

Factors influencing mobile health utilization among patients with diabetes: a cross-sectional study based on Andersen's behavioral model

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Abstract

Background: The development of mobile health (mHealth) in China has tremendous potential, especially for diabetes, which is one of the major chronic diseases affecting hundreds of millions of people. However, research on the current use of mHealth by patients with diabetes and the factors influencing their decision-making is insufficient. Most existing studies have approached the subject from a technological perspective and often overlooked the identity of patients as users of mHealth services.

Objective: Based on the Andersen behavioral model, this study aimed to investigate the factors affecting patients' adoption of mHealth, with a special emphasis on individual patient characteristics, and provided recommendations for the promotion of mHealth and the management of diabetes.

Methods: This was a cross-sectional study. A sample survey was conducted in one tertiary hospital and two community health service centers, and an anonymous self-administered questionnaire survey was conducted among patients with diabetes. Based on Andersen's behavioral model, the questionnaire divided the influencing factors into predisposing factors, enabling factors and need factors. Multivariate logistic regression analysis was used to explore the factors influencing the utilization of mHealth.

Results: A total of 533 questionnaires were valid. In this study, 36.8% of patients with diabetes utilized mHealth services. Among the predisposing factors, having better education and mHealth knowledge were found to be facilitators of mHealth utilization, and employment status was a factor associated with mHealth utilization. Among the enabling factors, patients with internet access and living in urban areas were more likely to have access to mHealth, and higher health literacy positively influenced mHealth utilization. Among the need factors, self-assessed health status was linked to mHealth utilization, and diabetes duration had a negative impact on mobile health utilization.

Conclusions: The rate of mobile health utilization remained low. In the future, improvements can be made in multiple aspects, such as policy, promotion, infrastructure, and health education, to advance the development of mobile health and the management and control of diabetes. Clinical Trial: uninvolved

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Original Manuscript

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Abstract

Background: The development of mobile health (mHealth) in China has tremendous potential, especially for diabetes, which is one of the major chronic diseases affecting hundreds of millions of people. However, research on the current use of mHealth by patients with diabetes and the factors influencing their decision-making is insufficient. Most existing studies have approached the subject from a technological perspective and often overlooked the identity of patients as users of mHealth services. Based on the Andersen behavioral model, this study aimed to investigate the factors affecting patients' adoption of mHealth, with a special emphasis on individual patient characteristics, and provided recommendations for the promotion of mHealth and the management of diabetes.

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Results: A total of 533 questionnaires were valid. In this study, 36.8% of patients with diabetes utilized mHealth services. Among the predisposing factors, having better education and mHealth knowledge were found to be facilitators of mHealth utilization, and employment status was a factor associated with mHealth utilization. Among the enabling factors, patients with internet access and

living in urban areas were more likely to have access to mHealth, and higher health literacy positively influenced mHealth utilization. Among the need factors, self-assessed health status was linked to mHealth utilization, and diabetes duration had a negative impact on mobile health utilization.

Conclusions: The rate of mobile health utilization remained low. In the future, improvements can be made in multiple aspects, such as policy, promotion, infrastructure, and health education, to advance the development of mobile health and the management and control of diabetes.

Keywords: Diabetes, mHealth, Andersen's behavioral model

Instruction

Diabetes mellitus (DM) is a chronic noncommunicable disease. As of 2021, there were approximately 537 million adults worldwide with DM, representing a prevalence rate of 10.5%.^[1,2] China has the highest number of individuals affected by diabetes, with approximately 140 million patients.^[3] Epidemiological survey data revealed that the treatment rate for diabetes in China was 32.2%, with only 49.2% of treated patients achieving adequate blood sugar control.^[3, 4] Poor blood sugar control can lead to various complications and impose a heavy economic burden on society.^[5] Furthermore, only 36.5% of patients with diabetes in China were actually aware of their condition. This lack of awareness not only impedes the prompt treatment and management of diabetes but also complicates disease control and diminishes the quality of life for patients. The heightened risk of severe complications and mortality presented a significant challenge to the healthcare system.^[4, 6]

mHealth refers to the provision of medical services and information to patients through mobile communication technologies or devices, such as smartphones, tablets and other wireless devices.^[7] mHealth care provides a convenient way for patients with diabetes to obtain information, and patients can record, transmit and receive feedback information anytime and anywhere; moreover, healthcare professionals can remotely monitor patients and provide timely healthcare advice.^[8,9] Research has indicated that mobile medicine can reduce the average glycated hemoglobin (HbA1c) levels of patients with type 2 diabetes mellitus (T2DM) and type 1 diabetes mellitus (T1DM) by 0.59% and 0.49%, respectively.^[10]

