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Patient-centered insights: Unraveling the drivers of AI acceptance in healthcare

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Abstract

The research study delved into the nuanced human aspect of artificial intelligence (AI) in health care, focusing on what is fundamentally important to patients in accepting this radical technology. With patients at the center of the research, it explored how social influence, individual backup choices, and trust influence the acceptance of AI healthcare services. The survey, which used 450 participants, tested Structural Equation Modeling (SEM) using AMOS and found the powerful role of such factors. Social influence (what do others think or say about AI) comes out strongly to shape patients' perceptions. Personal backup desire (the need to know or feel secure in human support being always an option) is another crucial variable. Last, and most importantly, trust in the reliability and safety of AI systems is the bedrock of acceptance. This study did not just deal with numbers but speaks a human story where trust, reliability, and social connection can drive AI adoption. These insights are a guide for practical recommendations to healthcare providers and policymakers on not only how to nurture trust but also engage with patients in meaningful ways and balance this with the human touch. This is how health care is transformed by AI, not as a replacement but in a way that patients can embrace with confidence and satisfaction.

Keywords: Artificial intelligence (AI), Desire for personal backup, Healthcare technology, Patient acceptance, Social influence, Trust.

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1. Introduction

Artificial Intelligence (AI) constitutes a rapidly evolving discipline with the primary objective of constructing intelligent machines proficient in undertaking intricate tasks [1, 2]. It has exhibited transformative potential across diverse industries, encompassing finance, manufacturing, and healthcare [2]. AI has added significant advancements, enabling its applications in domains previously governed solely by human experts in healthcare [3, 4]. AI, e.g., algorithmic machine learning, presents new prospects for innovation [5, 6]. AI can be utilized in healthcare as a clinical decision support system, aiding in patient-specific diagnosis and treatment decisions [7, 8]. Many companies have focused on integrating AI-based services into their strategies [5, 6, 9]. AI has prompted studies investigating its implementation and acceptance [5, 10]. Understanding the factors affecting users' acceptance of AI is important, particularly in healthcare, where AI can enhance patient care and manage medical data [11-13]. However, ethical societal trust and dependence on AI need further development [14-16].

Patients' attitudes and perceptions regarding AI are vital for successful implementation in healthcare. Failure to recognize their willingness to consent to AI devices may result in wasted resources and a loss of customers. Patient involvement is considered a critical factor in healthcare quality, emphasizing the importance of understanding patients' perspectives [17]. Although there is a growing interest in AI acceptance in healthcare, quantitative studies examining the impact of individual factors on AI acceptance are limited. Previous studies have primarily explored challenges related to technology use qualitatively, without incorporating relevant quantitative investigation [18, 19]. Existing studies on technology acceptance in healthcare have primarily focused on the design and execution of service provision, neglecting patients' perceptions and behavioral aspects related to technology usage [20].

This study addresses critical variables influencing patients' healthcare acceptance of AI. Adopting a patient-centric viewpoint seeks to understand patients' attitudes and perceptions toward AI-based devices. The study addresses the combined influence of social influence, trust, and desire for personal backup on AI acceptance. Integrating these factors into a single conceptual model will uncover their interrelationships and explore how they collectively influence patients' acceptance of AI-based devices in healthcare.

2. Theoretical Foundation and Hypothesis Development

The adoption of AI technology in healthcare has been an important issue that has drawn scholars' attention in various contexts. In a review by Shinners, et al. [21], the knowledge and experiences of healthcare workers with AI in healthcare provision were examined. Research fieldwork conducted by Fan, et al. [22] led to an understanding of the use of AI-assisted diagnosis technologies among Chinese medical practitioners. In their study, trust was added as another component to the UTAUT model. Findings indicated that trust, as well as performance expectancy, significantly affects the intention to use AI, with trust playing a more major role. Contrary to the original premise of UTAUT, the data indicated that social influence and effort expectation did not significantly affect behavioral intention. The above findings highlight the importance of trust as extremely valuable within the healthcare sector and indicate the broader role played by individual considerations in using technology within this sector.

