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Impact of Artificial intelligence on Mental Satisfaction of Mobile healthcare Users: A SEM Approach

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Abstract

Purpose: The purpose of this study is to investigate the impact of artificial intelligence (AI) on the mental satisfaction of users in the context of mobile healthcare applications. As AI technologies become increasingly integrated into mobile healthcare platforms, understanding their influence on user satisfaction is essential for optimizing these applications for the well-being of individuals.

Design/methodology/approach: Conduct an extensive review of existing literature on the utilization of AI in mobile healthcare and its effects on user satisfaction and mental well-being. Collect data through surveys or interviews from mobile healthcare application users to assess their experiences, perceptions, and levels of satisfaction, with a specific focus on the AI features. Employ SEM to analyze the relationships between AI utilization, user satisfaction, and its impact on mental well-being. Use established constructs and latent variables to model the complex interactions within the system.

Findings: The results revealed that Artificial Intelligence has a significant Impact on Mental Satisfaction of users. Additionally the sub-constructs have also shown a significant impact on the mental satisfaction of the users like Patient Engagement, Customer Review etc.

Practical implications: This study can guide mobile healthcare application developers in optimizing their platforms by providing insights into how AI features can positively influence user satisfaction and mental well-being By understanding the link between AI and user satisfaction, healthcare app designers can create more user-centric solutions, leading to improved overall healthcare experiences. Insights from this study may inform policy decisions related to the integration of AI in healthcare applications, ensuring user well-being and data privacy.

Originality/value: This research contributes to the literature by focusing on the relatively unexplored area of AI's impact on the mental satisfaction of mobile healthcare users. By applying SEM, the study aims to offer a holistic understanding of the complex relationships in this context, which has not been extensively examined before. The originality lies in bridging the gap between AI technology and user well-being in the specific context of mobile healthcare applications.

Key words: Artificial Intelligence, Mobile Healthcare, Mental Satisfaction, User Engagement, Treatment Adherence & SEM.

Introduction

The use of mobile technology in healthcare has revolutionized how people get and manage their healthcare in today's quick-paced, digitally linked society. A new era of patient-centric healthcare has begun with the emergence of mobile healthcare management, or M-Health, which offers ease, accessibility, and improved patient outcomes (Wigley & Akkoyunlu-Wigley, 2006). This change is based on how mobile devices, wireless connectivity, healthcare apps, and data analytics have all come together to provide people more power than ever to actively participate in their healthcare (Sirgy et al., 2011). The advent of mobile healthcare management can be attributed to the proliferation of smartphones and tablets worldwide, along with the constant evolution of mobile applications tailored to healthcare needs(Fang et al., 2015). These tools enable individuals to monitor their health, communicate with healthcare providers, access medical information, and adhere to treatment plans, all from the palm of their hands. Moreover, healthcare providers and institutions have embraced mHealth as a means to improve patient engagement, streamline clinical workflows, and enhance the overall quality of care (Godbole & Lamb, 2018). The impact of mHealth is so profound that it has become a global phenomenon, transcending geographical and demographic boundaries (Pawar & Sharma, 2019). Whether it's a rural patient in a developing country receiving medical advice via a text message, a city-dweller tracking their fitness and

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nutrition through a mobile app, or a healthcare professional accessing real-time patient data at the bedside, mobile healthcare management is shaping the future of healthcare on a global scale(Liu et al., 2020). Over the past ten years, mobile healthcare management has experienced exponential growth and ongoing innovation. The World Health Organization (WHO) describes mobile health as "a component of e-Health, and it is the use of mobile communication devices, such as smartphones, tablets, and other wireless technology, for healthcare purposes." This includes a wide range of applications, such as telemedicine, the sharing of health information, remote patient monitoring, assistance with medication adherence, and many more(Castellanos et al., 2020). The attractiveness of mobile health is its capacity to get over obstacles to healthcare access such distance from healthcare providers, lack of time, and scarce money(Naidoo, 2020). As mobile healthcare management continues to evolve and gain prominence, it is essential to understand the profound implications it holds for the future of healthcare(Liao et al., 2020). The integration of mobile technology into healthcare has the potential to bridge existing healthcare disparities, empower individuals to take control of their health, and ultimately redefine the patient-provider relationship(Abdel-Salam et al., 2021). This paper will discuss the key aspects of mobile healthcare management, drawing upon evidence-based research and case studies to shed light on the transformative impact of mHealth on the healthcare landscape. Through these insights, we aim to provide a comprehensive view of this dynamic and evolving field and its potential to revolutionize patient care in the digital age. The impact of artificial intelligence (AI) on the mental satisfaction of mobile healthcare users is profound(Pradhan et al., 2021; Rehman et al., 2023). AI-powered mobile healthcare applications offer personalized, data-driven insights and recommendations, enhancing the user experience and, subsequently, contributing to increased mental satisfaction(Banerjee et al., 2021). Through predictive algorithms, AI can tailor health recommendations and interventions to an individual's unique needs, fostering a sense of personalization and empowerment. Moreover, AI can facilitate early detection of mental health issues, offering timely interventions and support, which is crucial for mental well-being (Lapina, 2022; Muzzamil, 2021). Features like chatb-ots or virtual mental health assistants powered by AI provide a continuous source of support, reducing feelings of isolation and stress(Bhardwaj, 2022). By streamlining administrative tasks and automating routine processes for healthcare providers, AI frees up more time for empathetic and quality patient interactions, further improving the overall mental satisfaction of both patients and clinicians in the mobile healthcare ecosystem(Abdel-Salam et al., 2021).