The significance of mHealth in diabetes management is substantial; however, its utilization status remains suboptimal. A 2019 survey revealed that the utilization rate of mobile medical care for patients with diabetes in our country was only 15.44%.^[11] Exploring the factors that influence patients' use of mHealth is crucial for enhancing mHealth services for diabetes and improving disease management. Existing studies were mainly based on the Technology Acceptance Model or the Unified Theory of Acceptance and Use of Technology and explored the mHealth adoption

behavior of patients with diabetes from the perspective of information technology acceptance.^[12,13] However, focusing solely on technological issues can lead to the neglect of individual patient factors, resulting in findings with insufficient explanatory power. However, an exclusive focus on technological aspects may overlook critical individual patient factors, leading to conclusions with limited explanatory power. Incorporating the Andersen model into the study of mobile healthcare services enhances our grasp of how various factors impact outcome indicators, with a special focus on the role of individual patient characteristics in the utilization of mobile healthcare services. This method facilitates the generation of specific recommendations aimed at improving and promoting mobile healthcare for diabetes management. To address this gap, our study incorporated the Andersen behavioral model to examine the utilization of mHealth by diabetes patients and the factors that influence it. The Andersen model has been extensively applied in studying health service utilization across different populations and in various contexts, offering a comprehensive framework for analyzing the determinants of individual health service usage behaviors.^[14-16] Incorporating the Andersen behavioral model into the study of mHealth services enhances the understanding of how various factors impact outcome indicators, with a special focus on the role of individual patient characteristics in the utilization of mHealth services. In this research, we pursued two main goals: (1) to assess the rate at which mobile healthcare services are utilized by diabetes patients and (2) to explore the factors that influence the use of these services by diabetes patients. This study aimed to (1) assess the utilization rate of mobile healthcare services among diabetes patients, (2) explore the factors influencing their use of these services, and (3) provide recommendations to enhance and broaden the reach of mHealth for diabetes patients, facilitating better management and support for those affected by this condition.

Method

Participants and procedures

This study was a multicenter observational cross-sectional study. We recruited patients with diabetes from the outpatient departments of one tertiary hospital and two community health service centers in Sichuan Province between August 2021 and September 2022. The inclusion criteria were as follows: (1) were aged ≥ 18 years; (2) were diagnosed with diabetes according to the 2011 WHO diagnostic criteria; Exclusion criteria: (1) had severe mental disorders, cognitive impairment, or language communication disorders; and (2) had repeated visits during the survey period. This research project was approved by the Biomedical Ethics Committee of West China Hospital of Sichuan University (Batch Number: 2019 Review (515)).

Definitions of mHealth utilization

This study defined mHealth as the acquisition of medical services and information by patients with diabetes through mobile communication technology using smart devices such as mobile phones and tablets. This encompassed a range of activities, including (1) health information retrieval, (2) online appointment scheduling, (3) disease inquiry and consultation, (4) health management, (5) pharmaceutical e-commerce, and (6) social networking. mHealth utilization refers to whether the participants have had mHealth using, and they will choose “yes” or “no”.

Factors of the Andersen Behavioral Model

The model divided the influencing factors into: predisposing factors, enabling factors and need factors. Predisposing factors referred to the demographic and sociological characteristics and health perceptions that influence the utilization of mobile healthcare services by patients with diabetes.^[17] This study included sex, age, ethnicity, employment status, educational attainment, marital status, living arrangements, and mHealth knowledge.

