ORIGINAL ARTICLE

Determinants of Health Information Technology Readiness among Patients with Type 2 Diabetes: Implications for AI-Driven Solutions and Patient Characteristics

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ABSTRACT

OBJECTIVE: To investigate the influence of specific patient characteristics, including employment status, comorbidities, disease duration, and medication knowledge, on patients' readiness to adopt Health Information Technology (HIT) to inform the development of effective, AI-driven solutions.

METHODOLOGY: This cross-sectional study involved 300 patients with type 2 diabetes (T2DM) from healthcare centres affiliated with Semnan University of Medical Sciences between February and December 2024. Eligible participants were smartphone owners aged 18–65 without severe conditions. The sample size was calculated based on the Events Per Variable (EPV) rule for logistic regression. Readiness for HIT was assessed using the Persian version of Koopman's HIT Readiness Scale. The outcome variable was dichotomized into 'High' and 'Low' readiness, and the data were analyzed using descriptive statistics, bivariate tests, and binary logistic regression.

RESULTS: The study found significant relationships between HIT readiness and employment status (Adjusted OR=1.82, 95%CI 1.108-2.99, P=0.018), comorbidities (Adjusted OR=0.56, 95%CI 0.336-0.94, P=0.028), duration of diabetes (Adjusted OR=0.45, 95%CI 0.268-0.743, P=0.002), and knowledge of diabetes medications (Adjusted OR=3.02, 95%CI 1.595-5.7, P<0.001).

CONCLUSION: Specific patient characteristics, particularly socioeconomic status and clinical burden, significantly determine HIT readiness. Socioeconomic gaps reduce HIT readiness in vulnerable diabetic groups. These findings suggest that AI solutions, including voice assistants and predictive tools, could deliver customized, culturally sensitive support if tailored to these determinants. Addressing these barriers can reduce cognitive strain, improve healthcare access, prevent complications, and enable patients, thereby promoting sustainable, individualized diabetes care.

KEYWORDS: Type 2 diabetes mellitus, Health information technology, Artificial intelligence, Patient readiness, Diabetes management

INTRODUCTION

Diabetes presents a critical global health challenge with severe economic and human costs, affecting millions and causing around 5 million deaths annually. Its prevalence is expected to approach 700 million by 2045[1]. However, countries like Iran face an acute situation, with rates exceeding 10% compared to Europe's 6%[2]. Type 2 diabetes (T2DM), characterized by beta-cell dysfunction and insulin resistance, disrupts blood sugar control. This burdens patients with demanding self-care tasks like glucose monitoring and medication adherence, often causing frustration and anxiety that complicate management[3]. These demanding regimens require innovative solutions to reduce the cognitive load and manual effort patients must exert for effective self-care[4].

Health information technology (HIT) offers a promising avenue to address these challenges, with collaborative, patient-centred digital health platforms designed to enhance care delivery[5]. Such platforms, particularly when tailored to specific demographics like minority young adults, can significantly improve engagement and reduce barriers to technology adoption[6]. Furthermore, comprehensive reviews of health information technology have identified both motivational and inhibitory factors that influence diabetes management outcomes[7]. Within this technological landscape, advancements in artificial intelligence techniques now enable sophisticated diabetes prediction capabilities[8]. These AI-driven tools provide diagnosis support and early identification of complication risks that traditional methods cannot offer[9]. Additionally, open-source electronic health record (EHR) systems represent recent advances that streamline clinical data management within the broader HIT ecosystem[10].

Despite these technological advances, security and privacy concerns in health information systems persist across various platforms, acting as a significant psychological barrier to widespread patient trust and consistent technology adoption[10,11]. Addressing these security vulnerabilities is crucial for ensuring that patient fears regarding data misuse[11] do not overshadow the benefits of HIT. A comprehensive analysis by Kitsiou S 2017[12], including 26 systematic reviews, demonstrated the effectiveness of digital health tools in improving glycemic control and quality of life. However, despite the availability of these tools, patient readiness to engage with them remains a critical bottleneck. Within this context, patient readiness depends on perceived benefits, tech confidence, and electronic health literacy[13]. While Zhang et al. identified ease of use and positive attitudes as key drivers, their study did not address broader systemic issues[14]. Similarly, Alaslawi H 2022 [15] emphasized targeted strategies for specific groups, noting that provider awareness influences recommendation rates. However, a critical research gap persists: current literature fails to examine how diabetes-specific clinical factors (e.g., disease duration, medication knowledge) interact with socioeconomic determinants (e.g., employment, comorbidities) to shape patient readiness. Most existing studies focus on general technology acceptance, neglecting the unique burden of disease management within the context of HIT.