Another study by Alhashmi, et al. [23] presented the issue of AI usage for patients in the public healthcare system in Dubai. They used an extended Technology Acceptance Model (TAM) supplemented by different external variables that existed before the original TAM to examine the technical and strategic facets of technology use. Most hypotheses in the extended TAM have been validated, thereby supporting the original TAM model. In the same vein, a study conducted by Scheetz et al. in 2021 focused on finding the inclination of clinicians with respect to using AI in the healthcare sector. It was revealed that clinicians might be aware of the use of AI in certain areas of medicine. An assessment of how the population held public views regarding AI and robotics in the healthcare system was conducted by Stai, et al. [24]. It illustrated how the general public perceived the roles AI and/or robotics played in healthcare. Research analysis by [25] considered the adoption of AI in the practice of medicine; it provided a comprehensive view regarding the status and offered insight into the way forward. Tam-Seto, et al. [26] focused on the users' experiences among the Canadian Armed Forces to gain insights into AI-enhanced applications.

This study highlighted the individual or patient factors that affect the acceptance of AI usage. On an individual basis, the use of artificial intelligence (AI) in healthcare involves several patient characteristics that influence it. Three factors have been identified to further define these influences by comparing the qualitative results with the literature review: social influence, personal support, and trust.

2.1. Social Influence (SI)

Social influence can be conceptualized as the implementation of new technology based on the impacts of social networks [27]. The opinions of friends, family, and colleagues can significantly impact decisions to embrace innovative technologies [28]. Particularly in the initial stages of use, when individuals have limited or no personal experience with the new technology, they rely heavily on the viewpoints of those within their social circle, as highlighted by Teo and Pok [29]. The effect of social networks on technology adoption is an important factor to consider in understanding individuals' decision-making processes. Given that AI technology is still relatively new in the healthcare domain, patients' usage decisions are likely to be significantly affected by the recommendations and experiences shared by others. Therefore, it could be argued that:

$H_{1:}$ SI significantly and positively affects the patient's intention to use AI.

2.2. Desire for Personal Backup (PBU)

The desire for personal backup can be defined as a support system or resource that individuals rely on when they need assistance with an issue or concern. This may include human interaction, as some people may prefer to speak with a person rather than a machine in certain circumstances, such as when they need personal assurance [30]. Essentially, personal backup refers to the resources and options individuals have available beyond automated or technological solutions. It has been confirmed in Prior studies that Personal backup is a critical factor that affects patients' acceptance of AI Dabholkar and Bagozzi [31]. It was argued that individuals encourage others to use technology-based services without direct communication with customer service. They are not also concerned with the risk involved. Thus, it could be hypothesized that:

$H_{2:}$ Desire for Personal backup positively and significantly affects the patient's intention to use AI.

2.3. Trust (TR)

Trust refers to the extent to which an individual has confidence in the safety, dependability, efficacy, and absence of privacy risks related to using AI devices [32]. It is another critical factor in the adoption of AI in healthcare. Patients need to feel confident and comfortable with AI systems and the healthcare providers who use them. Patients who trust their healthcare providers and the technology they use may be more willing to adopt AI in healthcare. It was found that trust affects the usage behavior of ICT [33-35]. Consequently, it is hypothesized that:

H3: Trust is positive and significantly affects the intention to use AI.

The research hypotheses are presented in Figure 1.