Enabling factors were defined as the conditions that either facilitate or impede the utilization of medical services. This study investigated the factors that affect the accessibility of mHealth for diabetes patients, including socioeconomic status, coverage of medical expenses, internet accessibility, use of mobile intelligent devices, household location, health literacy, and institutions most frequently visited for diabetes treatment or counseling. Socioeconomic status was measured using the MacArthur Scale, which is structured as a ladder with 10 rungs. Scores range from 1 to 10, with higher scores indicating a higher socioeconomic status for the patient.^[18] Health literacy was measured by the Health Literacy Management Scale (HeLMS), which is a Chinese adaptation of the scale originally developed by Jordan and colleagues and further refined by Sun et al.^[19,20]. It employs a 5-point Likert scale, with a maximum possible score of 120 points. Higher scores indicate a better level of health literacy among patients.

Need factors referred to the patient's subjective understanding of their disease and the objective results of clinical diagnoses. These factors could affect individuals' perceived need for medical services. This study included self-assessed health status, types of DM, course of DM, treatment of DM, comorbidity conditions, and self-management ability. Comorbidity conditions were assessed using the Charlson Comorbidity Index (CCI).^[21] The CCI covered 17 disease categories, comprising a total of 19 items, with each item being scored from 1-6 points. A higher score indicated a greater number and more severe degree of comorbid conditions. The self-management ability of participants with diabetes was evaluated by the Summary of Diabetes Self-Care Activities (SDSCA) scale developed by Toobert et al.^[22]. This study used a version translated by the Chinese scholar Wan.^[23] The scale included five dimensions, diet, exercise, blood glucose testing, foot care and medication

compliance, with a total of 11 items. Each item was rated using a Likert scale with a score of 0-7, indicating how many days an activity was performed in the previous week. The higher the score is, the stronger the self-management ability of the subjects. A diagram of the theoretical framework of Andersen's behavioral model is shown in Fig. 1.

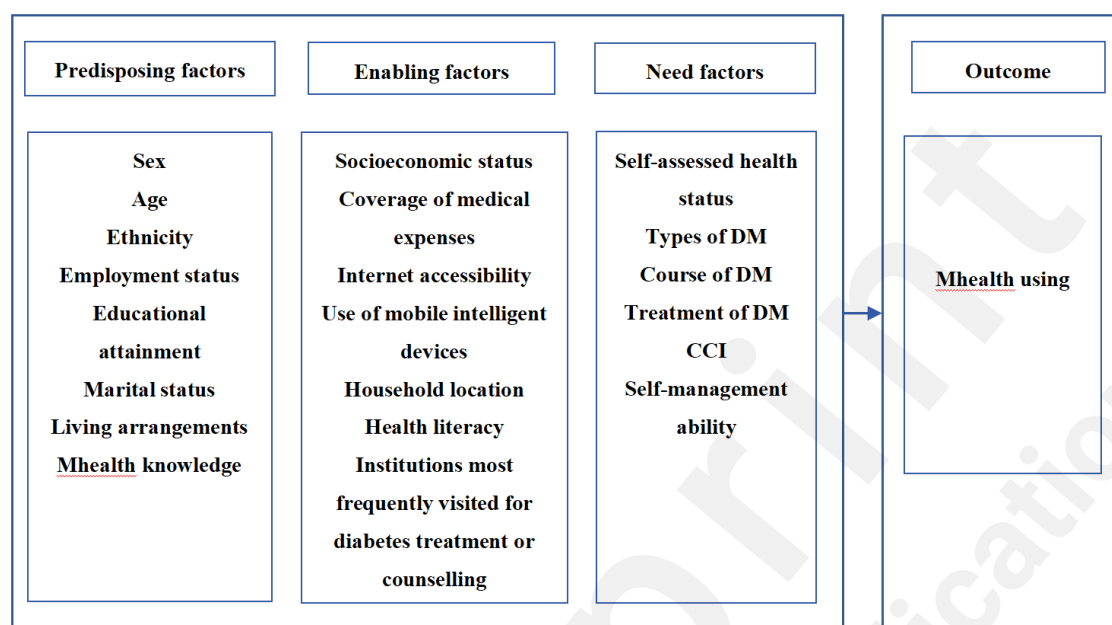


Figure 1: A diagram of the theoretical framework of Andersen's behavioral model.