Literature Review

Mobile healthcare management, often referred to as mHealth, is an evolving field that has garnered substantial attention in recent years due to its potential to revolutionize healthcare delivery(Pawar & Sharma, 2019). The integration of mobile technology into healthcare has the power to enhance patient engagement, improve treatment adherence, and increase the accessibility of healthcare services. A study by (Pradhan et al., 2021) highlights the utility of mHealth in resource-constrained settings, where mobile applications have been instrumental in extending healthcare to underserved populations. Moreover, mHealth has shown promise in chronic disease management, enabling patients to monitor their health in real-time and facilitating timely interventions(Banerjee et al., 2021). As the world becomes increasingly mobile-centric, the role of mHealth in healthcare management is poised to grow, ultimately reshaping the way individuals interact with and receive healthcare services (Lapina, 2022). A new era in healthcare administration has begun as a result of the incorporation of artificial intelligence (AI) into mobile healthcare applications, with an emphasis on raising patient mental satisfaction in particular. Users' mental health could be considerably improved by AI thanks to its data-driven insights, personalization, and predictive capabilities in the mobile healthcare ecosystem(Bhardwaj, 2022). In the context of mobile healthcare, this literature review investigates and synthesizes the body of evidence already available on the effect of AI on mental satisfaction(Martin et al., 2022). AI-powered mobile healthcare applications are increasingly being harnessed to offer personalized health interventions. A study by (Kumar et al., 2022) emphasizes the significance of personalization in mobile healthcare, indicating that it can positively influence patient engagement and satisfaction. AI-driven algorithms can analyze a user's medical history, preferences, and behaviors to provide tailored health recommendations and interventions, which have been found to enhance the overall user experience. Such personalization fosters a sense of empowerment and control over one's health, contributing to increased mental satisfaction among mobile healthcare users (Zhang & Nakajima, 2022). One of the most promising aspects of AI in mobile healthcare is its ability to facilitate the early detection of mental health issues. A study by (Aversa et al., 2022; Sikarwar et al., 2022) discusses the role of AI in mental health screening through natural language processing and sentiment analysis of user-generated data. These tools can identify signs of stress, anxiety, or depression, even before users may consciously recognize these issues themselves. Early detection and intervention are pivotal in mental healthcare, and the implementation of AI-driven systems for monitoring and alerting users to potential mental health concerns can

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contribute to improved mental satisfaction and overall well-being (Cannavale et al., 2022). The development of virtual mental health assistants, often in the form of chatbots, has gained considerable attention in recent years. These AI-powered tools offer users a continuous and non-judgmental source of support for mental well-being. (Alnsour et al., 2023; Rathish et al., 2022) conducted a study on the effectiveness of AI-driven mental health chatbots in reducing stress and reported positive outcomes, with users expressing satisfaction with the support they received. Virtual mental health assistants can engage users in conversations about their emotions, provide coping strategies, and offer information on available mental health resources, thereby reducing feelings of isolation and anxiety, ultimately contributing to higher mental satisfaction (Balasubramanian et al., 2023; Shah et al., 2023).AI has transformed the healthcare industry by streamlining administrative tasks and automating routine processes, which, in turn, has an indirect impact on mental satisfaction. A study by (Bhattamisra et al., 2023; Hameed et al., 2023) emphasizes that AI can reduce the time and effort required for routine tasks such as appointment scheduling, prescription refills, and accessing medical records. As a result, healthcare providers have more time for quality patient interactions, including addressing mental health concerns (Förster et al., 2023; Kannelønning, 2023) The efficient use of AI in healthcare reduces the administrative burden on clinicians, enabling them to provide more empathetic and patient-centered care, which positively influences patient and user satisfaction(Ali Mohamad et al., 2023; Muzzamil, 2021) The integration of AI into mobile healthcare applications is rapidly transforming the landscape of healthcare management. From personalized health interventions to early detection of mental health issues and the introduction of virtual mental health assistants, AI is proving to be a powerful tool for enhancing the mental satisfaction of mobile healthcare users (Sen & Guchhait, 2023). As AI continues to evolve and gain acceptance in healthcare, it holds the potential to significantly contribute to overall well-being and mental satisfaction, further reinforcing its role in the future of healthcare delivery (Kulkov, 2023).