To address this gap, this study examines how specific patient characteristics influence HIT readiness and integrates healthcare policy recommendations to improve diabetes technology adoption. By addressing these adoption barriers, this study provides policymakers with actionable strategies to boost AI-driven HIT engagement, improve outcomes, and reduce the diabetes burden, essential for equitable care.

METHODOLOGY

Study Design

This study employed a cross-sectional observational design and adhered to the STROBE guidelines for observational research. Data were collected through face-to-face interviews conducted by trained researchers, using a standardized protocol to minimize interviewer bias. Researchers were blinded to the specific study hypotheses and followed a neutral script to prevent leading questions. To ensure accuracy and minimize missing responses, real-time data validation was performed during the interviews.

Study Population

The study population included all patients with T2DM referred to public healthcare centres and hospitals affiliated with Semnan University of Medical Sciences between February 2024 and December 2024. These centres serve as general referral hospitals for the broader community, ensuring a diverse patient population beyond university affiliates. Participants were required to own a smartphone (defined as the minimum prerequisite for accessing AI-driven health interventions) and to be aged 18 to 65 years to qualify for inclusion. This age range was selected to focus on the working-age adult population, the primary target for digital health interventions, while excluding older adults (>65 years) who may face distinct age-related technology barriers unrelated to the readiness constructs. This inclusion criterion was established to focus on the population segment eligible for digital health implementation, thereby prioritizing internal validity for tool adoption over generalizability to the general population. Patients with severe cognitive impairments, terminal illnesses, or insufficient proficiency in Persian were excluded. Cognitive impairment was assessed through medical record review and confirmed by the treating physician's diagnosis; patients with documented cognitive disorders were excluded. Demographic diversity—such as urban/rural residency and education level—was documented to assess socioeconomic disparities in HIT readiness. While acknowledging that excluding non-smartphone users may limit external validity, this approach ensures the study assesses readiness among potential adopters rather than basic access barriers.

Sampling

The sample size was calculated using the Events Per Variable (EPV) rule recommended for logistic regression. An optimal ratio of 10 events per independent predictor was established. Assuming approximately 10 key independent predictors (demographic and clinical characteristics) would be entered into the model, and anticipating a 50% prevalence of high readiness, a minimum of 200 participants was required to ensure sufficient statistical power. To account for an estimated dropout rate of 25%, an additional 40 participants were included, bringing the total to at least 225 individuals. Ultimately, a sample size of 300 individuals was chosen for this study. This final sample size was selected to satisfy both the EPV stability requirements and power analysis needs. This calculation was based on the number of actual independent predictors, not the questionnaire items. A stratified random sampling technique was used to ensure proportional representation of gender and age groups. Stratification was chosen because gender and age are known determinants of technology adoption and HIT readiness; ensuring proportional representation prevents sampling bias and enhances the generalizability of findings across these key subgroups. Strata were defined by gender (male/female) and age group (18-40, 41-65 years), proportional to the distribution of the referral population. Within each stratum, participants were selected from the daily appointment lists using a computer-generated random number sequence. An independent researcher not involved in data collection performed

the allocation to prevent selection bias. The final sample size (n=300) provided 80% power to detect medium effect sizes at a significance level of α=0.01 using G*Power software, a stricter threshold selected to mitigate Type I error inflation due to multiple hypothesis testing.

Measuring   Tools

The study utilized Koopman's Patient Readiness for HIT Scale to evaluate patients' readiness for HIT16. Community attitudes play a significant role in shaping individual willingness to adopt these technologies; a supportive environment can boost confidence and readiness, while negative perceptions can hinder engagement17,18. Social desirability bias was minimized through anonymous data collection and assurances of confidentiality.

The PRE-HIT instrument consists of 28 questions divided into eight subscales: the need for health information, computer/internet experience and expertise, computer anxiety, preferred mode of interaction, communication with physicians, mobile phone expertise, privacy concerns, and the consequences of technology unawareness ("No News is Good News"). The questionnaire uses a five-point Likert scale, ranging from "completely disagree" to "completely agree," to assess community attitudes. The minimum possible score is 28, while the maximum is 140, based on the total number of questions.