Data processing and analysis

The data were double-entered and verified using Epidata 3.1, which was built in consistency checks to control the data input. Continuous variables were showed as the means and standard deviations, and categorical variables were represented as the totals and proportions. The continuous variables in this study were tested and found not to follow a normal distribution. Subsequently, univariate differences were analyzed using the chi-square test for categorical variables and the Wilcoxon test for continuous variables. Multivariate logistic regression models of mHealth utilization were established to explore the influence of the three factors in Andersen's behavioral model, and variables that were significant in the univariate analysis were included and screened using stepwise regression in multivariate logistic regression analysis. Stepwise regression adopted the backward selection method, with slentry = 0.05 as the criterion for variable inclusion and slstay = 0.05 as the criterion for variable exclusion. A p value < 0.05 was considered to indicate statistical significance. All the statistical analyses were performed using SPSS 23.0 software.

Results

A total of 559 patients were recruited for this study, 533 patients were included, and the effective recovery rate was 95.35%. A total of 26 patients were excluded for the reasons shown in Fig. 2. Univariate analysis revealed that predisposing factors (age, sex, employment status, mHealth knowledge, living arrangements), enabling factors (socioeconomic status, internet accessibility, use of mobile intelligent devices, household location, health literacy and institutions most frequently visited for diabetes treatment or counseling), and need factors (CCI, self-assessed health status, diabetes course, diabetes treatment, blood glucose monitoring frequency) significantly affected mobile health utilization (all $p < 0.05$).

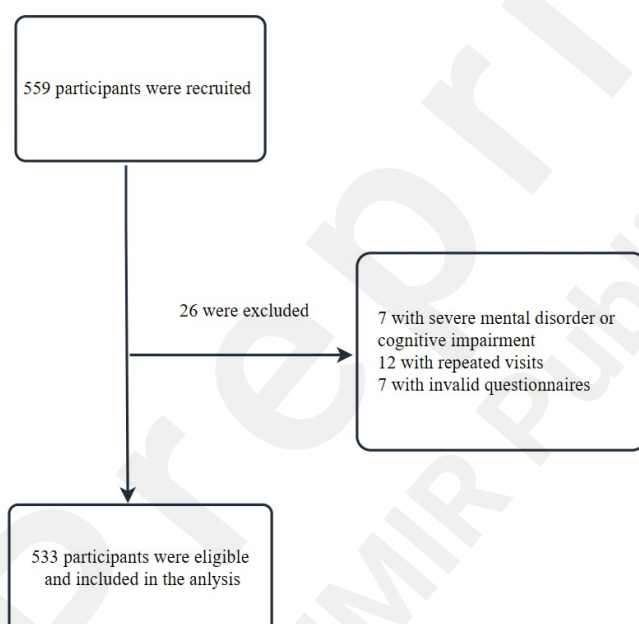


Fig. 2 Flow chart of participant enrollment.

Table 1 Univariate analysis of mHealth utilization (N = 533)

Variables			Yes group of mHealth using (N=196) N (%)	No group of mHealth using (N=196) N (%)	χ^2/Z	<i>P</i>
Predisposing factors						
Sex						
male			95(48.47)	131(38.87)	4.673	0.031
famale			101(51.53)	206(61.13)		
Age						
≤44			52(26.53)	8(2.37)	66.606	<0.001
45-59			86(43.88)	87(25.82)		
60-74			46(23.47)	172(51.04)		
≥75			12(6.12)	70(20.77)		
Ethnicity						
Ethnic Han			191(97.45)	333(98.81)	1.389	0.300
Ethnic minorities			5(2.55)	4(1.19)		
Education						
Elementary school or below		7(3.57)	145(43.03)	117.001	<0.001	
Junior high		41(20.92)	113(33.53)			
Senior high		47(23.98)	34(10.09)			
College or above		101(51.53)	45(13.35)			
Marital status						
Married			184(93.88)	311(92.28)	0.475	0.491
Others ^a			12(6.12)	26(7.72)		
Employment status						
Employed			112(57.14)	54(16.02)	48.589	<0.001
Nonworking			84(42.86)	283(83.98)		
mHealth knowledge						
Completely unaware			8(4.08)	204(60.53)	74.064	<0.001
Slight understanding			32(16.33)	82(24.33)		

General understanding	64(32.65)	37(10.98)
Excellent understanding	92(46.94)	14(4.16)

