriate time. These significant findings and the proposed model are expected to aid Jordan's national and governmental strategies and policies, particularly those related to the transition to a digital economy.

7. Limitations and Suggestions for Future Work

The first limitation in this study is related to the generalisation of the results. The researchers looked at Jordanian healthcare professionals who work in the public sector for this study. The second limitation is that the data in this study was not longitudinal in nature and was collected using cross-sectional methods. Future research is strongly encouraged to apply the proposed extended TAM model in other sectors, such as the private sector or different sectors in Jordan. This could improve the model's ability to predict behavioural intention to use BT and its outcome in an IS context. Furthermore, the data for the model could be collected from different sources (primary and secondary data) in the future, yielding different results.

8. Conclusion

The goal of this study was to predict healthcare professionals' behavioural intentions to use blockchain technology in Jordan. The study discovered that PU, PEOU, and PTR were predictors of BINT's intention to use the system. Furthermore, PRV influenced PU, PEOU, and PTR, whereas PSEC only influenced PEOU and PTR. PU, PEOU, and PTR also served as mediating role in the relationship between PRV and BINT. In addition, PEOU and PTR served as mediators between PSEC and BINT, whereas PU had no impact on this relationship. The findings of this study provide policymakers with valuable information for developing a successful implementation strategy for BT in the healthcare industry.

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Appendix A. TAM Model with Blockchain Technology in Previous Studies of IS (n=29)

Authors	Aim	Variables	Findings of the study
1. Albayati et al., (2020)	Applying the TAM model to investigate the behavioural factors that influence customers' intentions towards blockchain-based cryptocurrency transactions in Korea	**IV:** Attitude, PU, PEOU, Trust, Regulatory support, Experience, Social influence, Design **DV**: Behavioural intention (BINT)	When regulated and insured by the local government, people feel safe using Blockchain-based applications. Users feel confident using blockchain-based applications after a certain level of experience, and high trust supports technology adoption
2. (AlSuwaidan & Almegren, 2020)	Applying the TAM model to determine the critical factors affecting the adoption of BT in the Internet of Things (IoT) environment in Saudi Arabia	**IV:** Attitude-related factors, Social influence related factors, Data related factors, Security related factors, BINT **DV**: Adoption of BT	Data-related factors significantly affect IoT blockchain adoption and intention to use
3. (Atmoko et al., 2021)	Extending the TAM model to examine the factors that impact the acceptance of BT in the banking, telecommunications and government sectors in Indonesia	**IV:** PU, PEOU, Perceived security, Perceived trust, Perceived strategic value, Perceived risk, and Cost-saving, Attitude **DV**: Behavioural intention (BINT)	Perceived security, perceived risk, trust, perceived strategic value, and cost-saving had a significant effect on BT acceptance
4. (Adnan et al., 2022)	Examining the adoption of cryptocurrency through the lens of the TAM among users of cryptocurrency or individuals who are aware of cryptocurrency in India	**IV:** PU of investing in cryptocurrency (PUIC), perceived ease of investing in cryptocurrency (PEIC), perceived risk of investing in cryptocurrency (PRIC) **DV:** Behavioral intention to invest in cryptocurrency (BIIC)	PU, Perceived Ease of Investing in Cryptocurrency, and Perceived Risk significantly affect behavioural intention to invest in cryptocurrencies

Authors	Aim	Variables	Findings of the study
5. Altamimi et al. (2022)	Extending the TAM with five additional factors to investigate the factors that impact the adoption of BT for sustainable learning and education (SEL) in Jordanian universities	**IV:** Perceived convenience (PCV), Perceived facilitating condition (PFC), Perceived effort expectancy (PEE), Perceived cost (PC), Perceived social influence (PSI), PU, PEOU, Attitude **DV:** Behavioural intention (BINT)	The findings indicated that the adopted factors significantly affect the use of BT in SEL
6. Bhardwaj et al. (2021)	Examining the factors that influence the adoption of BT in the supply chains of SMEs in India by combining TAM, Diffusion of Innovation (DOI), and Technology-Organization-Environment (TOE) frameworks	**IV:** Relative advantage, Technology compatibility, Complexity, Technology readiness, Top management support, Security concerns, Cost concerns, PU, PEOU, Regulatory support, Vendor support **DV:** Behavioural intention (BINT)	Relative advantage, technology compatibility, technology readiness, top management support, PU, and vendor support positively affect Indian SMEs' intention to adopt blockchain technology in their supply chains. Technology complexity and cost prevent SMEs from adopting it. Security concerns, perceived ease of use, and regulatory support do not affect technology adoption
7. Bharadwaj & Deka (2021)	Combining the TAM with the Diffusion of Innovation Theory to examine the behavioural intention of Generation Z in India towards cryptocurrencies	**IV:** Relative advantage, PU, PEOU, Complexity, Compatibility, Trialability, Observability **DV:** Behavioural intention (BINT)	Complexity, compatibility, and observability affect perceived usefulness and ease of use, which affect BINT
8. Chengyue et al. (2021)	Examining the factors that influence the intention of professionals to adopt BT in complex industrial systems from retailing, e-commerce, manufacturing, and construction companies through an extended TAM model in India	**IV:** PU, PEOU, Perceived innovativeness, Knowledge, Risk, Trust **DV:** Behavioural intention (BINT)	All independent variables had a positive effect on professionals' intention to adopt BT, except perceived innovativeness