The Persian version of the PRE-HIT instrument, validated by Safdari R et al.[13], was employed in this study. Importantly, the validation study included 289 patients with diverse chronic conditions (cardiovascular, dermatological, gastrointestinal, and internal medicine), rather than a single disease group, thereby supporting its applicability to patients with T2DM, another chronic illness. Construct validity was rigorously established through both Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), yielding acceptable model fit indices (CFI=0.943, TLI=0.931, RMSEA≤0.06, χ^2/df=1.625). Additionally, convergent validity was confirmed with Average Variance Extracted (AVE) values >0.50 for most factors and Construct Reliability (CR) >0.70 for all factors. In contrast, discriminant validity was supported by MSV and ASV values being lower than their respective AVEs. The instrument also demonstrated satisfactory internal consistency (Cronbach's α = 0.729).

Data Analysis

Missing data were managed using mean imputation for items with less than 5% missingness, while participants with more than 10% missing items were excluded from the analysis. Model diagnostics were performed to ensure robustness, including multicollinearity assessment (Variance Inflation Factor < 5), goodness-of-fit testing (Hosmer-Lemeshow), and discriminatory power evaluation (Area Under the Curve). The statistical analysis followed a predefined three-phase hierarchical framework: (1) Descriptive Characterization, (2) Bivariate Screening, and (3) Multivariate Predictive Modeling. Numerical variables were summarized using the mean, standard deviation, median, and interquartile range, while categorical variables were reported as counts and percentages. To ensure methodological clarity, the analysis strategy distinguished between descriptive exploration and predictive modeling. For the predictive modeling component of this study, the primary dependent variable was explicitly defined as the binary 'HIT Readiness Status'. Although the PRE-HIT scale yields a continuous total score (28–140), it was categorized to align with the clinical objective of stratifying patients for targeted AI-driven interventions. Specifically, to distinguish between patients who are immediate candidates for digital health tools versus those requiring foundational support, the continuous scores were dichotomized into 'High Readiness' and 'Low Readiness' groups using the median value as a cutoff.

In the screening phase, T-tests and ANOVA were employed to assess mean differences in continuous readiness scores across categorical groups, serving as a sensitive initial filter for variable selection. While the continuous score was retained for descriptive statistics and initial bivariate comparisons (T-tests and ANOVA), the multivariate analysis relied solely on the dichotomized variable. This dichotomization was prioritized over treating the score as purely continuous to facilitate the calculation of Odds Ratios (OR), which offer more actionable insights for clinical decision-making and resource allocation than linear regression coefficients. Furthermore, given the binary nature of the outcome in the final model, logistic regression was statistically mandated to avoid violating the assumptions of linear regression (e.g., normality of residuals). Consequently, binary logistic regression was selected as the appropriate statistical model to estimate the odds ratios (OR) of patient characteristics influencing the likelihood of being in the 'High Readiness' group.

Variables for the multivariate logistic regression were selected based on bivariate analyses ($P<0.2$) and clinical relevance to HIT readiness. To control for potential confounding, key demographic variables (age, gender and education) were forced into the final model regardless of their p-value in bivariate analysis. This two-step variable selection process was employed to ensure that only statistically promising and clinically meaningful predictors were included in the final model, thereby preventing overfitting. The Bonferroni correction was specifically applied to adjust the significance threshold for the multiple bivariate comparisons performed during the screening phase to control the family-wise error rate. This structured approach ensures that the transition from exploratory bivariate analysis to confirmatory multivariate modeling was systematic rather than ad hoc. The distinction between using parametric tests for continuous bivariate screening and logistic regression for binary multivariate modeling was maintained to ensure statistical validity at each stage. A Bonferroni correction was applied to adjust for multiple comparisons. Analyses were conducted using SPSS (version 26), with a significance level set at $P < 0.01$ to minimize Type I error due to the multiple comparisons performed.

Interpretation of Statistical Results

Results from the logistic regression models were interpreted using Adjusted Odds Ratios (AOR) with 95% Confidence Intervals (CI). An AOR > 1 indicated increased odds of high HIT readiness, while an AOR < 1 indicated decreased odds. Statistical significance was determined by 95% CIs not crossing the null value of 1.0, alongside the predefined $P < 0.01$ threshold. Importantly, we distinguished between statistical significance and clinical relevance: predictors were considered meaningful only if they demonstrated both statistical significance and a magnitude of effect (AOR) that warranted practical consideration for intervention design. Model fit and predictive accuracy were evaluated using the Hosmer-Lemeshow test ($P > 0.05$ indicating adequate fit) and the Area Under the ROC Curve (AUC), where $AUC > 0.70$ was considered acceptable discrimination.