Research Methodology

3.1 Objective

The purpose of this study is to investigate the impact of artificial intelligence (AI) on the mental satisfaction of users in the context of mobile healthcare applications. As AI technologies become increasingly integrated into mobile healthcare platforms, understanding their influence on user satisfaction is essential for optimizing these applications for the well-being of individuals

3.2 Method

Conceptual Framework

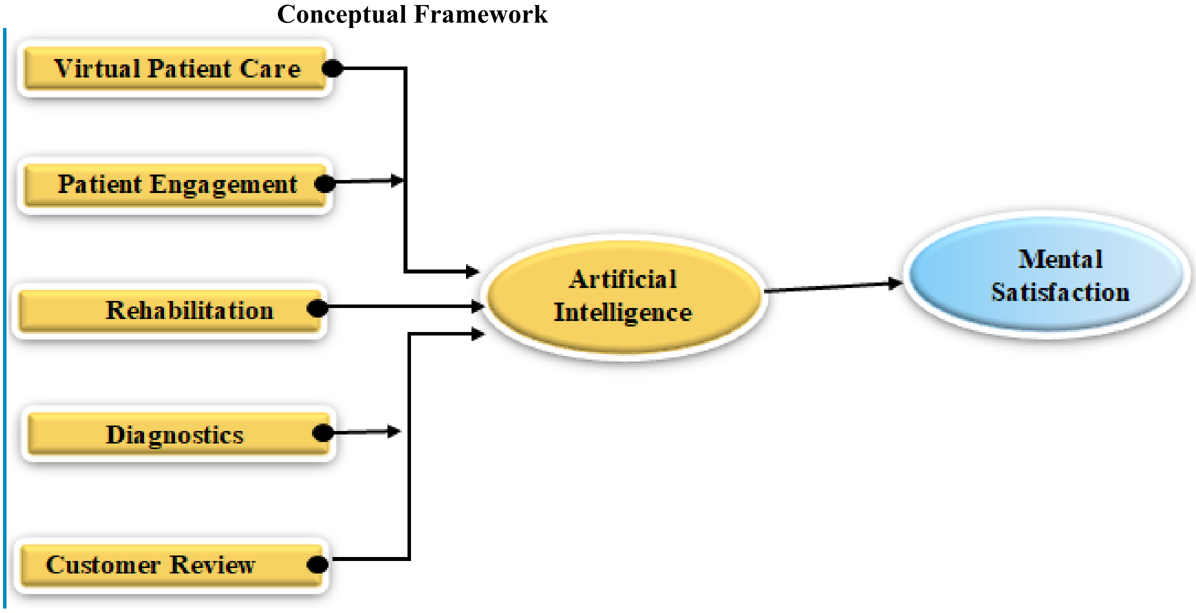

Figure 3.1

Figure 3.1 is the Conceptual Framework, developed through literature review and underpinning the related theories. There are two main constructs Artificial Intelligence and mental satisfaction. The Artificial Intelligence

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is further divided into Five more Sub-Constructs i.e. Virtual Patient Care, Patient Engagement, Rehabilitation, Diagnostics and Customer review.

The Population for this study comprised of Mobile Healthcare users, Using mobile for healthcare issues. The data was collected through Purposive Sampling all over Punjab from each District, a total of 460 questionnaire, out of which 376 were received and 300 were found fit for hypothesis testing and better results.

3.3 Measuring Instruments

The scale used for this study was divided into three parts, the first part deals demographics of the respondents, the second part deals with Artificial Intelligence with 25 questions and final part deals with Mental Satisfaction with 10 questions. All the statements used in the scale were taken from the existing literature.

3.4 Data Analysis

3.4.1 Instrument validity and reliability

The validity and reliability of the constructs were evaluated using the scale construction procedure proposed by (Rama et al., 2022).The reliability of the scale items was assessed after determining the convergent and discriminate validity of the scale items.