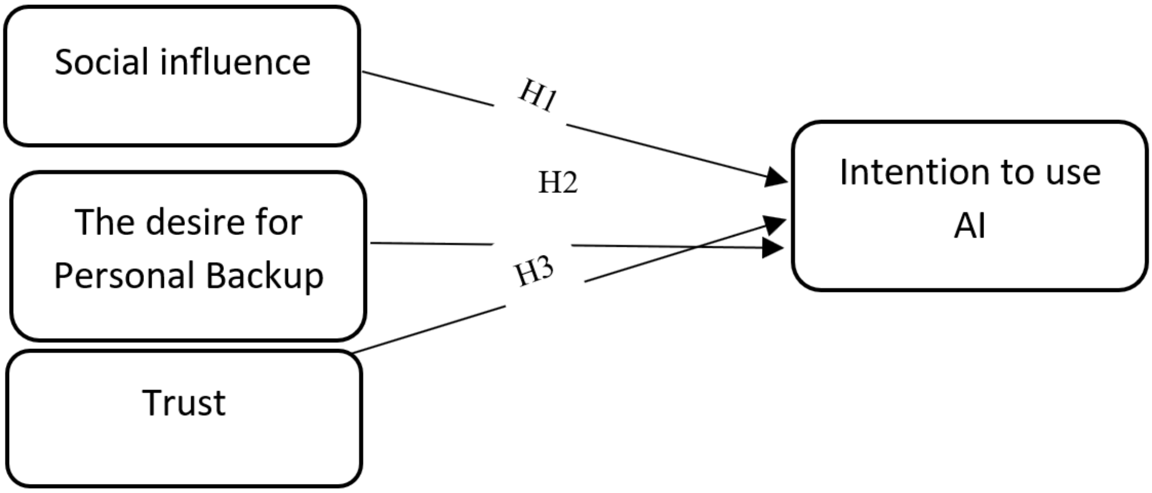

Figure 1.
Conceptual model.

3. Methods

3.1.Data Collection

The data collection involves the use of surveys to gather quantitative data on the variables that affect Tunisian patients' acceptance and resistance to AI in healthcare [36, 37]. Specifically, online surveys are deemed the most appropriate method for this research, according to Zikmund [38]. A combination of self-administered and interviewer-administered survey questionnaires is recommended [36]. Non-probability sampling techniques, including purposive, convenience, and snowball sampling, are employed to select suitable participants [39]. In measuring attitudes, the Likert scale is utilized [40]. Moreover, the questionnaire is translated into French using rigorous translation techniques to accommodate the primarily Tunisian sample. Before collecting the data, the questionnaire was piloted and tested to ensure its quality, resulting in improved length and clarity based on feedback from the respondents [41]. SEM was adopted in this study, and a sample size of 200 or above is considered appropriate [42, 43]. In total, 450 completed questionnaires are included in the analysis.

3.2. Measurement scale

To assess the social influence of AI use in healthcare, we drew inspiration from the works of Yang and Jolly [44] and Venkatesh, et al. [45]. Additionally, to construct the desire for personal backup, we utilized the measurement scale [30] developed to examine consumer behavior in using technology-enabled services. The scale used for measuring trust was drawn from Fan, et al. [22] work, which addressed trust in the context of healthcare professionals adopting AI-based medical diagnosis support systems (AIMDSS). Appendix A presents the factors in the model and their scale items. The reliability coefficients of the constructs were found to be satisfactory.

3.3. Interpretation of Collected Data

Data were analyzed using five steps: a specific analysis of demographics, a reliability test using Cronbach's Alpha, exploratory factor analysis (EFA), and confirmatory factor analysis (CFA). A reliability analysis was performed to determine internal consistency. EFA was conducted to check the total variance explained and identify the structures and dimensions of our measuring instruments. After that, CFA was adopted to examine the model (Figure 1). Subsequently, SEM was used to examine the causal links between the variables of our model and to ensure, using the indices, the adjustment of the theoretical model to the data gathered. The reliability test and EFA were performed using SPSS-20.