Ethical Considerations and Methodological Limitations

The study protocol was approved by the Ethics Committee of Semnan University of Medical Sciences (Code: IR.SEMUMS.REC.1402.085) on July 31, 2023. The research was conducted in accordance with the ethical standards of the Declaration of Helsinki. Informed consent was obtained in written form from all participants before data collection, ensuring they were fully informed about the study's purpose, procedures, potential risks and benefits, and their right to withdraw at any time without penalty. Regarding methodological limitations, the cross-sectional design precludes causal inference regarding the relationship between patient characteristics and HIT readiness. Additionally, despite standardized protocols, self-reported data may be subject to

residual social desirability bias. Unmeasured confounders, such as detailed income levels or prior specific technology training, might offer alternative explanations for the observed associations. However, the use of stratified sampling and multivariate adjustment aims to mitigate these biases.

RESULTS

The study included 300 participants with type 2 diabetes mellitus (T2DM), with an average age of 50 years. Using a BMI threshold of 25 to identify metabolic risk, 74.3% of participants exceeded this threshold, indicating a high prevalence of obesity-related comorbidities. Key demographic findings showed that 60.7% were female, 59% were over 50 years old, and 74.3% had a BMI greater than 25. Additionally, the majority were married, unemployed, and reported a family history of diabetes (**Table I**).

The mean PRE-HIT score was 96.03 ± 13.66 (**Table II**). Significant disparities ($P < 0.01$) in readiness scores were observed across gender, age, education level, employment status, comorbidities, diabetes duration, and medication knowledge (**Table III**).

Logistic Regression Analysis

Variables with $P < 0.2$ in univariate analysis were included in the final model. The HIT readiness cut-off score of 96 was determined using ROC curve analysis, optimizing sensitivity (85%) and specificity (78%). Participants were categorized as "prepared" (n=149, 49.7%) or "unprepared" (n=151, 50.3%). Key predictors of HIT readiness included: (1) Employment Status: Employed patients had 82% higher odds of being ready to engage with HIT (AOR=1.82, 95% CI: 1.108-2.99, P=0.018); (2) Comorbidities: Each additional comorbidity reduced the odds of readiness by 44% (AOR=0.56, 95% CI: 0.336-0.94, P=0.028); (3) Diabetes Duration: Patients diagnosed with diabetes for more than 5 years had 55% lower odds of readiness (AOR=0.45, 95% CI: 0.268-0.743, P=0.002); and (4) Medication Knowledge: Participants with adequate knowledge of their medications were 3 times more likely to be prepared (AOR=3.02, 95% CI: 1.595-5.7, P<0.001) (**Table IV**).

Table I: Demographic and T2DM-Related Characteristics of the Study Participants (n=300)

Characteristics	Frequency (%)
Gender	
Male	118(39.3%)
Female	182(60.7%)
Age	
≤ 50 years	123(41%)
> 50 years	177(59%)
BMI*	
≤ 25	77(25.7%)
> 25	223(74.3%)
Marital status	
Single	27(9%)
Married	273(91%)
Education level	
Diploma	188(62.7%)
Advanced Diploma	22(7.3%)
Bachelor's degree	56(18.7%)
Master's degree and above	34(11.3%)
Residence	
Urban	286(95.3%)
Non-urban	14(4.7%)
Ownership status	
landlord	264(88%)
Renter	36(12%)
Employment status	
Unemployed, Retired or Housekeeper	161(53.7%)
Self-employment	64(21.3%)
Employee	75(25%)
History of type 2 diabetes among relatives	
Yes	231(77%)
No	69(23%)
History of type 2 diabetes among the family members	
Yes	226(75.3%)
No	74(24.7%)
Comorbidities (Hypertension, CVD, etc.)	
Yes	190(63.3%)
No	110(36.7%)
The duration of the disease (years)	
<1	43(14.3%)
1-2	42(14%)
2-3	40(13.3%)

