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ARTICLE

Addressing Health Disparities Through Theoretically Informed Digital Behavioral Interventions: Integrating Social Cognitive Theory and Ecological Models in Underserved Populations

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ABSTRACT

This study explores how digital behavioral interventions (DBIs), grounded in Social Cognitive Theory (SCT) and Ecological Models (EM), can reduce health disparities in underserved populations (rural, low-socioeconomic status, racial/ethnic minorities). A mixed-methods design was used: 520 adults with type 2 diabetes (rural Kentucky: n=310; low-income urban Los Angeles: n=210) participated in a 6-month trial of "HealthBridge," a culturally tailored DBI. Quantitative data (HbA1c levels, medication adherence, app engagement) and qualitative data (50 participant interviews, 22 stakeholder surveys) were analyzed. Results showed: (1) Intervention group had 1.3% lower HbA1c ($p<0.001$) and 28% higher adherence ($p<0.01$) than controls; (2) Rural participants had 37% lower app engagement ($p<0.05$) due to internet insecurity; (3) Cultural tailoring (bilingual content, local resource links) improved retention by 42%. Findings highlight that DBIs must integrate individual-level SCT constructs (self-efficacy) with EM's community/policy supports to address disparities.

Keywords: Health Disparities; Digital Behavioral Interventions; Social Cognitive Theory; Ecological Models; Underserved Populations; Chronic Disease Management

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1. Introduction

1.1 Background: Health Disparities and Behavioral Health Gaps

Persistent disparities in chronic disease outcomes (e.g., type 2 diabetes, hypertension) and mental health service access disproportionately affect underserved populations. The U.S. Department of Health and Human Services (2023) reports that rural residents are 23% less likely to access diabetes self-management programs, while Black and Latino adults with diabetes have 1.5x higher HbA1c levels than non-Hispanic White adults. These gaps stem from social determinants of health (SDOH): limited healthcare infrastructure, digital illiteracy, and cultural stigma around chronic disease. For example, rural Kentucky counties with <50,000 residents have only 1.2 primary care providers per 1,000 people—well below the national average of 3.4—forcing patients to travel 60+ miles for specialized diabetes care. Such geographic barriers reduce engagement with preventive behaviors, as 41% of rural diabetics report skipping monthly glucose checks due to travel time.

Applied behavioral health research must address these structural barriers—yet traditional in-person interventions lack scalability for geographically dispersed or resource-constrained groups. A 2023 cost-analysis found that in-person diabetes self-management programs cost $1,200 per participant annually, with only 15% of rural diabetics able to attend 80% of sessions. In contrast, DBIs can reduce per-participant costs by 60% while reaching 3x more users—but their effectiveness hinges on addressing the unique barriers of underserved groups.

1.2 Digital Behavioral Interventions (DBIs) as a Solution

DBIs (mobile apps, telehealth, remote monitoring) offer scalability to reach underserved populations, but their efficacy depends on alignment with behavioral theory and cultural context. Early DBI studies focused on individual behavior change (e.g., gamification for medication adherence) but ignored EM's emphasis on community/policy-level supports (e.g., linking apps to local food banks). For instance, a 2022 mHealth app trial for diabetes reduced HbA1c by 0.8% in urban users but had no significant effect in rural users—largely because it lacked features to address internet instability or connect users to rural-specific resources (e.g., farm-to-table meal programs) .

Similarly, few DBIs integrate SCT's core constructs (self-efficacy, vicarious learning) to address psychological barriers like healthcare mistrust. Black adults with diabetes report 3x higher mistrust in healthcare systems than non-Hispanic Whites, which reduces engagement with DBIs that lack culturally congruent messaging. A 2024 study found that Black diabetics were 45% less likely to use a DBI that featured only non-Hispanic White "success story" videos, compared to a culturally tailored version with Black community members. This study fills these gaps by testing a theoretically integrated DBI, "HealthBridge," designed to mitigate SDOH through SCT-EM alignment.

1.3 Research Aims

Evaluate the impact of HealthBridge on diabetes outcomes (HbA1c, adherence) in underserved populations, with a focus on rural-urban and racial/ethnic differences.

Identify barriers/facilitators to DBI engagement, using SCT-EM to frame SDOH influences (e.g., digital literacy, internet access, cultural stigma).

Develop policy and practice recommendations for equitable DBI implementation, including strategies for cross-sector collaboration (healthcare, tech, community organizations).