3.4. Demographics characteristics of respondents

We have distributed a web-based survey to 600 participants. Of these, 450 participants completed the survey. The gender distribution shows that 50.7% (228) of the respondents are male, and 49.3% (222) are female, with nearly equal representation of both genders. In terms of age, the majority of respondents were in the 18-24 and 25-34 age categories, accounting for 27.6% and 25.8%, respectively. In terms of occupation, the sample comprises various professions, with the largest group being executive managers/directors at 24.9% (112), followed by students at 31.6% (142), and teachers/professors at 22.7% (102). The level of education ranges from primary education to doctoral degrees, with the majority having a bachelor's degree or equivalent tertiary education level at 34.7% (156) and doctoral degrees at 32.0% (144). The level of knowledge of AI varies, with 56.4% (254) having basic knowledge, while 2.2% (10) have no knowledge and 2.2% (10) have a superior understanding of AI. These demographic details offer an intensive overview of the sample and demonstrate the diversity of participants included in the study.

4. Results

4.1. Reliability and EFA of Constructs

The study employed EFA and a reliability test to assess four constructs: Social Influence, Personal Backup, Trust, and Intention to Use AI. Results indicated a unidimensional structure for each construct with high reliability: Social Influence (Cronbach's Alpha = 0.946), Personal Backup (Cronbach's Alpha = 0.900), Trust (Cronbach's Alpha = 0.956), and Intention to Use AI (Cronbach's Alpha = 0.944). These findings underscore the robust psychometric qualities of the measurement scales, demonstrating their suitability for further research and application in the field (Table 1).

Table 1.
Summary of results for measurement constructs.

Construct	KMO index	Bartlett's test (p-value)	Cronbach's alpha	Explained variance (%)
Social influence	0.888	2313.250 (p=0.000)	0.946	82.612
The desire for personal back-up	0.803	1285.411 (p=0.000)	0.900	78.052
Trust	0.793	2218.188 (p=0.000)	0.956	88.392
Intention to use AI	0.843	1770.865 (p=0.000)	0.944	85.910

4.2. The results of CFA

We need to go through a series of steps to test the overall measurement model. First, we need to ensure its goodness of fit by checking the indices of the model (Chi², GFI, AGFI, RMR, RMSEA, etc.). Then, we conduct a reliability test for the different constructs of the model using Jöreskog's ρ coefficient [46]. Finally, we continue with analyzing the convergent and discriminant validity of the different constructs in our measurement model.

4.2.1. Model's Goodness-of-Fit Indices

Drawn from the model-fit indices obtained from Table 2 and after incorporating modifications such as adding correlations between errors (e6/e7) and (e12/e13) and deleting item PBU4, the model demonstrated adequate and acceptable goodness-of-fit indices [47]. The chi-square to degree of freedom ratio ($\chi 2/df$) was 4.656, falling within the recommended range of $1 < \chi 2/df < 5$. The Root Mean Square Error of Approximation (RMSEA) was 0.094, which is below the threshold of 0.10, indicating a reasonable fit. The Root Mean Square Residual (RMR) was 0.045, which aligns with the suggested threshold (below 0.05). The Comparative Fit Index (CFI) was 0.958, confirming a good fit. The Goodness of Fit Index (GFI) was 0.900, and the Adjusted Goodness of Fit Index (AGFI) was above 0.8, both confirming an acceptable fit. The Normed Fit Index (NFI) was 0.947, exceeding the recommended threshold of 0.9. Such findings collectively show that the modified model fits the observed data well and appropriately represents the underlying constructs.

Table 2.
Goodness of fit indices for the model.

Model	Absolute indices		Incremental indices				Parsimony indices	
	RMSEA	RMR	CFI	GFI	AGFI	NFI	X²/ ddl	AIC
Before Modification	0.111	0,064	0,929	0,854	0,790	.918	6.498	814.687
After Modification	0.094	0.067	0.951	0.884	0.838	0.939	4.936	628.968
After deleting PBU4	0.094	0.045	0.958	0.900	0.852	0.947	4.656	628.968

4.2.2. Reliability and Validity Assessment

Regarding the reliability test of the factors in the measurement model, Jöreskog's rho coefficient [46] was preferred over Cronbach's alpha as it is less sensitive to the number of items per factor and more suitable for SEM methods. The constructs in the model demonstrated satisfactory internal consistency, with Jöreskog's rho coefficients of 0.948 for Social Influence, 0.899 for Personal Backup, 0.949 for Trust, and 0.946 for Intention to Use AI. This supports the reliability of the measurement constructs in consistently measuring the intended constructs of interest. These findings demonstrate the constructs' satisfactory internal consistency and reliability in measuring the intended constructs within the global measurement model (Table 4).