Table 1 continued

Variables	Yes group of mHealth using (N=196) N (%) / $\bar{x} \pm s$	No group of mHealth using (N=196) N (%) / $\bar{x} \pm s$	χ^2/Z	P
Residency				
Living alone	24(12.24)	27(8.01)	8.993	0.025
Living with spouse	104(53.06)	150(44.52)		
Living with children or other family members	66(33.67)	155(45.99)		
Others ^b	2(1.03)	5(1.48)		
Enabling factors				
Socioeconomic status	5.72±1.43	5.31±1.54	-3.921	<0.001
Coverage of medical expenses				
self-financed	46(23.47)	61(18.10)	3.275	0.195
Self-financing and insurance	53(27.04)	84(24.93)		
Insurance	97(49.49)	192(56.97)		
Internet accessibility				
Yes	193(98.47)	269(79.82)	37.321	<0.001
No	3(1.53)	68(20.18)		
Use of mobile intelligent devices				
Yes	192(97.96)	244(72.40)	64.366	<0.001
No	4(2.04)	93(27.60)		
Household location				
Urban	188(95.92)	273(81.01)	23.578	<0.001
Rural	8(4.08)	64(18.99)		
Institutions most frequently visited for diabetes treatment or counseling				
Clinics or pharmacies	0(0.00)	30(8.90)	135.359	<0.001
Community hospitals or health centers	23(11.73)	157(46.59)		
Diabetes Specialist Hospitals	7(3.57)	26(7.71)		
General hospitals	165(84.19)	117(34.72)		
Other medical institutions	1(0.51)	7(2.08)		

Health literacy	103.43±10.72	86.54±18.22	<0.001
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Table 1 continued

Variables	Yes group of mHealth using (N=196) N (%) / $\bar{x} \pm s$	No group of mHealth using (N=196) N (%) / $\bar{x} \pm s$	χ^2/Z	P
Needing factors				
Self-assessed health status				
Good	154(78.57)	215(63.80)	13.317	0.001
Normal	33(16.84)	103(30.56)		
Poor	9(4.59)	19(5.64)		
Socioeconomic status	5.72±1.43	5.31±1.54	-3.921	<0.001
Types of diabetes ^c				
T1DM	14(7.14)	11(3.26)	5.440	0.058
T2DM	179(91.33)	324(96.14)		
GDM	3(1.53)	2(0.60)		
Treatment of diabetes				
Lifestyle intervention	63(32.14)	62(18.40)	16.021	0.001
Oral hypoglycemic agents	94(47.96)	199(59.05)		
Inject hypoglycemic agents ^d	17(8.67)	21(6.23)		
Both oral and injection	22(11.23)	55(16.32)		
Self-management behaviors				
Smoking				
Yes	26(13.27)	59(17.51)	1.664	0.197
No	170(86.73)	278(82.49)		
Household location				
Diet	3.96±2.41	3.64±2.42	-1.822	0.069
Exercise	4.44±3.01	4.21±3.08	-0.268	0.788
Blood glucose monitoring	6.68±5.51	4.28±4.89	-5.023	<0.001
Foot care	1.64±2.27	1.48±1.71	-0.410	0.682
Drug use	6.53±1.28	6.37±1.32	-0.716	0.474
CCI	1.73±1.26	1.88±1.14	-2.221	0.026
Course of diabetes	6.52±5.44	7.93±7.72	-5.259	<0.001

T1DM: type 1 diabetes mellitus; T2DM: type 2 diabetes mellitus; GDM: gestational diabetes mellitus; a: marital status of the study subject as single, divorced, widowed or separated; b: the study subject was cared for by nurses or caregivers or lived in professional nursing institutions; c: the only types of diabetes in this study were T1DM, T2DM, and GDM, so the other types of diabetes were not included in the classification; d: injectable drugs included insulin and insulin analogs and glucagon-like peptide-1 receptor agonists.

