



A Mixed-Methods Assessment of Digital Health Engagement for Chronic Disease Management in Low- and Middle-Income Settings

1st Yintong Zheng*
Zhejiang University
Hangzhou, China
yintong789@outlook.com

2nd Haotian Ying
Zhejiang University
Hangzhou, China
347096624@qq.com

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Abstract—Chronic disease management in low- and middle-income countries requires digital interventions that remain usable under constrained infrastructure. This sequential explanatory mixed-methods study examined engagement with a chronic-care platform among 528 adults with hypertension and/or type 2 diabetes across three LMIC settings, followed by 35 semi-structured interviews. Structural equation modeling quantified Technology Acceptance Model constructs, and CFIR-guided thematic analysis explained the observed patterns. Perceived usefulness ($\beta = 0.45$, $p < 0.001$) and perceived ease of use ($\beta = 0.38$, $p < 0.001$) predicted behavioral intention; ease of use also increased perceived usefulness ($\beta = 0.59$, $p < 0.001$), with 62% of intention variance explained. Interviews identified connectivity, power, data cost, digital literacy, family support, self-entered-data review, and provider feedback as decisive implementation conditions. The findings support offline-capable, low-literacy, human-supported digital health architectures for equitable chronic disease care.

Keywords—Digital health; chronic disease management; low- and middle-income countries; mixed methods; technology acceptance model

1. INTRODUCTION

Chronic noncommunicable diseases (NCDs), particularly hypertension and type 2 diabetes, require sustained medication adherence, and clinical follow-up. Their burden is concentrated in settings where primary-care capacity and care continuity are constrained [1], [2]. Digital health tools—including mobile applications, SMS, asynchronous messaging, and remote review workflows—can extend patient contact between visits, but their value depends on access, usability, and integration with routine care [3].

Implementation in low- and middle-income countries (LMICs) remains uneven. Device affordability, connectivity, digital literacy, and local service capacity can prevent sustained use, while health-data poverty may deepen inequity when systems assume continuous access and high user

capability [4], [5]. Consequently, evidence obtained in high-income settings cannot be transferred unchanged to heterogeneous LMIC health systems.

Technology Acceptance Model (TAM) studies quantify perceived usefulness and perceived ease of use, whereas implementation research examines organizational, social, and infrastructural conditions. When these perspectives are applied separately, the mechanisms linking individual acceptance to real-world engagement remain under-specified.

This study identifies individual, technological, and contextual determinants of engagement with a chronic disease platform across three LMIC settings. It combines a 528-participant survey with 35 purposively selected interviews to connect statistically significant acceptance pathways with patient-reported implementation conditions.

The contributions are threefold: (1) a sequential explanatory mixed-methods design that links TAM pathways to CFIR-coded experiences; (2) a context-sensitive account of infrastructure, social support, and provider feedback as engagement determinants; and (3) an engineering-oriented set of design implications for low-bandwidth, low-literacy, and human-supported chronic-care platforms.

2. RELATED WORK

Digital health research for chronic disease management in LMICs spans patient communication, self-management applications, and provider-supported care coordination. This section classifies representative work by intervention function, acceptance framework, and implementation context, then identifies the gap addressed by the present mixed-methods study.

2.1. Digital Health Interventions in LMICs

Digital interventions for chronic disease management can be grouped into three functional classes: low-bandwidth communication, patient-facing self-management, and provider-supported coordination. A scoping review of LMIC

*Yintong Zheng, Zhejiang University, Hangzhou, China, yintong789@outlook.com

primary care found limited coverage across the World Health Organization intervention categories and heterogeneous clinical effects, despite more favorable behavioral and service-implementation outcomes [6].

For hypertension, SMS-based adherence support was evaluated in a single-blind trial in South Africa [7], and a systematic review documents the expanding use of technology for prevention, detection, and management across sub-Saharan Africa [8]. In diabetes, mobile messaging has been evaluated to support lifestyle modification in India [9], while app research highlights the importance of usability and contextual fit for self-management rather than a uniform country-specific effect [10]. Sustainability evidence further shows that financing, workforce support, governance, and local infrastructure influence whether technically feasible interventions persist beyond initial deployment [11].

2.2. Models of Technology Adoption

TAM and the Unified Theory of Acceptance and Use of Technology provide parsimonious explanations of intention formation, with perceived usefulness and perceived ease of use as central constructs [12]–[14]. However, adoption models alone do not represent the organizational or environmental conditions of implementation. The updated Consolidated Framework for Implementation Research (CFIR) addresses this limitation by organizing intervention, setting, individual, and process determinants that influence implementation outcomes [15].

2.3. Barriers and Facilitators to Engagement

Prior LMIC research consistently reports barriers related to digital literacy, data cost, device availability, network reliability, privacy, and health-system capacity [4], [5], [11]. Provider adoption and workflow support also affect whether digital tools become credible components of care [16]. Existing studies commonly examine these factors in isolation. The remaining gap is an integrated account that relates quantitative acceptance pathways to the contextual mechanisms experienced by patients using a chronic-care platform in diverse LMIC settings.