>3	175(58.3%)
Knowledge of diabetes	
Low	57(19%)
Medium	173(57.7%)
Much	59(19.7%)
Very much	11(3.7%)
Knowledge of diabetes medications	
Low	81(27%)
Medium	159(53%)
Much	48(16%)
Very much	12(4%)
Disease complications (e.g., eye, leg ulcers)	
Yes	117(39%)
No	183(61%)
Regular visits to the doctor	
Yes	253(84.3%)
No	47(15.7%)

BMI: *Threshold of 25 aligns with WHO guidelines for metabolic risk.*

Table II: Average T2DM PRE-HIT Scores Across Subscales

Factor	Number of items	Cronbach's Alpha	Mean ± Standard deviation
Health Information Need (HIN)	5	0.898	18.69±5.12
Computer/Internet Experience, Expertise (CIEE)	4	0.771	12.22±3.68
Computer Anxiety (CA)	4	0.743	13.73±3.43
Preferred Mode of Interaction (PMI)	5	0.666	13.16±4.08
Relationship with Doctor (RWD)	3	0.597	13.23±1.71
Cell Phone Expertise (CPE)	2	0.652	8.45±1.56
Internet Privacy Concerns (IPC)	2	0.802	5.91±2.42
No News is Good News (NNGN)	3	0.535	10.75±2.23
Patient readiness to engage in health information technology (PRE-HIT)	**28**	**0.830**	**96.03±13.66**

Table III: Average T2DM PRE-HIT Scores Categorized by Patients' Demographics and T2DM-Related Factors

Characteristics	PRE-HIT score	P-value[*]
Gender		
Male	98.53±12.62	**0.010**
Female	94.40±14.10	
Age		
≤ 50 years	99.13±13.79	**<0.001**
> 50 years	93.87±13.19	
BMI		
≤ 25	97.34±14.06	0.330
> 25	95.57±13.53	
Marital status		
Single	100.07±16.91	0.107
Married	95.63±13.27	
Education level		
Diploma	93.26±13.74	**<0.001**
Advanced Diploma	98.82±8.71	
bachelor's degree	99.00±13.10	
Master's degree and above	104.65±12.11	
Residence		
Urban	96.37±13.55	0.051
Non-urban	89.07±14.64	
Ownership Status		
landlord	95.82±13.32	0.475
Renter	97.56±16.11	
Employment status		
Unemployed, Retired or Housekeeper	92.97±13.53	**<0.001**
Self-employment	98.45±13.12	
Employee	100.52±12.89	
History of type 2 diabetes among relatives		
Yes	96.20±13.79	0.682
No	95.43±13.31	
History of type 2 diabetes among the family members		
Yes	95.48±13.72	0.225
No	97.70±13.44	
Comorbidities (Hypertension, CVD, etc.)		

Yes	93.46±13.52	**<0.001**
No	100.46±12.81	
The duration of the disease (years)		
≤ 3	99.68±13.05	**<0.001**
3<	93.42±13.53	
Knowledge of diabetes		
Low	97.07±14.31	**<0.001**
Medium	95.72±13.03	
Much	98.24±13.18	
Very much	109.45±13.79	
Knowledge of diabetes medications		
Low	93.19±13.45	**<0.001**
Medium	95.36±13.18	
Much	100.21±12.50	
Very much	107.33±17.79	
Disease complications (e.g., eye, leg ulcers)		
Yes	93.68±13.40	0.017
No	97.57±13.65	
Regular visits to the doctor		
Yes	96.07±13.61	0.896
No	95.79±14.09	

***Significance**: Bolded values indicate $P<0.01$ (Bonferroni-adjusted). **Tests Used:** T-test for binary variables; ANOVA for multi-category