Logistic regression analysis indicated that among patients with diabetes, having a senior high school education or above positively influenced the utilization of mHealth services (senior high school: OR=3.43, 95% CI: 1.28~9.38, $p=0.015$; college and above: OR=3.64, 95% CI: 1.88~7.05, $p<0.001$). Compared with nonworking patients, employed patients were 2.74 times more likely to use mHealth (95% CI: 1.36~5.52, $p=0.005$). In terms of enabling factors, patients who had some, general, or excellent understanding of mHealth were 1.66 (95% CI: 1.21~2.26, $p\leq 0.001$), 2.87 (95% CI: 1.79~4.63, $p\leq 0.003$), and 4.27 times (95% CI: 2.10~8.65, $p<0.001$) more likely to utilize mHealth services, respectively, than those who were completely unaware. The mHealth utilization rate for patients with internet access was 3.51 times greater than that for patients without access (95% CI: 1.40~8.83, $p=0.001$). Compared with rural patients, urban patients had a 2.77-fold greater mHealth utilization rate (95% CI: 1.54~4.92, $p=0.002$). Higher health literacy positively influenced mHealth utilization (95% CI: 1.013~1.075, $p=0.005$), with a 1.04-fold increase in the utilization rate for every one-point increase in the health literacy score. Patients with a normal self-assessed health status exhibited a 3.55-fold greater mHealth utilization rate than did those with a good self-rated health status (95% CI: 1.58~7.93, $p=0.002$). There was no statistically significant difference in mHealth utilization between patients with poor and good self-rated health status (95% CI: 0.23~2.77, $p=0.728$). The duration of diabetes had a negative impact on mobile health utilization, with a decrease of 0.90 times in the utilization rate for every additional year of disease duration (95% CI: 0.83~0.97, $p=0.004$).

Table 2 Multivariate logistic regression analysis of mHealth among patients with diabetes based on Andersen's behavioral model

Variables	OR	95%CI	P
Predisposing factors			
Education(Elementary school or below)			0.010
Junior high	2.58	0.79~8.48	0.118
Senior high	3.43	1.28~9.38	0.015
College or above	3.64	1.88~7.05	<0.001
Employment status□Nonworking□	2.74	1.36~5.52	0.005
mHealth knowledge Completely unaware			<0.001
Slight understanding	1.66	1.21~2.26	0.001
General understanding	2.87	1.79~4.63	0.003
Very familiar	4.27	2.10~8.65	<0.001
Enabling factors			
Internet accessibility(No)	3.51	1.40~8.83	0.001
Household location(Rural)	2.77	1.54~4.92	0.002
Health literacy	1.04	1.01~1.08	0.005
Need factors			
Self-assessed health status(Good)			0.003
Normal	3.55	1.58~7.93	0.002
Poor	0.80	0.23~2.77	0.728
Course of Diabetes	0.90	0.83~0.97	0.004

Discussion

In this study, 36.8% of patients with diabetes utilized mHealth services, showing an improvement compared to previous research.^[11] This increase in usage could be attributed to the impact of the COVID-19 pandemic. In China, governmental policy mandated that internet medical facilities offer online follow-up services for common chronic conditions.^[24] As a result of concerns about viral transmission, patients with diabetes were increasingly opting for mHealth services. Despite this trend, the overall utilization rate of mobile healthcare remains relatively low, limiting the full potential benefits and impact on disease management.

Among predisposing factors, patients with higher education levels tended to have a greater utilization rate of mHealth, consistent with findings from previous research.^[25] Kumar highlighted that individuals with lower education levels might find mHealth resources more challenging due to their limited e-health literacy and difficulties accessing, processing, understanding, and using technological features.^[26] Therefore, when developing an mHealth platform, it is crucial to implement technical features that mitigate the impact of literacy barriers, ensuring that the interface is simple, user friendly, and easily navigable. Furthermore, employed patients demonstrated higher rates of mHealth utilization, attributed to their broader social networks and increased access to diverse sources of information. Their limited time flexibility also contributed to this trend. Moreover, a positive understanding of mHealth correlated with increased utilization of mHealth. Chen^[27] also found that participants with a better understanding of mobile medical care were more likely to engage in health management through mobile platforms. The study revealed that 39.8% of patients with diabetes reported a lack of understanding regarding mHealth, which hindered its utilization. To address this issue, it is recommended to actively promote and raise awareness about mHealth among diabetic patients. This can be achieved by leveraging mainstream social platforms and communication channels to disseminate information about the benefits of mobile medical functionalities and relevant policy measures, ensuring that patients can easily access and comprehend pertinent information.^[28]