3. METHODOLOGY AND SYSTEM DESIGN

3.1. Study Design and Setting

This study used a sequential explanatory mixed-methods design: a cross-sectional survey identified statistical associations among engagement constructs, followed by interviews that examined the mechanisms and contexts underlying those associations [17]. Data were collected from May 2024 to October 2025 at an urban public hospital in Southeast Asia, rural primary-care clinics in sub-Saharan Africa, and a community health center in Latin America. The three settings were selected to represent contrasting service structures, connectivity conditions, and socioeconomic environments.

3.2. Participants and Recruitment

The quantitative phase enrolled a convenience sample of 528 adults aged 18 years or older with hypertension and/or type 2 diabetes diagnosed for at least one year. Participants were recruited from outpatient waiting areas, owned a mobile phone, and provided informed consent. For the qualitative phase, purposive sampling selected 35 survey participants with variation in age, gender, education, diagnosis, and reported digital health engagement.

3.3. The Digital Health Intervention: System Design

The participating facilities were piloting ChronicCare Connect, a unified platform for chronic disease management. The client application was a lightweight progressive web app (PWA) designed to operate across device types with minimal local storage. A cloud-based microservices back end separated core functions, supporting modular deployment and fault tolerance. The implementation pathway was manual input or SMS notification, local/offline capture where needed, secure synchronization, clinician review, and asynchronous feedback.

The user interface was co-designed with patient representatives and used high-contrast icons, minimal text, and voice-note capability. Core functions were: (1) manual entry of blood pressure, blood glucose, and medication intake with immediate color-coded feedback on entered values; (2) scheduled medication and education notifications delivered through push notifications or SMS; and (3) secure asynchronous messaging with a designated provider. Data were encrypted in transit using TLS 1.3 and at rest using AES-256.

3.4. Data Collection and Instruments

The overall study workflow is shown in Figure 1.

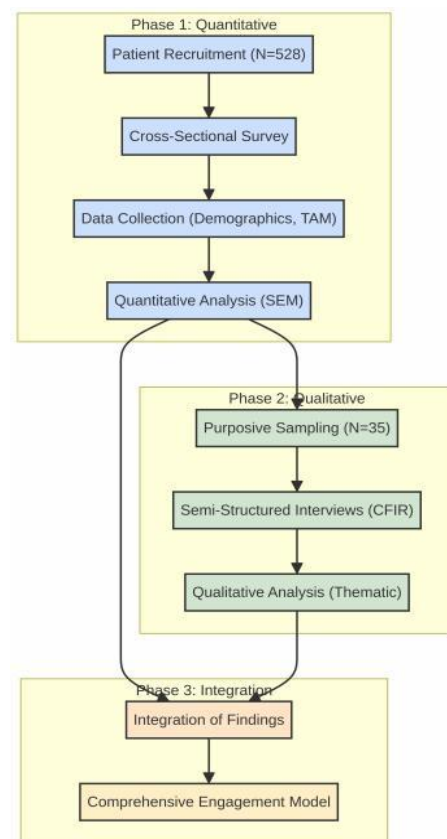


Figure 1. Sequential explanatory mixed-methods workflow. Source: Authors' study design.

Trained local research assistants fluent in the respective local languages conducted all field procedures.

Quantitative phase: Interviewer-administered surveys were completed on tablets running Open Data Kit, enabling offline capture and secure synchronization. The English instrument was translated into Swahili, Spanish, and Tagalog and independently back-translated to confirm conceptual equivalence. A 30-patient pilot (10 per site) refined wording

and flow. The final survey captured sociodemographic and clinical information, self-assessed digital literacy, and TAM measures adapted from established scales [12]–[14]. Perceived usefulness and perceived ease of use were measured with four items each; behavioral intention was measured with three items on 5-point Likert scales (1 = strongly disagree; 5 = strongly agree).

Qualitative phase: Semi-structured interviews with the 35 purposively selected participants lasted 45–60 minutes and were conducted privately at participating facilities. The CFIR-guided interview guide covered daily platform use, technical barriers, affordability, family and community support, and communication with providers. Interviews were audio-recorded, transcribed verbatim, and anonymized.

3.5. Data Analysis

Quantitative analysis: SPSS 28 and AMOS 28 were used for descriptive statistics, exploratory group comparisons, reliability assessment, confirmatory factor analysis, and structural equation modeling (SEM). The structural model specified perceived ease of use (PEOU) as an exogenous construct, perceived usefulness (PU) as an endogenous mediator, and behavioral intention (BI) as the final outcome. In standardized form, the model estimated $PU = \beta_1 \cdot PEOU + \zeta_1$ and $BI = \beta_2 \cdot PEOU + \beta_3 \cdot PU + \zeta_2$, where ζ_1 and ζ_2 are residual terms. This specification separated direct usability effects from usefulness-mediated effects. Model fit was evaluated with χ^2 , CFI, TLI, RMSEA, and SRMR. Prespecified adequacy thresholds were CFI and TLI above 0.95, RMSEA below 0.06, and SRMR below 0.08. Two-sided p values below 0.05 were treated as statistically significant.