The convergent validity of all constructs in the tested model has been determined according to the criteria posited by Fornell and Larcker [46]. The t-test associated with each factor loading was examined and found to be significant, with all exceeding 1.96. Average variance extracted (AVE) values for each factor were also considered, with all being above the recommended minimum threshold of 0.5, ranging between 0.693 and 0.823 for those constructs. Therefore, all these values indicate good convergent validity for the measurement model, as the factor loadings were significant, and the shared average variance between the variables and their measures exceeded the recommended threshold (Table 3).

Table 3.
Validity and reliability results.

	Factor loadings	**CR**	**AVE**
Social Influence		0.948	0.786
SI1 <--- SI	0.932		
SI2 <--- SI	0.972		
SI3 <--- SI	0.890		
SI4 <--- SI	0.837		
SI5 <--- SI	0.792		
Personal Backup		0.899	0.693
PBU1 <--- PBU	0.875		
PBU2 <--- PBU	0.924		
PBU3 <--- PB	0.859		
PBU4 <--- PBU	0.698		
Trust		0.949	0.823
TR1 <--- Trust	0.781		
TR2 <--- Trust	0.897		
TR3 <--- Trust	0.991		
TR4 <--- Trust	0.948		
Intention to Use AI		0.946	0.812
IU1 <--- IU	0.928		
IU2 <--- IU	0.897		
IU3 <--- IU	0.921		
IU4 <--- IU	0.859		

The discriminant validity of the underlying variables can be tested by showcasing that the extent of shared variance between each construct and its associated items is larger than the shared variance with other constructs. For this purpose, we contrasted the correlation between latent variables and the square root of AVE. Findings indicate the fulfillment of this criterion, confirming the presence of discriminant validity.

4.3. The Results of SEM

After the adjustment of the model, a second section is proposed to test the conceptual model of the research. The model testing is conducted through the use of structural equation modeling methods, the steps of which are detailed and explained. The interpretation of the research hypothesis results was undertaken in two phases. Firstly, we ensure the quality of fit of the structural model. Secondly, we examine the significance and direction of the postulated cause-and-effect relationships.

4.3.1. Adjustment of the Global Structure Model

The structural model's fit was examined through AMOS 27.0, with the results indicating a good fit to the observed data. The χ^2/df was 4.656 (within the acceptable range of $1 < \chi^2/df < 5$), showing a reasonable fit. The Root Mean Square Error of Approximation (RMSEA) was 0.094 (below the threshold of 0.10), further confirming the model's acceptability. The Root Mean Square Residual (RMR) value was 0.045 (below 0.05), indicating small residuals and a well-fitting model. Additionally, the Comparative Fit Index (CFI) reached 0.958 (exceeding the minimum of 0.90), which suggests a strong fit. The Goodness of Fit Index (GFI) was 0.900, meeting the recommended threshold, while the Normed Fit Index (NFI) of 0.947 (>0.90) also supported the model's robustness. Finally, the Adjusted Goodness of Fit Index (AGFI) was 0.870 (>0.80), providing further evidence of model adequacy. Collectively, these indices confirm the model's suitability for further hypothesis testing by indicating a good fit between the proposed model and the data.