3.4.2 Convergent Validity

The criterion "that items that are measures of a construct share a large proportion of their variance" is referred to as "convergent validity" (Hair et al., 2014)The convergent validity of the scale items was assessed using three factors. First, as (Hair et al., 2019)indicated, Second, each construct's composite reliability should be more than 0.70, and factor loadings should be higher than 0.50. According to (Chen, 2021) the resulting average variance extracted (AVE) for each construct must be higher than the suggested cut-off of 0.50.

3.4.3 Measurement model assessment

Tables 1 and 2 present the measuring model's findings. The measurement model was evaluated using Cronbach's alpha, composite reliability (CR), average extracted variance (AVE), and factor loadings. According to(Hair et al., 2019; Stensland et al., 2021), the reference value for factor loading must be greater than 0.700, however under specific circumstances, values of 0.4, 0.5, and 0.6 are acceptable. The criteria for CA, CR, and AVE are, respectively, 0.7, 0.7, and 0.5. The findings presented in both tables imply that each of these requirements has been satisfied, which suggests that the measurement model's convergent validity can be assumed. The SmartPLS output of the measurement model evaluation is shown in Fig. 1.

Table 1. Cronbach's alpha, composite reliability, average variance extracted

Construct	Cronbach's alpha	Composite reliability	(AVE)
CR	0.845	0.894	0.679
D	0.845	0.888	0.615
MS	0.898	0.915	0.521
PE	0.759	0.782	0.684
R	0.863	0.9	0.696
VPC	0.942	0.955	0.611

*Source: Smart PLS 4. CR- Customer Review**, D- Diagnostics, MS- Mental Satisfaction, P- Patient Engagement, R- Rehabilitation**, VPC- Virtual Patient Care**

The measures in the table include Cronbach's alpha, composite reliability (rho_a), composite reliability (rho_c), and average variance extracted (AVE). These are common evaluations of validity and reliability in the domains of psychometrics and structural equation modelling. Cronbach's alpha is a statistic for measuring the reliability of internal consistency. It demonstrates how closely related a group of things are to one another. The numbers between 0.759 and 0.942 show that internal consistency is often excellent to very good. Composite dependability is an additional metric for measuring internal consistency, similar to Cronbach's alpha. It assesses the proportion of the true score variance to the overall variance of the observed scores. The range of rho_a and rho_c values in the table, respectively, demonstrate good to exceptional levels of internal consistency (0.799). The abbreviation AVE stands for the average variance estimated from the latent construct variables in relation to the measurement error. It demonstrates how closely a construct's constituent parts correspond to the construct

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itself. The AVE ranges in value between 0.521 and 0.679. Generally speaking, an AVE value of higher than 0.5 is considered to be adequate. The figures in the table suggest that the constructs have acceptable extracted average variance and good to exceptional internal consistency. This demonstrates how the measurement items for each construct are connected to one another and that they accurately assess the underlying construct that is intended to be measured.

Table 2. Factor Loadings

Items	CR	D	MS	PE	R	VPC
CR1	0.844					
CR2	0.796					
CR3	0.865					
CR4	0.789					
D1		0.702				
D2		0.751				
D3		0.844				
D4		0.821				
D5		0.796				
MS1			0.774			
MS10			0.749			
MS2			0.732			
MS3			0.712			
MS4			0.774			
MS5			0.769			
MS6			0.774			
MS7			0.741			
MS8			0.752			
MS9			0.723			
PE1				0.823		
PE2				0.835		
PE3				0.758		
PE4				0.702		
R1					0.911	
R2					0.897	
R3					0.851	
R4					0.765	
VPC1						0.868
VPC2						0.901
VPC3						0.912
VPC4						0.912
VPC5						0.912

*Source: Smart PLS 4. CR- Customer Review**, D- Diagnostics, MS- Mental Satisfaction, P- Patient Engagement, R- Rehabilitation**, VPC- Virtual Patient Care**

Frequently utilized in factor analysis are factor loadings. The connections between latent factors and observable variables, or items, are represented by factor loadings. There are six latent factors: MS, CR, PE, VPC, D & R based on the table. The direction and degree of the association between a latent factor and an observable variable are represented by factor loadings. Usually, they fall between -1 and 1. Some items also appear to have no appreciable loadings on these three variables. These items could not have a significant impact on the parameters under consideration. For instance the factor loadings for item CR 6 was in negative so that item was deleted and was not included in further analysis.