Qualitative analysis: Two researchers independently coded the first five transcripts using a CFIR-informed codebook, reconciled discrepancies, and refined the coding definitions. Inter-coder reliability exceeded Cohen's $\kappa = 0.80$. The final codebook was applied to the remaining transcripts in NVivo 12, using thematic analysis, constant comparison

across sites, and representative quotations to identify recurrent mechanisms and divergences [18].

Mixed-methods integration: Significant SEM pathways were aligned with corresponding CFIR themes, frequencies, and illustrative quotations in a joint display matrix. For each pathway, the matrix recorded the quantitative coefficient, the most closely related patient-reported mechanism, and the resulting system-design implication. This procedure enabled convergence to be examined at the level of a concrete design decision, such as offline capture, caregiver onboarding, or provider feedback, rather than only at the level of a general thematic label. The completed joint display is presented in Table 5.

3.6. Ethical Considerations

The study protocol received ethical approval and the respective institutional review boards at each of the three international sites. All participants provided written informed consent in their native language before any study procedures. Participants were assured of confidentiality and their right to withdraw at any time without affecting their medical care. A small, culturally appropriate compensation was provided for their time.

4. RESULTS

4.1. Participant Characteristics

All 528 enrolled patients completed the survey. The mean age was 54.7 years (SD = 11.2), and 58.1% were female. Hypertension was reported by 72.5% of participants and type 2 diabetes by 52.5%; 25.0% reported both conditions. In total, 35.6% had completed primary school or less, and 42.8% reported monthly household income below the national poverty line of their respective countries. The qualitative subsample reflected variation in age, gender, diagnosis, and socioeconomic status. Table 1 summarizes the sample, and Figure 2 provides the corresponding visual distribution.

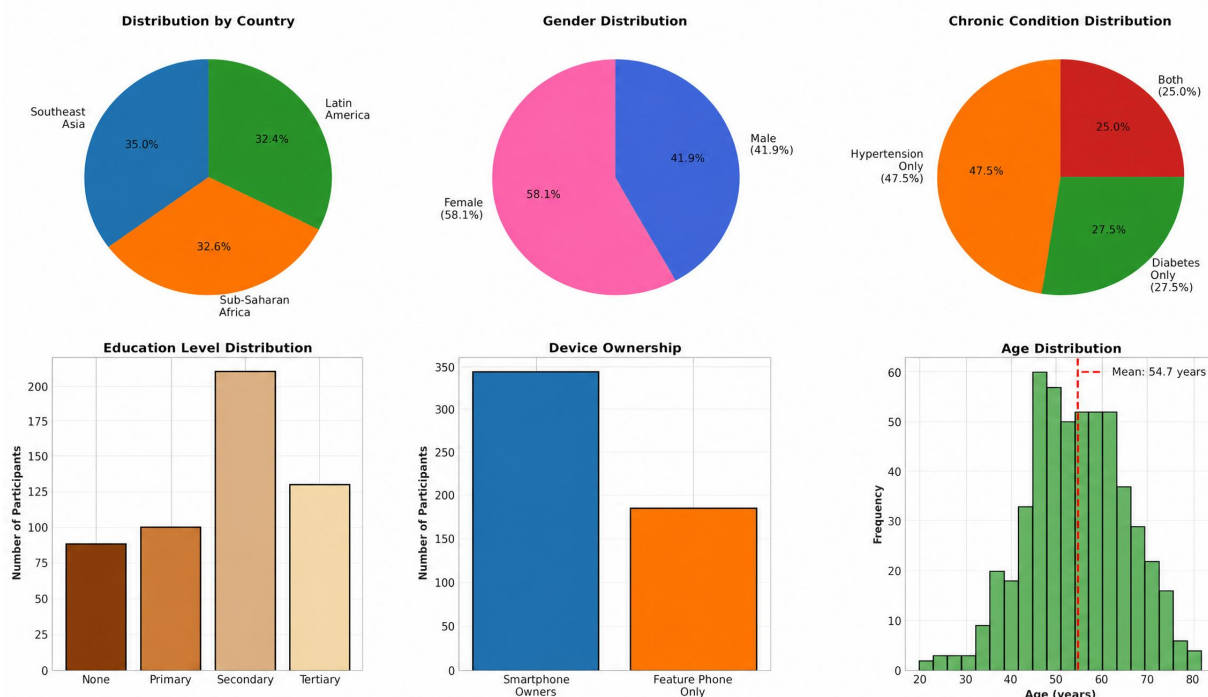


Figure 2. Sample characteristics distribution. Source: Survey data (N = 528).