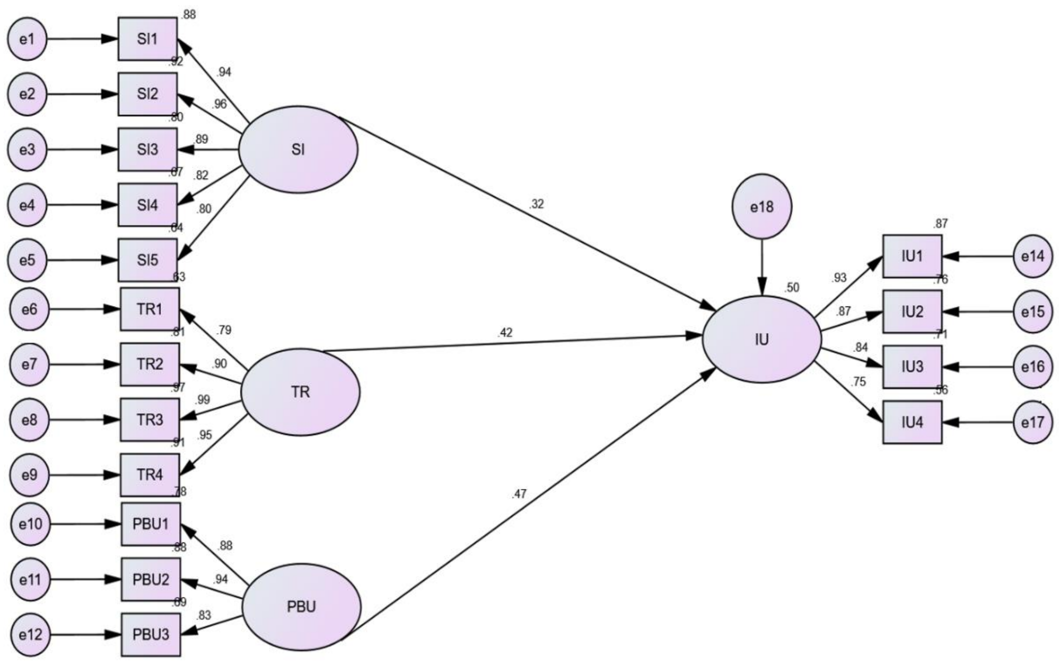

Figure 2.
Structural model.

4.3.2. The Test of the Direct Links Between Individual Context and Intention to Use AI.

The analysis tested the direct links between individual context factors (social influence, personal backup, and trust) and patients' intention to adopt AI in healthcare. The results supported all three hypotheses, confirming the significant relationships between these factors and the intention to use AI. Social influence showed a positive and relatively strong relationship (standardized coefficient = 0.317), highlighting the impact of interpersonal connections and recommendations on patients' decision-making processes. Personal backup demonstrated a significant relationship (standardized coefficient = 0.474), highlighting the importance of reliable support systems in influencing patients' intentions. Trust exhibited a strong positive relationship (standardized coefficient = 0.424), emphasizing the crucial role of trustworthiness in AI systems. This underscores the influential role of social influence, personal backup, and trust in shaping patients' intentions to adopt AI technologies in healthcare (Table 4).

Table 4.
Hypotheses' Results

Hypothesis	Standardized coefficient	CR	P-value	Validation
H1: Social Influence -> Intention to Use AI	0.317	8.111	0.000	Confirmed
H2: Desire for Personal Backup -> Intention to Use AI	0.474	11.520	0.000	Confirmed
H3: Trust -> Intention to Use AI	0.424	11.212	0.000	Confirmed

5. Discussion

This study examines the effects of individual factors on the intention to adopt AI in the Tunisian healthcare system, which led to the formulation of three hypotheses. H1: Social factors positively affect Tunisian patients' intention to use AI. H2: Personal backup positively affects Tunisian patients' intention to use AI. H3: Trust positively affects Tunisian patients' intention to use AI. The data analysis supported all three hypotheses, indicating the significant role of these individual factors in determining individuals' intention to adopt AI technology.