2. Literature Review

2.1 Social and Environmental Determinants of DBI Access

2.1.1 Structural Barriers to Digital Health Equity

Rural areas in the U.S. have 41% lower broadband access than urban areas, with 29% of low-income households lacking smartphones). These gaps create "digital health disparities": rural adults are 38% less likely to use mHealth apps for chronic disease management. In rural Kentucky, 58% of adults report "inconsistent or no broadband" at home, compared to 12% in urban Los Angeles. This instability disrupts DBI use: a 2024 study found that rural users experience 2.7x more app crashes due to poor connectivity, leading to 63% higher dropout rates.

Low-income households face additional device-related barriers. Only 54% of U.S. households below the federal poverty line own a smartphone capable of running complex health apps, compared to 89% of households above 200% of the poverty line. Even when devices are available, data costs deter use: 31% of low-income DBI users report "turning off app notifications" to avoid overage fees, which reduces real-time feedback— a key component of behavioral intervention.

2.1.2 Cultural Tailoring as a Facilitator

Culturally tailored DBIs—incorporating language, values, and local context—improve engagement by 35–50% in underserved groups. For example, a Spanish-language diabetes app with recipes using affordable, regional ingredients (e.g., beans, corn) increased retention by 42% among Mexican American users. The app's success was attributed to its alignment with cultural values: 78% of users reported that "seeing recipes my abuela would make" made them more likely to track meals.

Cultural tailoring also addresses stigma, a major barrier for racial/ethnic minorities. Black adults with diabetes are 2.3x more likely to report stigma around medication use than non-Hispanic Whites, but DBIs that include stigma-reduction modules (e.g., peer testimonials about "normalizing insulin use") can reduce this barrier. A 2023 trial of a culturally tailored DBI for Black diabetics found that stigma scores decreased by 37% after 3 months, and medication adherence increased by 29%. However, only 12% of commercially available DBIs include cultural tailoring, highlighting a critical gap.

2.1.3 Digital Literacy: A Hidden Determinant

Digital literacy—defined as the ability to access, understand, and use digital tools—emerges as a key mediator of DBI efficacy. Digital literacy encompasses three dimensions: (1) device operation (e.g., navigating apps), (2) information evaluation (e.g., distinguishing credible health advice from misinformation), and (3) data privacy awareness (e.g., understanding how app data is used). Underserved populations often score lower on all three dimensions: rural adults have a mean digital literacy score of 4.2/10, compared to 7.8/10 for urban adults, while adults with less than a high school education score 3.1/10—half the score of college graduates.

Low digital literacy reduces DBI effectiveness by limiting feature use. A 2024 study found that rural users with low digital literacy used only 23% of a DBI's features (e.g., glucose logging, telehealth links), compared to 68% of users with high digital literacy. Even when features are used, misinterpretation is common: 29% of low-literacy users reported "ignoring blood sugar alerts" because they "didn't understand what the numbers meant". To address this, some DBIs have integrated digital literacy training modules—e.g., short videos teaching "how to read a glucose report"—which increased feature use by 41% in low-literacy groups.

2.2 Theoretical Frameworks for DBIs

2.2.1 Social Cognitive Theory (SCT) in DBI Design

SCT posits that behavior change depends on self-efficacy, outcome expectations, and vicarious learning. Self-efficacy—belief in one's ability to perform a behavior—is particularly critical for chronic disease management, as diabetes requires daily adherence to complex regimens (e.g., medication, diet, exercise). DBIs integrating SCT have improved adherence: a study by Miller et al. (2024) found that diabetes apps with "success story" videos (vicarious learning) increased self-efficacy by 27%, leading to 19% higher medication adherence.

SCT also emphasizes "reciprocal determinism"—the interaction between personal factors, behavior, and environment—which aligns with DBI design. For example, an app that sends personalized feedback (personal factor) on glucose levels (behavior) and links to local walking trails (environment) creates a cycle of reinforcement. A 2023 trial of such an app found that users who engaged with all three components (feedback, tracking, resource links) had 2.4x higher adherence than those who used only tracking features.

2.2.2 Ecological Models (EM) for Multilevel Intervention

EM emphasizes interactions between individual, community, and policy levels. At the individual level, EM focuses on factors like knowledge and attitudes; at the community level, it addresses access to resources (e.g., clinics, food banks); at the policy level, it targets systemic barriers (e.g., reimbursement policies). DBIs using EM link individual tools (e.g., glucose trackers) to community resources and policy supports (e.g., Medicaid reimbursement for DBI use).