TABLE I. DEMOGRAPHIC CHARACTERISTICS OF SURVEY PARTICIPANTS (N = 528)

Characteristic	Category	n (%)
Age (Mean, SD)		54.7 (11.2)
Gender	Female	307 (58.1)
	Male	221 (41.9)
Country	Southeast Asian Nation	185 (35.0)
	Sub-Saharan African Nation	172 (32.6)
	Latin American Nation	171 (32.4)
Chronic Condition	Hypertension only	251 (47.5)
	Type 2 Diabetes only	145 (27.5)
	Both	132 (25.0)
Education Level	No formal education	88 (16.7)
	Primary school	100 (18.9)
	Secondary school	210 (39.8)
	Tertiary or higher	130 (24.6)
Smartphone Ownership	Yes	343 (65.0)
	No (feature phone only)	185 (35.0)

4.2. Quantitative Findings: Technology Acceptance Model

Internal consistency was high for perceived usefulness (Cronbach's $\alpha = 0.88$), perceived ease of use ($\alpha = 0.85$), and behavioral intention ($\alpha = 0.91$). The SEM also showed strong global fit: CFI = 0.99, TLI = 0.98, RMSEA = 0.035, SRMR = 0.028, and $R^2 = 0.62$ (Table 2).

TABLE III. STANDARDIZED STRUCTURAL PATHS AND PEARSON CORRELATION

Path	Standardized β	Unstandardized B	SE	p-value	Significance
PEOU $\rightarrow$ PU	0.59	0.68	0.08	< 0.001	**
PEOU $\rightarrow$ BI	0.38	0.42	0.09	< 0.001	**
PU $\rightarrow$ BI	0.45	0.51	0.10	< 0.001	**
PU $\leftrightarrow$ BI (Correlation)	0.52	—	—	< 0.001	**

^a PEOU = Perceived Ease of Use; PU = Perceived Usefulness; BI = Behavioral Intention; SE = Standard Error; β = Standardized Path Coefficient; B = Unstandardized Path Coefficient. The PU-BI correlation is reported as Pearson's r rather than a structural path coefficient. ** $p < 0.01$.

Participants from Southeast Asia had the highest observed mean TAM scores, while the sub-Saharan African group had the lowest. Smartphone owners also showed higher observed scores across the three TAM constructs than feature-phone-

TABLE II. MODEL FIT INDICES AND EVALUATION CRITERIA

Model Fit Index	Value	Threshold	Interpretation
χ^2 (Chi-square)	8.45	$p > 0.05$	Excellent
df (Degrees of Freedom)	5	—	—
CFI (Comparative Fit Index)	0.99	> 0.95	Excellent
TLI (Tucker-Lewis Index)	0.98	> 0.95	Excellent
RMSEA (Root Mean Square Error)	0.035	< 0.06	Excellent
SRMR (Standardized RMR)	0.028	< 0.08	Excellent
R^2 (Variance Explained)	0.62	> 0.50	Excellent

All hypothesized TAM paths were positive and statistically significant. Perceived usefulness predicted behavioral intention ($\beta = 0.45$, $p < 0.001$), perceived ease of use predicted behavioral intention ($\beta = 0.38$, $p < 0.001$), and perceived ease of use predicted perceived usefulness ($\beta = 0.59$, $p < 0.001$). The relative magnitude of the PEOU $\rightarrow$ PU path shows that usability was not only a direct driver of intention but also a mechanism through which usefulness was formed. The reported Pearson correlation between perceived usefulness and behavioral intention was $r = 0.52$ ($p < 0.001$). Table 3 separates structural paths from this correlation and reports the corresponding statistics, avoiding the conflation of a modeled directional relationship with a bivariate association.

only users. These descriptive patterns are shown in Figure 3; they identify access-related variation for implementation planning rather than a tested interaction effect.