Social influence emerged as a main factor for the adoption of new technologies, displaying a positive effect on the intention to use AI. This finding aligns with earlier studies, indicating that individuals' decisions about technology adoption are affected by the opinions and behaviors of others [48, 49]. Sources of social influence include healthcare professionals, family, and friends who promote the use of AI in healthcare settings; their influence explains how it provides assurance, information, and social support, thereby strengthening the intention to use AI [45]. It can be observed that the intense impacts of social influence on AI usage intention are traceable to social norms and the opinions and behaviors of others regarding individual decision-making. Several studies confirm that social influence plays a significant role in shaping an individual's attitude and behaviors towards adopting technology such as AI.

According to Venkatesh, et al. [45], the role of social influence on technology use intention is positive. This study highlighted the importance of social norms regarding the role played by peers, colleagues, and experts in shaping individuals' perceptions about technology's usefulness and ease of use. In this context, Park, et al. [50] specifically tested the role of social influence on the intention to adopt services such as mobile health care. The results showed that social influence positively affected individuals' intentions toward adopting mobile health services through perceived subjective norms and the influence of significant others. This suggests that patients would, therefore, use more technology when the hypotheses of the study indicate that the intention to adopt such technologies is perceived to have strong support from influential people—endorsement.

It is widely accepted that the adoption and use of AI technology rely heavily on social support in enhancing positive endorsements by healthcare professionals, peers, and public awareness of benefits in the AI domain. Such loud expressions of support should greatly influence the intentions of patients to adopt and use AI. Another individual aspect is the desire for personal backup. This shows how it positively affects the intent to use AI. It is the support system or resources that people rely on when they are at full stretch. It mainly influences attitudes toward using AI, as it encapsulates the areas of life when people need assistance and guidance to get through problems or doubts associated with the application of AI. People with heightened desires for personal backup are much more likely to seek and adopt the requisite technology that provides them with that support and assistance. This is consistent with past studies on the importance of self-efficacy in technology acceptance [51].

Research by Agarwal and Prasad [52] studied the influence of facilitating conditions on individuals' intentions to use technology, which they defined as the availability of resources and support for easing technology usage. This study found that the availability of resourceful personal backup would enhance the intention to use technology; individuals tend to use it when they perceive vital resources and assistance. In addition, Hong, et al. [53] investigated social influence and facilitating conditions regarding people's acceptance of mobile technology. Facilitating conditions included personal backup.

As an example, the study by Gefen, et al. [54] assessed the impact of trust on individual intention towards e-commerce adoption. They found a positive outcome of trust on individuals' intention towards the adoption of e-commerce websites. When individuals view the e-commerce platform as a trustworthy source, they show a greater inclination to engage in such online transactions. This finding could also be applied to the notion of AI, where trust in AIs is expected to enhance positive sentiments towards using such AI technologies.

Furthermore, Venkatesh, et al. [45] researched the factors affecting individuals' intention to adopt information technologies. Along with this concept was the development of how trust has been established in an individual regarding technology adoption, as it was proven that individuals' intentions to use a given technology are positively impacted by trust. When people trust technology, they are inclined to believe that it will perform as expected and will be reliable. Thus, trust has been accepted as an important emerging variable in individuals' adoption and intention to use AI technologies. Such trust is underpinned by several variables, including reliability, accuracy, transparency, and ethical dimensions. When people trust that an AI system will be able to carry out tasks competently, providing accurate recommendations and being respectful with sensitive data, they will surely be more inclined to use and embrace AI technologies. Based on these hypotheses, credible evidence is presented for the role of personal variables in influencing one's intention toward adopting AI into Tunisian healthcare systems. Results thus align with earlier findings that emphasize the significance of social influence, personal backup, and trust for technological acceptance.

6. Implication

This research deeply contributed to theory and practice in terms of AI acceptance in healthcare. First, it takes a patient-centric view, understanding that patients play an important part as recipients and beneficiaries of healthcare services. Such a point of view permits one to consider private factors that would influence the acceptance of AIs by patients in healthcare. Understanding patients' views will have to be done by healthcare providers and hospitals, intending to successfully implement AI models because they are fundamental to the model's successful integration into healthcare delivery.