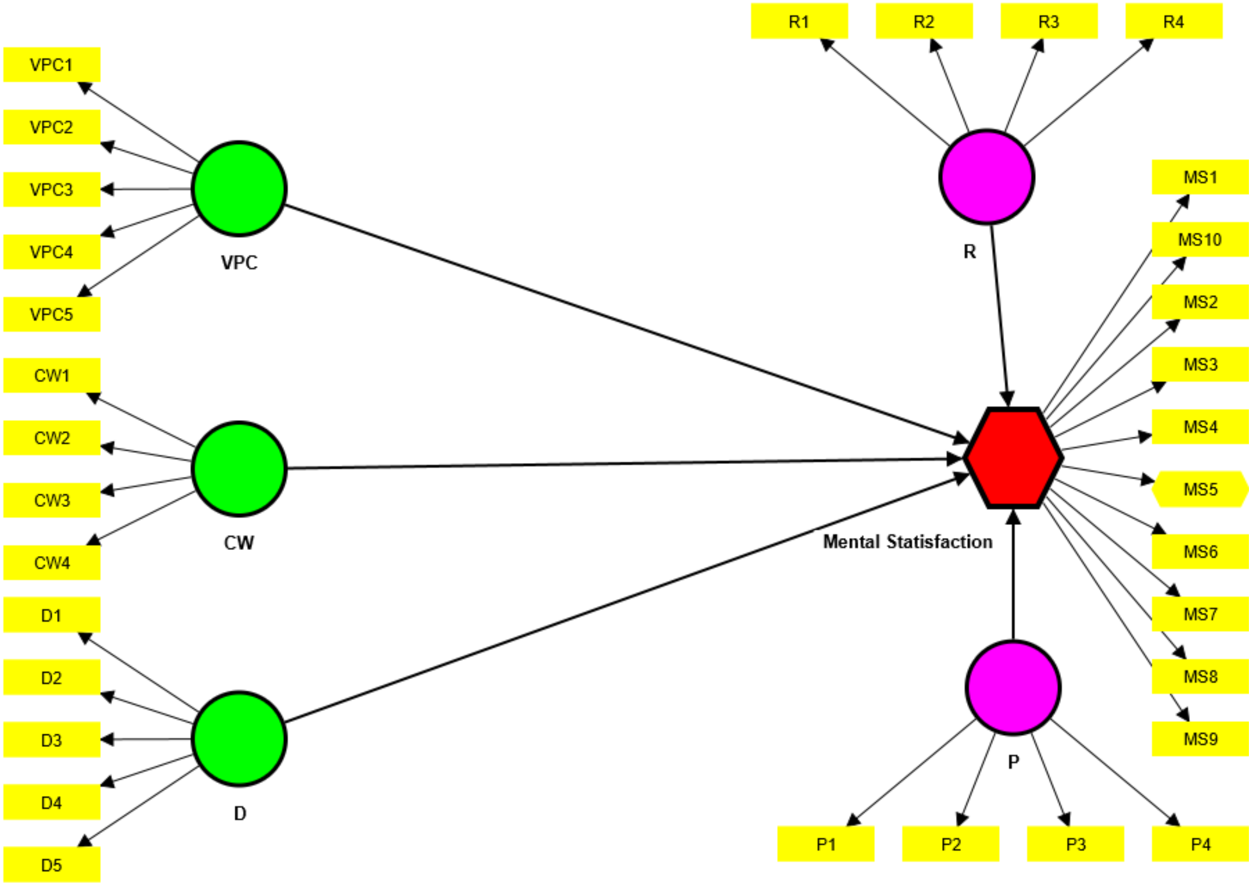

Figure 2. SmartPLS output of the measurement model.

3.4.4 Discriminant Validity

The heterotrait-monotrait correlation ratio (HTMT) was employed to assess the measurement model's discriminant validity. Henseler, Ringle, and Sarstedt (2015) claim that the heterotrait-monotrait is a useful metric for evaluating discriminant validity is the monotrait ratio of correlations (HTMT). Kline (2011) recommended a value of not more than 0.85 while Gold, Malhotra, and Segars (2001) recommended a value of no more than 0.9. Each of these requirements was satisfied, as shown in Table 3, allowing the measurement model to be declared to have discriminatory validity.