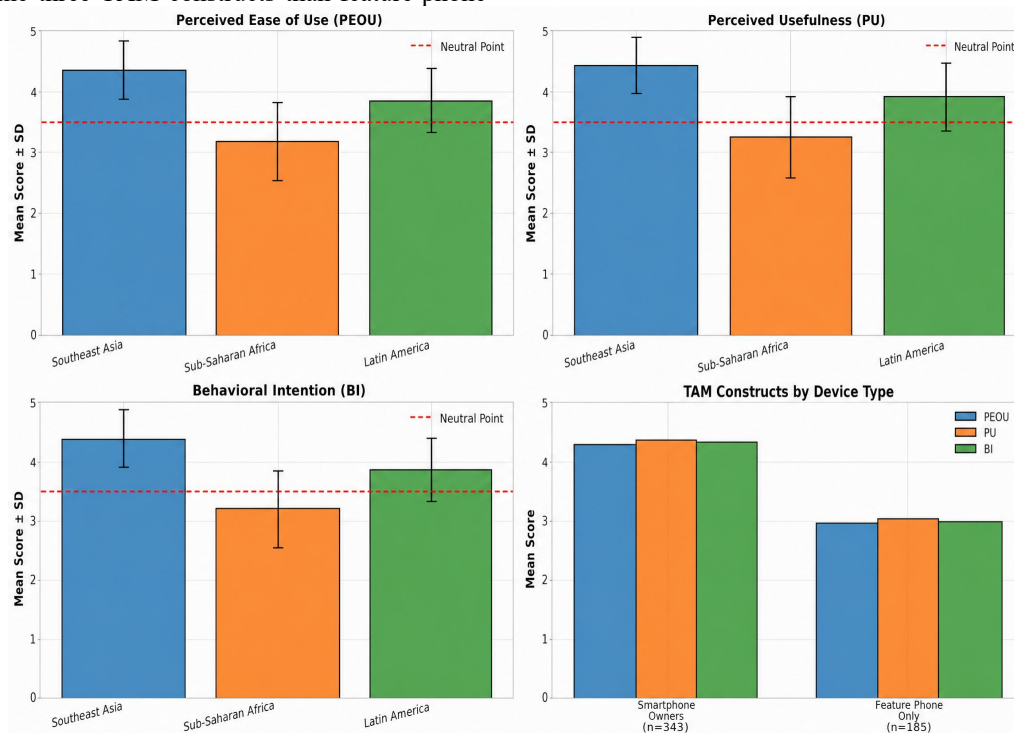


Figure 3. Descriptive statistics of TAM constructs by demographic group.

4.3. Qualitative Findings: Barriers and Facilitators to Engagement

The thematic analysis of 35 interviews explained the quantitative findings through CFIR domains. Table 4

TABLE IV. QUALITATIVE THEMES ORGANIZED BY CFIR DOMAINS

CP's Domain	Theme	Sub-theme	Facilitator/Barrier	Frequency
Interaction Characteristics	Simplicity & Usability	Intuitive Design	Facilitator	3,063
		Feature Limitations	Barrier	835
	Design Quality	User-Friendly Interface	Facilitator	3,233
Outer Setting	Infrastructure	Internet Connectivity	Barrier	2,180
		Power Reliability	Barrier	2,065
		Cost Barriers	Barrier	3,080
Inner Setting	Provider Support	Personalized Feedback	Facilitator	3,205
		Access to Skilled Health Data	Facilitator	3,005
		Family Involvement	Facilitator	2,791
Individual Characteristics	Digital Literacy	Prior Tech Experience	Facilitator	1,925
		Satisfaction of Engagement	Facilitator	2,581
Process	Engagement Journey			

The Pearson matrix showed significant inter-correlations among all TAM constructs ($p < 0.001$): PEOU–PU, $r = 0.59$; PEOU–BI, $r = 0.48$; and PU–BI, $r = 0.52$ (Figure 4).

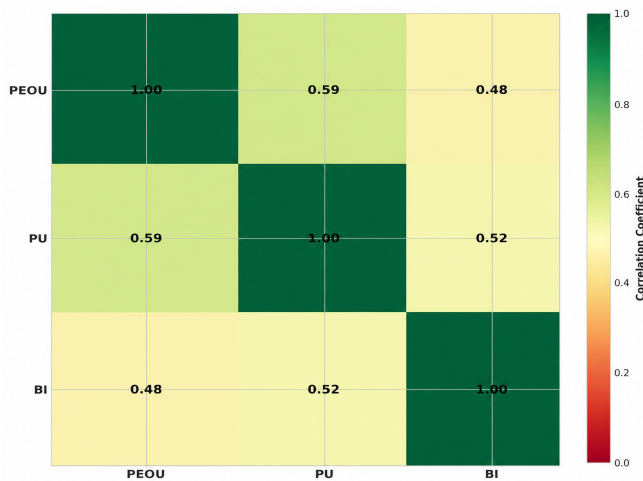


Figure 4. Pearson correlation matrix of TAM constructs.

4.4. Theme 1: Intervention Characteristics - The Double-Edged Sword of Simplicity

Ease of use was a dominant facilitator. Patients with limited digital experience valued the minimal interaction burden, whereas more technologically experienced users described the same design as functionally restrictive. The contrast indicates that a single interface configuration does not fit all capability profiles.

“It’s very simple. I just open it, type the number, and it’s done. No confusion. That’s why I use it.” — (P12, 62-year-old female, hypertension)

“I wish it could do more. Maybe connect to my glucometer automatically? Or show me graphs of my progress. It feels a bit too basic.” — (P28, 34-year-old male, type 2 diabetes)

4.5. Theme 2: Infrastructural conditions were recurring barriers, particularly in rural settings.

Unreliable connectivity, power interruptions, and mobile-data charges constrained the regular transmission and review of manually recorded values, independent of positive attitudes toward the platform.

A critical barrier, particularly in rural areas, was the challenging external environment. Unreliable internet

summarizes the themes, their facilitators or barriers, and their reported frequencies.

connectivity, frequent power outages, and the high cost of mobile data were cited as major impediments to consistent engagement. These structural barriers often overshadowed individual attitudes towards the technology.