Authors	Aim	Variables	Findings of the study
9. Chowdhury et al., (2022)	Investigating the relationship between the business environment, resilience, TAM and the intention of operations managers in the United Kingdom to adopt BT for risk management	**IV:** Business environment **(**Volatility, Uncertainty, Complexity, Ambiguity), PU, PEOU, Resilience **DV:** Behavioural intention (BINT)	All factors had a significant and positive effect on the intention to adopt BT
10. Esfahbodi et al., (2022)	Determining the factors that impact consumers' intention to adopt BT in e-commerce in China	**IV:** PU, PEOU, cost saving, traceability, data privacy and security **DV:** Behavioural intention (BINT)	Cost-saving and traceability positively affected the PU, while no significant relationship was found between data privacy security and PU or between PEOU and consumers' adoption intention
11. Ferri et al., (2021)	Integrating TAM3 Model with UTAUT model to provide an empirical perspective on the readiness of the auditing professions to adopt BT in Italy	**IV:** Perception of external control, Self-efficacy, Job relevance, Output quality, Results Demonstrability, Effort expectancy (EE), Performance expectancy (PE), Social influence (SI), Age, Gender, Role in firm **DV**: Behavioural intention (BINT)	PE and SI were the primary predictors of BINT to use Blockchain. The EE was found to be a reliable predictor of the implementation of BT
12. Gao & Li, (2021)	Examining the adoption of blockchain-based games among users in China	**IV:** Perceived security, Privacy, Trust, PU, PEOU, Perceived enjoyment, Subjective norms (SN) **DV:** Behavioural intention (BINT)	Trust, PU, perceived enjoyment, and PEOU were crucial factors in users' intention to use blockchain-based games. SN did not positively influence users' intention to use these games

Authors	Aim	Variables	Findings of the study
13. Kamble et al., (2019)	Integrating the TAM, the Technology Readiness Index (TRI), and the Theory of Planned Behavior (TPB), to comprehend the adoption of BT in supply chains in India	**IV:** Discomfort, Insecurity, Subjective norms (SN), Perceived behavioural control (PBC), PEOU, PU, Attitude **DV**: Behavioural intention (BINT)	The constructs of insecurity and discomfort have little effect on PEOU and PU. BINT is influenced by PU, attitude, and PBC. SN does not affect BINT
14. Kabir, (2021)	Evaluating the intention of tax stakeholders in Bangladesh to adopt BT based on the TAM model and self-determination theory (SDT) in Bangladesh	**IV:** PU, PEOU, Autonomous motivation, Perceived trust **DV:** Behavioural intention (BINT)	PU had a significant impact on the intention to adopt BT. Autonomous motivation also had a positive and significant effect on the intention to adopt BT. Furthermore, trust is identified as a significant factor in explaining stakeholders' intention to adopt BT
15. Kumar et al., (2022)	Extending TAM model to investigate the beliefs and behaviour of educated individuals toward adopting BT in Indian higher education	**IV:** Trust, Perceived security and privacy (PSP), PEU, PU, Attitude **DV**: Behavioural intention (BINT)	TRT and PSP had a significant positive influence on BINT to adopt BT in higher education. PSP had emerged as powerful factor affecting PU, PEOU, and trust towards BT
16. Lian et al., (2020)	Applying TAM Model to explore the critical factors that impact the BINT to accept and use Blockchain-based smart lockers (BBSL) in Taiwan	**IV:** Individual-technology fit, Task-technology fit, PU, PEOU, Perceived safety, Network externality, Attitude **DV:** Behavioural intention (BINT)	PEOU and PU were crucial. When using a blockchain-based smart locker, safety is not the main concern. The service provider's security will be trusted by users. Users do not worry about security. Finally, smart locker has negligible network externality
17. Liu & Ye, (2021)	Investigating the relationship between trust and user acceptance based on TAM in China	**IV:** Output quality, Information quality, PU, PEOU, Trust, Calculation-based trust **DV:** Behavioural intention (BINT)	Trust and information quality had positive effects on BINT to accept BT, while OQ had no effects on the BINT to accept BT