The results of a national survey on China's e-health behavior profile indicated that household location played a significant role in predicting mHealth utilization.^[29] The mHealth utilization rate

among rural residents was notably lower than that among urban residents, which aligned with the findings of this study. The Chinese government has been actively promoting the use of China's robust telecommunications infrastructure to support the national healthcare reform plan. This initiative led to the establishment of an increasing number of government-funded internet hospitals and e-health interventions.^[30] However, an analysis of emerging e-health data revealed that most mobile medical interventions had been primarily implemented in urban areas, with minimal involvement in rural regions.^[31] Coleman et al. suggested that the low internet penetration rate and inadequate broadband infrastructure in rural areas may be contributing factors to the limited utilization of mHealth among rural residents.^[32] To enhance the adoption of mHealth, efforts should be made to expand network coverage, explore the integration of new technologies such as 5G, artificial intelligence, and the Internet of Things, increase investment, and bolster rural mobile medical services. It is imperative to address the gaps in healthcare services and establish an inclusive rural service network that bridges the gap between urban and rural areas. Previous studies have demonstrated a positive correlation between health literacy levels and the utilization of mobile health care, indicating that diabetic patients with higher health literacy levels are more likely to benefit from mobile health interventions.^[33-35] Despite the prevalence of limited health literacy among patients with diabetes, efforts such as training and public awareness campaigns have been made to enhance their health literacy. However, sustaining the effects of these interventions remains challenging.^[36] The integration of personalized diabetes health education with mobile medical care appears to be a promising direction for future research.

This study revealed a negative correlation between the duration of diabetes and the utilization rate of mHealth among patients with diabetes. A prolonged diabetes course was identified as a risk factor for clinical inertia, leading to reduced patient engagement in active health management and a decreased likelihood of utilizing mHealth.^[37] Health education for long-term patients should emphasize the consequences of poor diabetes control and stress the importance of timely intensive treatment to mitigate clinical inertia.^[38] Patients with a normal self-assessed health status were found to have a greater rate of mHealth utilization than those with a good self-assessed health status. Excessive confidence in one's health may lead to the neglect of medical services, resulting in adverse health outcomes.^[39] Therefore, to enhance the adoption of mobile medicine, it is crucial to enhance the health awareness of diabetic patients, cultivate a scientific understanding of health, instill correct health values, and prevent patients from overlooking disease risk management due to unwarranted health confidence.

This study had several strengths. First, China bears the largest diabetes burden worldwide and offered the most extensive potential market for diabetes-related mHealth. While there was a wealth of research on the general adoption of mHealth services, studies specifically focusing on diabetic patients are rare. This research focused on demographics and investigated how various factors influence the use of mHealth, providing insights for the optimization of diabetes mHealth services. Second, this study employed Andersen's behavioral model, a well-established and mature theoretical framework, to analyze the utilization of mHealth in diabetes patients. This application helped to enhance the understanding and elucidation of the factors affecting health service usage, offering practical significance. However, the use of nonprobability sampling in this study might introduce biases into the findings. Additionally, the research was conducted through a cross-sectional survey, which constrained the ability to draw causal inferences. Future research could benefit from conducting cohort studies to validate the findings and provide more definitive insights.

Conclusion

According to Anderson's model, need factors were influenced by individuals' perceptions of their own health, understanding of diseases, and clinical diagnosis of individual constitutions and played a crucial role in determining the utilization of health services. However, these findings indicated that the primary factors influencing patients' use of mHealth were social-level issues rather than need-related factors. Therefore, interventions should focus on addressing these social aspects to enhance the use of mHealth among diabetic patients. This can be achieved by (1) policy improvement and the establishment of a robust policy framework for mobile healthcare aimed at optimizing the pathway for integration at the policy level, providing a solid foundation for the development and implementation of mHealth initiatives. (2) Promotion and collaboration should increase promotional efforts for mobile healthcare services. This includes expanding the channels of publicity and fostering collaboration among governments, medical institutions, and enterprises. A concerted effort in this direction will ensure that patients have comprehensive access to mobile health services. (3) Technological enhancement and investment in strengthening the technological backbone of mobile healthcare services. This involves optimizing and simplifying user interfaces, developing high-quality and efficient websites, and tackling the challenges of insufficient network coverage and poor signals in certain areas. (4) Health education: Health education for diabetic patients should be prioritized. Cultivate appropriate health values, enhance patients' health literacy, and promote the adoption of new perspectives among diabetic patients regarding the utilization of mobile healthcare.