The app is good, but the network here is a problem. Sometimes for two days, there is no internet. So how can I send my readings? The hospital thinks I am not trying. — (P07, 55-year-old male, hypertension, rural Africa)

“Data is not free. I have to choose between buying data for the app or for my children’s schoolwork. The family comes first.” — (P19, 48-year-old female, diabetes, Southeast Asia)

4.6. Theme 3: Inner Setting and Individual Characteristics - The Crucial Role of Social Support and Trust

Family members—especially younger relatives with greater technology experience—often enabled onboarding, data entry, and troubleshooting. This support extended the effective user unit beyond the individual patient.

“My daughter set it all up for me. Every evening, she asks me for my numbers and puts them in the phone. Without her, I would not be able to use this thing.” — (P04, 68-year-old female, hypertension & diabetes)

Personalized provider feedback was a further facilitator. Participants valued the knowledge that entered values could be reviewed by a trusted nurse or clinician. In Table IV, “review of self-entered data” denotes immediate in-app review of values recorded manually by the patient, reinforced by the platform’s color-coded feedback and asynchronous provider communication.

“Knowing that Nurse Maria is seeing my numbers makes me feel safe. It makes me more careful to check my pressure every day. It’s like she is watching over me.” — (P31, 59-year-old male, hypertension, Latin America)

4.7. Theme 4: Process - From Skepticism to Empowerment

Engagement evolved from initial skepticism to a more active self-management routine when participants could connect repeated manual entries with visible feedback and daily choices. This process linked routine logging to perceived agency rather than treating platform use as a one-time adoption decision.

“At first, I thought, ‘Another task.’ But after a few weeks, I started to see how the food I eat affects my sugar. Now I check before and after meals. It has taught me about my own body. I am in control now.” – (P25, 45-year-old female, type 2 diabetes)

Table 5 integrates the significant TAM pathways with the CFIR themes and design implications. The joint display shows that acceptance perceptions were strengthened by usable interaction and provider support, but their practical realization depended on connectivity, affordability, and social assistance.

TABLE V. JOINT DISPLAY OF QUANTITATIVE AND QUALITATIVE FINDINGS

Quantitative pattern	Integrated CFIR explanation and design implication
PEOU $\rightarrow$ PU: $\beta = 0.59$	Intuitive design (28/35) increased perceived value; progressive disclosure can preserve simplicity while exposing optional detail.
PU $\rightarrow$ BI: $\beta = 0.45$	Feedback (32/35) and review of self-entered data (30/35) supported engagement; retain immediate feedback and clinician messaging.
PEOU $\rightarrow$ BI: $\beta = 0.38$	Family involvement (27/35) and prior experience (19/35) supported use; provide caregiver onboarding and low-literacy guidance.
Access variation (Fig. 3)	Connectivity (31/35), power (29/35), and data cost (26/35) constrained use; provide offline PWA, SMS fallback, and queued synchronization.

5. ANALYSIS AND DISCUSSION

The integrated analysis shows that engagement with ChronicCare Connect was shaped by the interaction of individual acceptance, system design, and implementation context. This interpretation is consistent with implementation reviews of chronic disease digital health, which emphasize that adoption, feasibility, and sustainability must be considered alongside technical capability [19].

5.1. The Primacy of Usability and the Paradox of Simplicity

The largest modeled relationship, PEOU $\rightarrow$ PU ($\beta = 0.59$), indicates that usability was the main route through which the platform acquired practical value. In healthcare settings, cognitive effort can directly constrain acceptance when users are managing symptoms, treatment routines, and limited digital skills [20]. The qualitative “simplicity paradox” adds an engineering requirement: low-literacy interfaces should remain simple by default while allowing optional depth, such as richer trend visualization, for users who can benefit from it. This supports the use of progressive disclosure rather than a single fixed feature set. Engagement measurement should similarly distinguish initial intention from continued self-management behavior [21].

5.2. Beyond Individual Cognition: The Overriding Influence of the Socio-Technical Context

The results also demonstrate that positive acceptance perceptions were insufficient when connectivity, electricity, or data affordability interrupted use. Recent LMIC scale-up research identifies cross-sector capacity, service integration, and resource alignment as implementation prerequisites [22], while broader evidence links equity to digital literacy, infrastructure, and access conditions [23]. The PWA-plus-SMS architecture used here provides a technically appropriate response: offline-capable data capture, queued

synchronization, and low-bandwidth notification can reduce dependence on continuous connectivity. A practical deployment sequence is to validate locally stored entries, preserve timestamps and entry status, synchronize once a connection is available, and issue SMS reminders independently of app access. This arrangement reduces data-loss risk and allows the care team to distinguish an unsubmitted entry from a clinical nonresponse. These choices align with established guidance for scaling digital health in resource-constrained settings [24].