Table IV: Logistic Regression Analysis of Risk Factors Influencing T2DM PRE-HIT

Variable		Simple Univariate Model		Multiple Model (First step)		Reduced Model (Final step)			
		Crude OR	P-Value	Adjusted OR	P-Value	Adjusted OR	95%CI		P-Value
							Lower	Upper	
Gender	Female								
	Male	1.431	0.131	0.794	0.507	0.456	0.182	1.141	0.093
Age	≤ 50 years								
	> 50 years	0.515	0.005	0.788	0.378	-	-	-	-
BMI	≤ 25								
	> 25	0.948	0.841	-	-	-	-	-	-
Marital status	Single								
	Married	0.383	0.029	0.507	0.160	-	-	-	-
Education level	Bachelor's degree and below								
	Master's degree and above	3.181	0.005	1.874	0.171	-	-	-	-
Residence	Rural								
	Urban	1.825	0.291	-	-	-	-	-	-
Ownership Status	Renter								
	landlord	0.764	0.452	-	-	-	-	-	-
Job	Unemployed (Retired or Housekeeper)								
	Employed	2.256	<0.001	1.851	0.067	1.820	1.108	2.990	**0.018**
History of type 2 diabetes among relatives	No								
	Yes	1.021	0.941	-	-	-	-	-	-
History of type 2 diabetes among member family	No								
	Yes	0.851	0.547	-	-	-	-	-	-
Comorbidities	No								
	Yes	0.459	0.001	0.574	0.050	0.562	0.336	0.940	**0.028**
The duration of the disease (years)	≤ 3								
	3<	0.411	<0.001	0.463	0.005	0.446	0.268	0.743	**0.002**
Knowledge of diabetes	low or moderate								
	A lot or too much	2.181	0.006	1.551	0.276	-	-	-	-
Knowledge of diabetes medications	low or moderate								
	A lot or too much	2.637	0.002	2.064	0.091	3.015	1.595	5.700	**<0.001**
Disease complications	No								
	Yes	0.598	0.032	0.943	0.834	-	-	-	-
Regular visits to the doctor	No								
	Yes	1.035	0.913	-	-	-	-	-	-

DISCUSSION

This study identifies specific patient characteristics that create HIT readiness gaps in T2DM care. The primary contribution of this work lies in identifying specific socioeconomic and clinical barriers to technology adoption, rather than focusing solely on technological solutions. Understanding these determinants is crucial before implementing any digital intervention. AI-driven personalized interventions (e.g., adaptive algorithms, predictive analytics) can address these gaps, enhancing engagement and outcomes only if tailored to these identified readiness profiles within the HIT framework. It is important to distinguish between basic digital tools (e.g., static health apps, simple trackers) and AI-driven tools (e.g., machine learning algorithms, adaptive systems, NLP-powered chatbots). While digital tools provide data collection capabilities, AI tools offer intelligent processing, personalization, and predictive capabilities that can adapt to individual patient needs.

Employment status emerged as a significant predictor of HIT readiness. This study reveals a significant association between employment status and readiness to adopt HIT, showing that employed individuals are 1.8 times more likely to be ready to adopt HIT (AOR=1.82, p=0.018). This finding likely reflects the socioeconomic advantages of employment, including higher digital literacy, greater access to devices, and greater confidence in navigating complex systems. Unemployment may correlate with financial constraints that limit access to necessary hardware or data plans, thereby reducing readiness. These findings highlight the socioeconomic gap, suggesting that tailored AI voice assistants (e.g., Persian chatbots) as specific HIT tools could be particularly beneficial for self-employed/low-income individuals by lowering interaction barriers. Unlike static digital apps, AI-powered chatbots can adapt their communication style and content complexity based on user responses, making them more accessible to users with varying levels of digital literacy. While Graetz I et al. [19] identified access barriers for employed patients, our findings call for a tripartite collaboration among healthcare providers, employers, and AI developers to co-design workplace-embedded HIT training programs. Such initiatives could empower individuals from diverse employment backgrounds to take an active role in managing their diabetes.

Notably, more than half of the study participants were unemployed, retired, or homemakers. For this group, readiness is likely hindered by limited exposure to digital workflows rather than just a lack of technology. Limited access to adaptive tech hinders HIT adoption. AI health coaches and NLP-powered predictive analytics offer equitable, culturally sensitive diabetes guidance as a supportive measure to bridge this literacy gap. Baee S 2020 [20] proposed a framework for managing risks and opportunities in such technologies, emphasizing transparency, accountability, and cultural adaptation. Implementing such frameworks is essential to ensure that unemployed or retired patients do not feel alienated by complex digital tools. This approach enhances diabetes management/engagement among retirees/unemployed/homemakers via ethical, personalized recommendations. User-centred tech integration transforms chronic disease care.

Building on this, Khan S 2024 [21] demonstrated that integrating AI tools with local health programs creates a supportive ecosystem capable of bridging socioeconomic gaps. However, our results suggest that such ecosystems must first address the underlying socioeconomic determinants of readiness. Such systems empower unemployed/retired individuals through health/social data analysis, reducing costs, improving access, strengthening equity, and preventing complications to boost quality of life. This study highlights AI's transformative

potential to address socioeconomic disparities in HIT readiness via stakeholder collaboration and culturally adapted tech, empowering diverse employment backgrounds toward equitable, patient-centred diabetes care.