Table 3. HTMT assessment of discriminant validity

	CR	D	MS	PE	R	VPC
CR						
D	0.618					
MS	0.388	0.498				
PE	0.307	0.483	0.361			
R	0.243	0.255	0.227	0.388		
VPC	0.138	0.213	0.266	0.244	0.253	

*Source: Smart PLS 4. CR- Customer Review**, D- Diagnostics, MS- Mental Satisfaction, P- Patient Engagement, R- Rehabilitation**, VPC- Virtual Patient Care**

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Table 4. Fornel & Larcker

Construct	CR	D	MS	PE	R	VPC
CR	0.824					
D	0.505	0.784				
MS	0.363	0.462	0.722			
PE	0.251	0.417	0.298	0.696		
R	0.219	0.218	0.224	0.267	0.834	
VPC	0.132	0.276	0.256	0.138	0.273	0.901

*Source: Smart PLS 4. CR- Customer Review**, D- Diagnostics, MS- Mental Satisfaction, P- Patient Engagement, R- Rehabilitation**, VPC- Virtual Patient Care**

To guarantee the measurement model's internal consistency, construct reliability—typically measured through composite reliability or Cronbach's alpha—should above a predetermined level. Additionally, through various statistical tests and indices, convergent and discriminant validity should be proven, proving that constructs are distinct and measure what they are supposed to measure. For SEM analyses to be robust and reliable, adherence to Farnel and Larcker's criteria is essential. The table 4. Represents the values of Farnel and Larcker Criteria and all the values are fit to the best fitness of the relationship among variables.

Cross Loading

Items	CR	D	MS	PE	R	VPC
CR1	**0.844**	0.422	0.309	0.216	0.169	0.088
CR2	**0.796**	0.384	0.362	0.183	0.207	0.223
CR3	**0.865**	0.432	0.251	0.208	0.17	0.048
CR4	**0.789**	0.436	0.238	0.228	0.162	0.024
D1	0.517	**0.756**	0.244	0.234	0.218	0.123
D2	0.461	**0.751**	0.353	0.317	0.132	0.199
D3	0.381	**0.844**	0.477	0.378	0.198	0.213
D4	0.406	**0.82**	0.319	0.348	0.139	0.131
D5	0.275	**0.796**	0.354	0.328	0.177	0.109
MS1	0.293	0.332	**0.774**	0.202	0.134	0.143
MS10	0.206	0.26	**0.649**	0.176	0.093	0.149
MS2	0.235	0.272	**0.73**	0.212	0.198	0.125
MS3	0.333	0.364	**0.712**	0.253	0.13	0.215
MS4	0.324	0.428	**0.774**	0.259	0.216	0.206
MS5	0.259	0.364	**0.769**	0.213	0.148	0.231
MS6	0.329	0.376	**0.774**	0.185	0.29	0.283
MS7	0.267	0.342	**0.741**	0.196	0.207	0.209
MS8	0.148	0.211	**0.652**	0.222	0.067	0.141
MS9	0.126	0.307	**0.623**	0.247	0.037	0.071
PE1	0.238	0.401	0.273	**0.823**	0.134	0.003
PE2	0.245	0.393	0.246	**0.835**	0.216	0.075
PE3	0.083	0.112	0.122	**0.758**	0.224	0.212
PE4	0.051	0.121	0.139	**0.702**	0.251	0.239
R1	0.232	0.216	0.265	0.218	**0.911**	0.306
R2	0.214	0.19	0.171	0.261	**0.897**	0.293
R3	0.107	0.147	0.151	0.212	**0.851**	0.147

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R4	0.145	0.168	0.068	0.263	**0.658**	0.021
VPC1	0.074	0.154	0.239	0.094	0.258	**0.868**
VPC2	0.113	0.193	0.241	0.121	0.245	**0.901**
VPC3	0.139	0.215	0.242	0.131	0.221	**0.914**
VPC4	0.087	0.166	0.217	0.139	0.273	**0.912**
VPC5	0.183	0.167	0.211	0.137	0.234	**0.912**

*Source: Smart PLS 4. CR- Customer Review**, D- Diagnostics, MS- Mental Satisfaction, P- Patient Engagement, R- Rehabilitation**, VPC- Virtual Patient Care**

3.4.5 Structural model assessment

In order to identify whether the model has a multicollinearity problem, the Variance Inflation Factor (VIF) was assessed. The results, shown in Table 4, demonstrated that there is no issue of multicollinearity. Considering that all VIF values are significantly below 3.3 (Diamantopoulos & Siguaw, 2006).As a general rule, we require a VIF of 5 or lower to avoid the collinearity problem (Hair et al., 2011). Additionally, several studies have found that "VIF values higher than 3.3 can be considered as indicative of collinearity" (Knock & Lynn, 2012)