Second, the paper adopts a quantitative method. Quantitative analysis brings evidence and insight into the relationship of the relevant factors such as social influence, trust, desire for personal backup, and acceptance of AI into the general population. It adds further evidence and depth to the findings, bringing patients' AI technology acceptance in healthcare understanding to an entirely different level. The study investigated the effect on AI acceptance in healthcare that comes from the interaction of factors such as social influence, trust, and desire for personal backup. Incorporated into one conceptual model, the study probes for interconnections and finally investigates the salience they present altogether toward the acceptance of patients toward existing devices. This holistic approach will provide an exhaustive typology of patient-centric factors shaping the acceptance of AI. This would allow healthcare providers and hospitals to develop focused strategies that take into account such interrelated variables.

The managerial implications of these results are important as well. A summary of the results of the hypotheses testing showed significant positive relationships between social influence, personal backup, trust, and patients' intention regarding the use of AI in healthcare. These results underline the importance of designing and implementing AI technologies by considering these factors. Providers and hospitals can exert social influence by encouraging strong interpersonal relationships and positive recommendations. Moreover, building trust through transparent practices, effective communication, and data security measures is necessary to gain patients' trust in AI systems. Sufficient personal backup resources, such as assistance from health professionals and reliable technical support, can go a long way in building acceptance and use of AI-based devices by patients.

7. Conclusion

The results of this study showed significant positive relationships among social influence, personal backup, trust, and intention to use AI in the health domain, with theoretical and practical benefits, as well as the need to consider these factors in designing and implementing AI-based systems. The study advanced knowledge regarding acceptance, engendering practical implications for healthcare providers and hospitals. The unique position of patients and the interplay of social influence, trust, and personal backup would enable stakeholders to design strategies for successfully integrating AI technologies. Future research needs to probe these factors further and additional variables that help bring depth to our understanding of AI acceptance in healthcare and services for improving patient care in an evolving healthcare landscape. However, this study has certain limitations. Firstly, the research was conducted in a specific healthcare setting, possibly limiting its ability to fully capture the diversity of patient populations. Future studies should replicate the findings in different healthcare contexts and include a more diverse sample of patients. Secondly, the study focused on the direct links between individual factors and the intention to use AI, without considering other potential mediating or moderating variables. Future research could explore the complex interplay between these factors and additional variables to better understand AI acceptance in healthcare.

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Appendix A.
Constructs and measurement items.

Constructs	Measurement items
Social Influence (SI)	SI1 "People who influence my behavior would think that I should use AI technology for health management (routine check-ups, treatment, diagnosis)". SI2 "People who are important to me would think that I should use AI technology for health management (Routine check-ups, Treatment, Diagnosis)". SI3 "People around me will take a positive view of me using AI technology for health management (routine check-ups, treatment, diagnosis)". SI4 "People around me might think that I should not use AI technology for health management (routine check-ups, treatment, diagnosis)". SI5 "I think (my) doctor would want me to use AI-based systems for health management (routine check-ups, treatment, diagnosis)".
The Desire for Personal back-up (PBU)	PBU1 "I need to know that someone is there with the power to fix problems if they occur". PBU2 "I need to know that someone is there to listen to me if I have a question or problem". PBU3 "I like to have someone to whom I can complain if I need to". PBU4 "I find that AI-enabled services can be frustrating to use".
Trust (TR)	TR1 "I believe AI-based systems could provide accurate assistant service". TR2 "I believe AI-based systems could provide reliable assistant service". TR3 "I believe AI-based systems are trustworthy". TR4 "AI technology would be trustworthy for improving my healthcare routine".
Intention to Use AI (IU)	IU1 "I intend to use AI Technology in the future to manage my health conditions". IU2 "I intend to use AI Technology frequently in my medical treatment, daily health management, and diagnosis". IU3 "I intend to recommend that other people use AI technology in health management". IU4 "I would like my doctor to use AI technology".