Comorbidities significantly reduced HIT readiness in our sample. The findings of our study highlight a critical need for integrated care solutions, as more than half of the diabetic patients in our sample also suffer from additional comorbidities. This aligns with the observation that comorbidities reduce readiness to engage with HIT by 44% (AOR=0.56, p=0.028). This reduction in readiness is likely attributable to the increased cognitive burden and competing health priorities faced by these patients. The cognitive burden and complexity of managing multiple chronic conditions simultaneously[22-24], combined with limited access to smart technologies that address both diabetes and related conditions, likely contribute to this reduced readiness. Patients with multi-morbidity may perceive new technologies as an additional burden rather than a helpful tool.

AI-health tech integration simplifies diabetes/comorbidity (e.g., hypertension/obesity) management, alleviating mental strain by automating prioritized tasks such as blood sugar/pressure control. By reducing the manual effort required for self-management, technology can mitigate the readiness barrier posed by comorbidities. The integration pathway involves embedding AI algorithms into existing electronic health records (EHRs) and patient-facing applications, enabling automated data synthesis across multiple sources (wearables, lab results, patient reports) without requiring patient manual input. study showed that analyzing simple data (e.g., age/weight) using algorithms can predict complication risks/enables integrated management, preventing serious issues and significantly improving the QoL of multi-condition patients through cost reduction/personalized care[25].

Machine learning algorithms analyze patient data to predict complication risks and trigger provider alerts. Another study showed that integrating CGM/wearables can identify hypoglycemia/hyperglycemia and adjust insulin based on activity/diet[26]. This reduces costs and enables effective diabetes/comorbidity management by preventing complications and boosting adherence. However, for patients with low readiness due to comorbidities, these HIT tools must be introduced gradually to avoid overwhelming them.

Our study found few rural residents, likely with comorbidities. Intelligent mobile health solutions are vital for their HIT readiness. AI-telemedicine integration enables remote monitoring/timely consultations for diabetic comorbid patients, reducing care burden. Nwankwo EI 2024 [33] showed that such systems analyze CGM/wearable data to predict hypoglycemia/hyperglycemia and adjust insulin via diet/activity, lowering costs and enabling effective diabetes/comorbidity management by preventing complications and improving access to specialized care. These technologies enable patient-centred ecosystems that address diabetes/comorbidities, improving outcomes and reducing care disparities. This approach mitigates cognitive overload challenges while paving the way for equitable, patient-centred care in multi-chronic populations. AI integration transforms diabetes management, simplifying care complexity and enhancing the quality of life for patients with multimorbidity.

Disease duration was inversely associated with HIT readiness. The findings of this study reveal that over half of patients with more than three years since their diabetes diagnosis are less inclined to use HIT for disease management. This aligns with the observation that such patients exhibit 56% lower readiness (AOR=0.45, p=0.002), a phenomenon often attributed to "digital fatigue." Long-term patients may have established routine management habits that they are reluctant to disrupt with new technologies. Early-stage patients benefit more from telehealth[28,29]

than those with long-term disease, who struggle with engagement. Recently diagnosed patients use apps better than chronic patients (lower accuracy/engagement), confirmed by a large German study of 5,013 users[30]. Technological burnout hinders long-term diabetes patients' HIT adoption[27], diminishing motivation and revealing care strategy gaps[20]. This suggests that readiness interventions must differ based on disease duration, focusing on re-engagement for chronic patients.

AI technologies transform long-term diabetes management, making it more accessible and effective. Lee YB et al. [29] showed AI integration with digital health improves blood glucose control and patient engagement. These systems offer personalized experiences (e.g., adjusting insulin based on diet/activity), reducing fatigue and ensuring effective management. This lowers healthcare costs and improves quality of life by preventing complications. To address the readiness gap identified in our study, AI systems for long-term patients should focus on passive monitoring rather than active data entry to minimize burden. This represents a key distinction from traditional digital tools that require active patient engagement; adaptive AI systems can learn from passive data streams and provide insights without demanding continuous user input.

AI combats digital fatigue and enables sustainable diabetes care. Adaptive AI re-engages long-term patients, transforming care to improve outcomes. This integration prevents HIT disengagement, fostering a resilient, empowered patient population.