5.3. The Social Scaffolding of Engagement: Family, Community, and Trust

Family support created a distributed model of use. Relatives acted as onboarding partners, interpreters, and practical technology stewards, extending established evidence on family participation in chronic disease self-management into the digital workflow [25]. Provider feedback created a second layer of support. Rather than replacing the patient-provider relationship, the platform supplied an asynchronous channel through which trusted clinical personnel could reinforce engagement. This finding is compatible with evidence that provider adoption and workflow support shape the implementation of eHealth tools [16].

Personalized feedback from nurses transformed manual logging into a supported care activity. Such provider support depends on organizational readiness, workflow ownership, and usability, which are recurring considerations in eHealth adoption research [16]. The system should therefore assign a defined review responsibility and response window rather than treating asynchronous messaging as an unsupervised adjunct.

5.4. Engagement as a Dynamic Journey of Empowerment

Engagement was therefore dynamic rather than binary. Repeated manual recording, immediate feedback, and trusted communication enabled patients to interpret data in relation to everyday behavior. System design should connect simple logging with visible trends, accessible explanation, and provider-supported follow-up so that usefulness can be reinforced over time.

5.5. Limitations

The convenience sample and cross-sectional survey limit causal inference and statistical generalization. Behavioral intention was self-reported and did not measure back-end use logs or clinical outcomes. The platform pilot used manual rather than device-integrated data capture, so usability results should inform the design of automated sensing modules only after they are separately evaluated. Although the study included three LMIC settings, local variation in infrastructure, service organization, and culture remains substantial. Future longitudinal deployments should link platform analytics, blood-pressure and glycemic outcomes, implementation costs, and user-experience measures. They should also test an offline-first baseline against caregiver-supported onboarding and device-integration variants, using common measures of completion, synchronization delay, provider response time, and sustained monthly use.

6. CONCLUSION

This study combined TAM-based SEM with CFIR-guided interviews to identify the technical and contextual

determinants of digital health engagement in chronic disease care across three LMIC settings. Perceived usefulness and ease of use significantly predicted behavioral intention, and the joint display showed why these perceptions translated unevenly into practice. The engineering contribution is a deployment model centered on low-burden manual entry, immediate feedback, SMS fallback, secure asynchronous provider messaging, and support for family-assisted use.

For resource-constrained health systems, effective chronic-care platforms must be designed as socio-technical infrastructure rather than as stand-alone applications. The reported findings support offline-capable, low-data, low-literacy, and human-supported architectures that can improve the feasibility of equitable digital chronic disease management.