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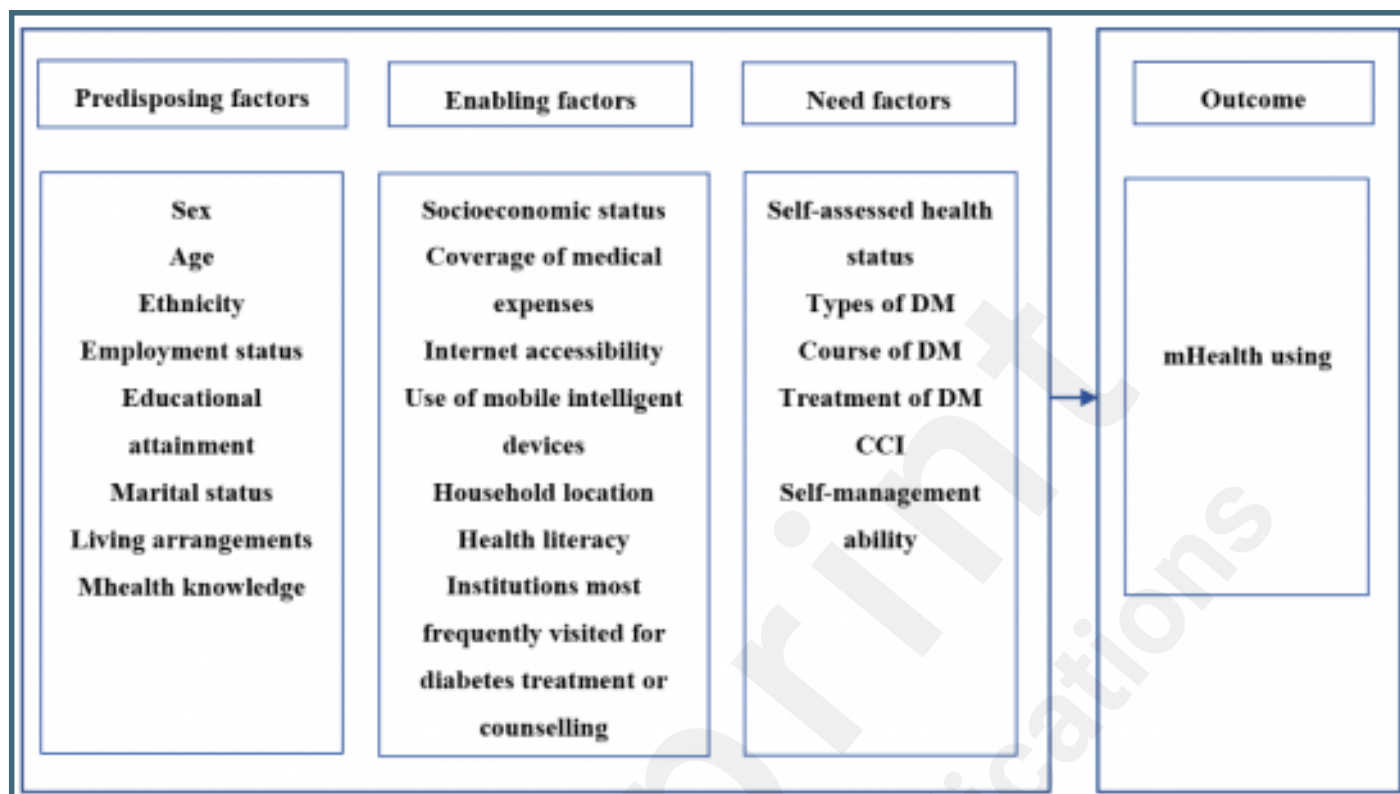
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Supplementary Files

Figures

A diagram of the theoretical framework of Andersen's behavioral model.



Flow chart of participant enrollment.