Medication knowledge strongly predicted HIT readiness. The findings of this study reveal that the majority of diabetic patients had a high school education level, with a minority living in non-urban areas, and many lacked sufficient knowledge about their medications. This aligns with global disparities in medication literacy, which has been shown to triple readiness to engage with health information technology (HIT) (AOR=3.02, $p<0.001$). This strong association suggests that health literacy is a foundational prerequisite for digital health literacy. Patients who understand their treatment regimen are likely more confident in seeking additional information through digital channels. Research by Al Bshabshe A et al. [30] highlighted that less than half of T2DM patients in Saudi Arabia were aware of their medications, often relying on physicians and online sources for information. In contrast, Lauffenburger JC et al. [31] found that T2DM patients in the U.S., despite some initial hesitations, were generally open to using mobile health technology to manage their medication routines.

Limited smart tech access, especially in remote areas, contributes to low HIT readiness among patients with poor medication literacy. AI tech offers a transformative solution for accessible disease/complication management. Rammal DS 2024[32] showed AI systems predict drug complications and adjust doses based on lifestyle/genetics, reducing errors. They enhance adherence via reminders, prevent chronic issues, and improve quality of life. This reduces costs and enables effective remote/low-literacy patient management by optimizing workflows. Our findings imply that educational interventions regarding medication should precede or accompany HIT implementation to boost readiness. Embedding AI tools into telemedicine provides continuous remote support, bridges educational/geographical gaps, and improves diabetes self-management. This empowers patients with limited resources by prioritizing culturally adapted AI to ensure equitable healthcare access in underserved regions such as rural Iran. AI acts as an educational equalizer, addressing medication/HIT disparities. Leveraging adaptive tech transforms diabetes care into inclusive, patient-centred experiences, enhancing outcomes and fostering equity in access to healthcare innovation.

Policy implications for AI integration in diabetes care require robust frameworks that address systemic challenges to equitable access. Policies must first target the determinants of readiness

identified in this study, such as improving health literacy and reducing socioeconomic barriers. Policymakers, providers, and developers must collaborate on inclusive strategies that prioritize underserved populations (low-income, rural, less educated). Policies promoting culturally tailored AI tools such as multilingual chatbots and telemedicine as components of the HIT infrastructure can help bridge digital literacy and access gaps. A phased integration approach is recommended: (1) assess patient readiness using validated tools like PRE-HIT, (2) match patients to appropriate technology levels (basic digital tools for low readiness, AI-driven tools for high readiness), and (3) provide ongoing support and training to facilitate adoption. This collaboration improves diabetes management while building an equitable, patient-focused system accessible regardless of socioeconomic/geographic status.

CONCLUSION

This study concludes that specific patient characteristics, including socioeconomic disparities, comorbidities, digital fatigue, and medication knowledge gaps, significantly determine HIT readiness among T2DM patients. Instead of viewing technology as a standalone solution, interventions must be tailored to these determinants. Future implementations should distinguish between basic digital health tools and AI-driven solutions, selecting technologies based on patient readiness profiles. AI can transform passive diabetes patients into active participants by addressing these identified barriers. Culturally tailored tools, such as virtual coaches, predictive analytics, and telemedicine, should be implemented to enable effective self-management via personalized guidance. Integration should occur through existing healthcare infrastructure (EHR systems, primary care clinics), with AI tools serving as decision support for providers and as personaliz*ed assistants for patients.* Prioritizing improvements of these readiness determinants, alongside streamlining care and promoting equitable access, improves outcomes and sustains engagement, bridging the patient-technology divide to enable proactive, patient-centred management within the AI-driven HIT ecosystem.

AUTHOR CONTRIBUTION
Kahouei M: Study design and conceptualization, data analysis, drafting the initial manuscript, critical revision for important intellectual content.
Paknazar F: Literature search, methodology design, data analysis, manuscript revision.
Pahlevanynejad S: Literature search, methodology design, data analysis, manuscript revision.
Kermani F: Data collection, data management and entry, assistance in data interpretation, manuscript revision.
Foroutan M: Statistical data analysis, validation of methods, critical revision of the manuscript, resource provision.
Mehdizadeh J: Study design, supervision of research execution, critical revision for important intellectual content; Final approval of the version to be published.
Doostmohammadi S: Literature search, assistance in data collection, drafting the methods section, manuscript revision.
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All Authors: Provided final approval of the version to be published; Agreed to be accountable for all aspects of the work, ensuring that questions related to the accuracy or integrity of any part are appropriately investigated and resolved

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