Table 5. Multicollinearity of Artificial intelligence on Mental Satisfaction

Items	VIF
CR1	2.137
CR2	1.479
CR3	2.791
CR4	2.011
D1	1.596
D2	1.646
D3	1.912
D4	2.222
D5	2.004
MS1	2.445
MS10	2.111
MS2	2.193
MS3	1.851
MS4	2.514
MS5	2.486
MS6	2.062
MS7	2.355
MS8	2.491
MS9	1.824
PE1	1.687
PE2	1.762
PE3	1.664
PE4	1.588
R1	2.332
R2	2.899
R3	2.728
R4	1.721
VPC1	2.823

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VPC2	1.799
VPC3	2.197
VPC4	1.471
VPC5	2.491

*Source: Smart PLS 4. CR- Customer Review**, D- Diagnostics, MS- Mental Satisfaction, P- Patient Engagement, R- Rehabilitation**, VPC- Virtual Patient Care**

In SEM, high VIF values can suggest problems such as overly redundant latent variables, which can lead to unstable estimates and difficulty in interpreting the model. Researchers typically aim for low VIF values, often below 5, to ensure the independence of latent variables and enhance the reliability of the SEM analysis

3.4.6 Hypotheses Testing

In order to test hypotheses bootstrapping procedure was used in Smart Pls. According to Arnau (1998), the second order approach is preferable over the first order approach when the goal of the study is to offer higher theoretical generalizability. Second-order factor models "can provide a more parsimonious and interpretable model," according to Chen, Sousa, and West (2005). Using these defenses as support the second-order construct were created for both the variables.

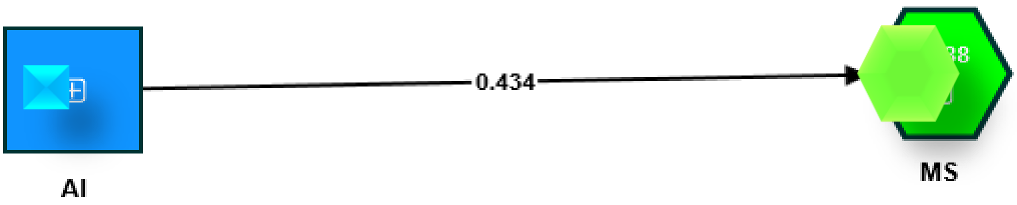

Figure 2. Hypotheses testing using bootstrapping

Table 6. Path Coefficients

Hypothesis	β	Sample mean	Standard deviation (STDEV)	T-Value	P-value
CR -> MS	0.154	0.155	0.072	2.146	0.032
D -> MS	0.302	0.302	0.074	4.081	0.000
PE -> MS	0.398	0.111	0.069	3.416	0.003
R -> MS	0.458	0.071	0.056	2.038	0.029
VPC -> MS	0.461	0.149	0.064	2.438	0.015
AI -> MS	0.408	0.346	0.089	3.786	0.004

*Source: Smart PLS 4. CR- Customer Review**, D- Diagnostics, MS- Mental Satisfaction, P- Patient Engagement, R- Rehabilitation**, VPC- Virtual Patient Care**

Table 6. shows the hypothesis results of the developed relationships, Customer review has a significant impact on mental satisfaction if implemented ***(β-0.154, t-value-2.146 & p-value-0.032),*** Diagnosis review has a significant impact on mental satisfaction if implemented ***(β-0.302, t-value-4.081 & p-value-0.000),*** Patient Engagement has a significant impact on mental satisfaction if implemented ***(β-0.398, t-value-3.416 & p-value-0.003),*** Rehabilitation has a significant impact on mental satisfaction if implemented ***(β-0.458, t-value-2.038 & p-value-0.029),*** Virtual Patient Care has a significant impact on mental satisfaction if implemented ***(β-0.461, t-value-2.438 & p-value-0.015)*** and Artificial intelligence has a significant impact on mental satisfaction if implemented ***(β-0408, t-value-3.786 & p-value-0.004).***

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Table 7. R -Square and R-square adjusted