Authors	Aim	Variables	Findings of the study
18. Namahoot & Rattanawibo onsom, (2022)	Extending the TAM model with innovativeness, and analysing the mediation effect of attitude and perceived risk on the adoption of cryptocurrency platforms in Thailand	**IV:** PU, PEOU, Innovativeness, Perceived risk, Attitude **DV:** Cryptocurrency platform adoption	The results indicated a strong positive relationship between PU, PEOU, innovativeness, attitude, perceived risk, and the adoption of cryptocurrency platforms. Furthermore, attitude played a mediating role in the relationship between PU, PEOU, innovativeness, and the adoption of cryptocurrency platforms
19. Nuryyev et al., (2020)	Extending TAM model to investigate the factors that influence the BINT to adopt cryptocurrency payments among SMEs in tourism and hospitality sector in Taiwan	**IV:** PU, PEOU, Strategic orientation (SO), Social influence (SI), Owner/Manager personal characteristics (OMPC), Self-efficacy, Complexity and security, Age, Gender **DV:** Behavioural intention (BINT)	SO, OMPC and SI had a strong effect on the BINT to adopt cryptocurrency payments. PU mediated the effects of SO and SI. Finally, PEOU mediated the effect of self-efficacy on the BINT to adopt cryptocurrency payments
20. Palos-Sanchez et al., (2021)	Extending TAM to investigate the adoption of the Bitcoin cryptocurrency based on BT, and its utilisation as a payment method in businesses in Spain	**IV:** Trust, PU, PEOU, Risk, Privacy, Perceived security, Attitude **DV:** Behavioural intention (BINT)	The results showed that privacy is a crucial factor affecting PU, and trust has a substantial impact on privacy and PEOU, indirectly impacting the intention to use cryptocurrencies
21. Prisco et al., (2022)	Examining the factors that impact the adoption of BT in Italy	**IV:** Attitude, Subjective norms, Perceived benefit (PB), PU, PEOU, PBC **DV:** Behavioural intention (BINT)	The results showed that PBC was a strong predictor of the intention to use BT. Additionally, it was discovered that PB had a significant impact on PU
22. Saputra & Darma, (2022)	Using the extended TAM model to analyse the level of intention to use BT in Indonesia	**IV:** PU, PEOU, Attitude, Trust, SI, User interface, Government regulation, Security **DV:** Behavioural intention (BINT)	Public influence is the biggest factor in usefulness perception. The user interface most affects perceived ease of use. User's positive behaviour strongly affects use intention

Authors	Aim	Variables	Findings of the study
23. Sciarelli et al., (2022)	Determining the factors that influence the adoption of BT by users in Italian SMEs	**IV:** PU, PEOU, Attitude, Reduced cost, Efficiency and security **DV:** Behavioural intention (BINT)	Efficiency and security play a significant role in companies' decisions to adopt BT. Additionally, the results suggest that PU is a strong factor in predicting a company's intention to use BT in their business operations
24. Singh et al., (2019)	To assess the acceptance of BT among stakeholders and to examine how cryptography can be used to improve corporate governance and resolve long-standing issues in financial record-keeping in India	**IV:** PU, PEOU, Attitude, Behavioural intention (BINT) **DV:** Actual usage	According to the conceptual model, the study empirically tests all the relationships of attitude, PEOU, and PU with behavioural intention. The manuscript shows that model fit indexes for various constructs match the theorised model
25. Tolu et al., (2022)	Designing a TAM model to accept financial transactions using BT and cryptocurrency transactions in Iran	**IV:** PU, PEOU, Attitude **DV:** Behavioural intention (BINT)	PEOU and PU have a positive effect on Iranian users' attitude towards cryptocurrency transactions facilitated by BT. Additionally, this attitude has a positive influence on users' BINT towards using BT. Furthermore, with a certain level of experience, users feel confident and can trust blockchain-based applications
26. Ullah et al., (2021)	Expanding TAM Model with diffusion of innovation (DOI) theory to explore factors affecting the BINT to use BT for e-learning in Malaysia	**IV:** Trialability, Relative advantage, Compatibility, PU, PEOU **DV:** Behavioural intention (BINT)	Compatibility had a significant impact on blockchain use in smart learning environments. Blockchain technology adoption was also affected by other factors

Authors	Aim	Variables	Findings of the study
27. Ullah et al., (2022)	Extending the TAM model with trust and cost-saving to examine the crucial factors affecting a user's intention to adopt BT for financial institutions in Malaysia	**IV:** PU, PEOU, Trust, Cost saving **DV:** Behavioural intention (BINT)	All variables except trust on PU had a significant effect on the implementation of BT in Malaysia
28. Wahyuni et al., (2021)	Integrating the Technology Readiness Index (TRI) and TAM models to examine multiple variables in Indonesia	**IV:** Trust, PU, PEOU, Attitude **DV:** Behavioural intention (BINT)	TRI had a significant impact on PEOU and PU. Moreover, PEOU is significant towards PU and BINT to use. Furthermore, PU is significant for attitude. Finally, the attitude toward variable is significant for the intention to use BT
29. Wang et al., (2022)	Integrating TAM with technology–organization–environment (TOE) framework to explore the factors that impact the adoption of BT in the construction sector in China	**IV:** PU, PEOU, Relative advantage, Perceived cost, Technological maturity, Organizational readiness, Competitive pressure, Policy **DV:** Behavioural intention (BINT)	Competitive pressure has the greatest impact on TAM's internal variables. Blockchain adoption behaviour is unaffected by perceived adoption cost. Organisational readiness negatively impacts perceived usefulness, contrary to previous research.