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REFERENCES

- [1] World Health Organization, "Noncommunicable diseases," Fact sheet, Sep. 2023. [Online]. Available: <https://www.who.int/news-room/fact-sheets/detail/noncommunicable-diseases>
- [2] L. N. Allen, S. Wigley, H. Holmer, and P. Barlow, "Non-communicable disease policy implementation from 2014 to 2021: A repeated cross-sectional analysis of global policy data for 194 countries," *Lancet Global Health*, vol. 11, no. 4, pp. e525–e533, 2023, doi: 10.1016/S2214-109X(23)00042-6.
- [3] World Health Organization, *Global Strategy on Digital Health 2020–2025*. Geneva, Switzerland: WHO, 2021. [Online]. Available: <https://www.who.int/publications/i/item/9789240020924>
- [4] A. Makri, "Bridging the digital divide in health care," *Lancet Digital Health*, vol. 1, no. 5, pp. e204–e205, 2019, doi: 10.1016/S2589-7500(19)30111-6.
- [5] H. Ibrahim, X. Liu, N. Zariffa, A. D. Morris, and A. K. Denniston, "Health data poverty: An assailable barrier to equitable digital health care," *Lancet Digital Health*, vol. 3, no. 4, pp. e260–e265, 2021, doi: 10.1016/S2589-7500(20)30317-4.
- [6] S. Xiong et al., "Digital health interventions for non-communicable disease management in primary health care in low- and middle-income countries," *npj Digit. Med.*, vol. 6, no. 1, Art. no. 12, 2023, doi: 10.1038/s41746-023-00764-4.
- [7] K. Bobrow et al., "Mobile phone text messages to support treatment adherence in adults with high blood pressure (SMS-Text Adherence Support [StAR]): A single-blind, randomized trial," *Circulation*, vol. 133, no. 6, pp. 592–600, 2016, doi: 10.1161/CIRCULATIONAHA.115.017530.
- [8] K. Stokes, B. Oronti, F. P. Cappuccio, and L. Pecchia, "Use of technology to prevent, detect, manage and control hypertension in sub-Saharan Africa: A systematic review," *BMJ Open*, vol. 12, no. 4, Art. no. e058840, 2022, doi: 10.1136/bmjopen-2021-058840.
- [9] A. Ramachandran et al., "Effectiveness of mobile phone messaging in prevention of type 2 diabetes by lifestyle modification in men in India: A prospective, parallel-group, randomised controlled trial," *Lancet Diabetes Endocrinol.*, vol. 1, no. 3, pp. 191–198, 2013, doi: 10.1016/S2213-8587(13)70067-6.
- [10] B. Jeffrey et al., "Mobile phone applications and their use in the self-management of type 2 diabetes mellitus: A qualitative study among app users and non-app users," *Diabetol. Metab. Syndr.*, vol. 11, Art. no. 84, 2019, doi: 10.1186/s13098-019-0480-4.
- [11] S. S. Kaboré et al., "Barriers and facilitators for the sustainability of digital health interventions in low and middle-income countries: A systematic review," *Front. Digit. Health*, vol. 4, Art. no. 1014375, 2022, doi: 10.3389/fgth.2022.1014375.
- [12] A. A. AlQudah, M. Al-Emran, and K. Shaalan, "Technology acceptance in healthcare: A systematic review," *Appl. Sci.*, vol. 11, no. 22, Art. no. 10537, 2021, doi: 10.3390/app112210537.
- [13] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Q.*, vol. 13, no. 3, pp. 319–340, 1989, doi: 10.2307/249008.
- [14] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS Q.*, vol. 27, no. 3, pp. 425–478, 2003, doi: 10.2307/30036540.
- [15] L. J. Damschroder, C. M. Reardon, M. A. O. Widerquist, and J. Lowery, "The updated Consolidated Framework for Implementation Research based on user feedback," *Implement. Sci.*, vol. 17, no. 1, Art. no. 75, 2022, doi: 10.1186/s13012-022-01245-0.
- [16] J. Li, A. Talaei-Khoei, H. Seale, P. Ray, and C. R. MacIntyre, "Health care provider adoption of eHealth: Systematic literature review," *Interact. J. Med. Res.*, vol. 2, no. 1, Art. no. e7, 2013, doi: 10.2196/ijmr.2468.
- [17] J. W. Creswell and V. L. Plano Clark, *Designing and Conducting Mixed Methods Research*, 3rd ed. Thousand Oaks, CA, USA: SAGE, 2017.
- [18] V. Braun and V. Clarke, "Using thematic analysis in psychology," *Qual. Res. Psychol.*, vol. 3, no. 2, pp. 77–101, 2006, doi: 10.1191/1478088706qp063oa.
- [19] C. Pong, R. M. W. W. Tseng, Y. C. Tham, and E. Lum, "Current implementation of digital health in chronic disease management: Scoping review," *J. Med. Internet Res.*, vol. 26, Art. no. e53576, 2024, doi: 10.2196/53576.
- [20] R. J. Holden and B.-T. Karsh, "The technology acceptance model: Its past and its future in health care," *J. Biomed. Inform.*, vol. 43, no. 1, pp. 159–172, 2010, doi: 10.1016/j.jbi.2009.07.002.
- [21] C. Duckworth et al., "Characterising user engagement with mHealth for chronic disease self-management and impact on machine learning performance," *npj Digit. Med.*, vol. 7, no. 1, Art. no. 66, 2024, doi: 10.1038/s41746-024-01063-2.
- [22] J. J. Nathan et al., "Scaling digital health in low- and middle-income countries: Lessons from Malaysia's cross-sector capacity-building approach," *J. Glob. Health*, vol. 15, Art. no. 03044, 2025, doi: 10.7189/jogh.15.03044.
- [23] B. Sylla, O. Ismaila, and G. Diallo, "25 years of digital health toward universal health coverage in low- and middle-income countries: Rapid systematic review," *J. Med. Internet Res.*, vol. 27, Art. no. e59042, 2025, doi: 10.2196/59042.
- [24] A. B. Labrique et al., "Best practices in scaling digital health in low and middle income countries," *Glob. Health*, vol. 14, no. 1, Art. no. 103, 2018, doi: 10.1186/s12992-018-0424-z.
- [25] A.-M. Rosland, M. Heisler, H. J. Choi, M. J. Silveira, and J. D. Piette, "Family influences on self-management among functionally independent adults with diabetes or heart failure: Do family members hinder as much as they help?" *Chronic Illn.*, vol. 6, no. 1, pp. 22–33, 2010, doi: 10.1177/1742395309354608.

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AVAILABILITY OF DATA

Not applicable.

ETHICAL STATEMENT

All participants provided written informed consent prior to participation. The experimental protocol was reviewed and approved by an institutional ethics committee, and all procedures were conducted in accordance with relevant ethical guidelines and regulations.

AUTHOR CONTRIBUTIONS

Yintong Zheng conducted the participant recruitment, survey administration, semi-structured interviews, quantitative and qualitative data analysis, mixed-methods integration, and contributed to manuscript preparation, while Haotian Ying conceived and supervised the study, designed the mixed-methods research framework and digital health intervention strategy, led the interpretation of the TAM-based structural equation modeling and CFIR-guided thematic findings, and contributed to manuscript revision and finalization.

COMPETING INTERESTS

The authors declare no competing interests.

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