Column1	R-square	R-square adjusted
MS	0.675	0.636

The findings in table 7 suggest that Variable MS and Variable AI have a robust and statistically significant positive connection. Variable AI tends to increase along with Variable MS, according to the path coefficient of 0.675. Given the low p-value of 0.000, it is highly improbable that this link is the result of coincidence. This could imply that, in your data, variations in Variable AI are meaningfully and consistently driving variations in Variable MS. R-square, sometimes referred to as the coefficient of determination, is a statistical indicator that shows how much of the variance in the dependent variable in a regression model can be accounted for by the independent variable or variables. There is no variance in the dependent variable that can be explained by the independent variable(s) when the range of the variable is 0 to 1.A value of 1 indicates that the independent variable(s) fully explain the variance in the dependent variable. The independent variable(s) in the model account for approximately 67.4=5% of the variance in the dependent variable, according to the 'MS' model's R-square value of 0.675. This value denotes a modest amount of explanatory power, suggesting that the independent variable(s) may have some influence on the variation in the dependent variable. R2 adjusted, often known as adjusted R-square: The number of independent variables in the model is taken into account in this R-square variant. It changes R-square by penalizing the addition of unnecessary independent variables. This is quite useful when dealing with several regression models with different numbers of predictors. The updated R-square value for the 'MS' model is 0.636. This demonstrates that the independent variable(s) in the model, after adjusting for the number of independent variables, accounts for around 63.6% of the variance in the dependent variable. Tables 7 and 6 illustrate the results. The hypothesis is accepted as table 5's P value is less than 0.05. According to this, artificial intelligence has a substantial impact on the mental pleasure in mobile healthcare management. Cohen (1988) said that R-Square should be at least 0.35, however this study's R-Square was 0.674, proving that the estimated model is significant. 0.636 is the modified R-Square value. This shows that Artificial Intelligence is responsible for 67% of changes or variations in users' mental satisfaction.

Conclusion & Discussion

The impact of artificial intelligence (AI) on the mental satisfaction of mobile healthcare users is a topic of growing importance in the healthcare industry. Mobile healthcare, or m-Health, has become an integral part of modern healthcare delivery, and AI has the potential to enhance and transform the user experience in this domain. Artificial intelligence (AI) is transforming the mobile healthcare scene, and its effect on consumers' mental well-being is a critical factor. AI has the ability to offer proactive, 24/7 accessible, and personalized healthcare services, greatly increasing users' mental well-being. Early intervention, specialized health education, and a sense of empowerment are all promised. To ensure consumer happiness and trust, it is necessary to address worries about data security and privacy. Maintaining a human touch in healthcare is also crucial since the development of AI should enhance rather than replace the compassionate relationship between patients and healthcare professionals. Consequently, while AI shows enormous promise in mobile healthcare, obtaining the highest level of mental well-being requires a balanced strategy that takes into account both the benefits and Potential challenges of AI implementation. Applications for mobile healthcare powered by AI have the potential to offer highly individualized care. These apps can customize healthcare recommendations and interventions to a person's specific requirements using predictive analytics and machine learning algorithms. Users may feel more mentally satisfied as a result of this customization because they believe that their particular health concerns are being addressed. AI can deliver tailored health information and educational content to users. Informed individuals are likely to experience greater mental satisfaction with their healthcare journey. AI can also empower users to take charge of their health, which can lead to a sense of control and reduced anxiety. While AI can enhance the mental satisfaction of mobile healthcare users, it also raises concerns about data privacy and security. Users may experience stress and anxiety if they do not trust that their personal health information is adequately protected. It is crucial for healthcare providers and AI developers to address these concerns to ensure user satisfaction.

Practical Implications

To practically enhance the mental satisfaction of mobile healthcare users through artificial intelligence (AI), a comprehensive approach is essential. This includes developing AI algorithms that provide personalized health plans, integrating 24/7 virtual health assistants for immediate support, implementing early warning systems to detect health issues in their infancy, and offering tailored health education modules. Ensuring robust data privacy and security measures, creating user-friendly interfaces, and maintaining a balance between human touch and AI are equally crucial. Feedback mechanisms for continuous improvement, user accessibility, education, and ethical guidelines must be established. Moreover, healthcare professionals and users should be trained to effectively utilize AI tools, and a commitment to ongoing system updates and improvements should be in place. This multifaceted strategy aims to build trust, reduce anxiety, and ultimately enhance mental satisfaction among mobile healthcare users, making AI a valuable asset in their healthcare journey.

Limitations and Direction for Future Research

Even though artificial intelligence (AI) has enormous potential to improve the mental happiness of mobile healthcare users, there are a number of restrictions and areas for future research that need to be taken into account. AI-driven healthcare solutions rely significantly on data, which may cause user fear due to privacy and security issues. To solve these challenges, future research should look at more sophisticated encryption techniques and privacy-preserving AI technologies. Furthermore, the challenge of integrating AI with a human touch requires in-depth investigation, potentially through the development of AI-driven empathy models. Additionally, the usability and accessibility of AI-powered healthcare apps, especially for elderly or disabled users, are important areas for further research, ensuring that these technologies benefit a broad demographic. Lastly, investigating the long-term effects of AI-based interventions on user mental satisfaction and health outcomes would provide valuable insights. Continuous research and development are essential to harness the full potential of AI in mobile healthcare while mitigating its limitations, ultimately ensuring enhanced mental satisfaction for all users.

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