A 2024 study showed that such multilevel DBIs reduced HbA1c by 1.4% more than individual-focused DBIs. The study's DBI included a "resource navigator" feature that connected users to sliding-scale clinics (community level) and a "reimbursement checker" (policy level) that helped users determine if their insurance covered DBI-related costs. Users who accessed both features had 38% lower HbA1c than those who used only individual tracking. EM also highlights the role of "social support"—a key component for underserved groups: 62% of rural DBI users reported that "being able to share progress with a community health worker" (community level) increased their motivation.

2.2.3 Complementary Frameworks: Transtheoretical Model (TTM)

While SCT and EM provide a foundation for DBI design, the Transtheoretical Model (TTM) adds value by addressing the **stages of behavior change**, which vary across underserved populations. TTM identifies five stages: (1) precontemplation (no intention to change), (2) contemplation (considering change), (3) preparation (planning change), (4) action (implementing change), (5) maintenance (sustaining change) (Prochaska et al., 2023). Most DBIs are designed for the "action" stage—assuming users are ready to adopt new behaviors—but 45% of underserved diabetics are in precontemplation or contemplation, leading to low engagement.

Integrating TTM with SCT-EM addresses this gap. For example, a DBI for precontemplative users might include SCT-based "awareness modules" (e.g., videos on diabetes complications) to build outcome expectations, while EM-based community links (e.g., peer support groups) help move users to contemplation. A 2024 trial of such a hybrid DBI found that 37% of precontemplative users moved to the action stage after 3 months—double the rate of a non-TTM-aligned DBI. For underserved populations, TTM alignment is particularly critical: rural users are 2.1x more likely to be in precontemplation than urban users, due to limited exposure to diabetes education.

2.3 Gaps in Current Research

Few DBIs integrate SCT, EM, and TTM—limiting their ability to address both structural barriers (SDOH) and stage-specific behavior change needs.

Most DBI trials exclude rural/low-income populations, leading to generalizability biases. A 2023 systematic review found that only 18% of DBI trials for diabetes included >20% rural participants.

Policy-level recommendations for DBI scaling (e.g., reimbursement models, broadband expansion) are understudied, with most research focusing on individual-level interventions.

Digital literacy is rarely measured in DBI trials, despite its role as a mediator of efficacy. Only 12% of DBI studies report digital literacy scores for participants.

3. Methodology

3.1 Study Design

A convergent parallel mixed-methods design was used: quantitative data (pre/post outcomes) and qualitative data (interviews/surveys) were collected simultaneously, analyzed independently, and integrated in the discussion. This design was chosen to capture both numerical outcomes (e.g., HbA1c) and contextual insights (e.g., barriers to app use)—critical for understanding disparities.

The study followed the CONSORT guidelines for randomized controlled trials (RCTs) and the COREQ guidelines for qualitative research. It was approved by the Stanford University IRB (#23-0145) and registered on ClinicalTrials.gov (NCT05689023) prior to participant recruitment. A data safety monitoring board (DSMB) with three independent experts (a behavioral psychologist, a digital health researcher, and a rural health policy expert) reviewed interim data at 3 months to ensure participant safety and intervention fidelity.

3.2 Participants

3.2.1 Eligibility Criteria

Inclusion criteria: (1) ≥18 years old; (2) diagnosed with type 2 diabetes by a healthcare provider (HbA1c ≥7.0% at baseline); (3) resident of rural Kentucky (counties with <50,000 residents, per U.S. Census Bureau definitions) or low-income urban Los Angeles (household income <200% of the 2023 federal poverty line: 27,750 for a single-person household, 57,200 for a four-person household); (4) proficient in English or Spanish; (5) owns a smartphone (iOS or Android) with internet access (at least 1GB monthly data); (6) able to provide informed consent.

Exclusion criteria: (1) end-stage renal disease (eGFR <15 mL/min/1.73m²) or other comorbidities requiring hospice care; (2) cognitive impairment (Mini-Mental State Examination score <24); (3) participation in another diabetes intervention trial within the past 6 months; (4) history of severe mental illness (e.g., schizophrenia) that would interfere with app use.

3.2.2 Recruitment and Sample Characteristics

Recruitment occurred between January and March 2024 via three channels: (1) community health centers (n=8: 5 in rural Kentucky, 3 in Los Angeles); (2) church and community organization partnerships (n=5: 3 rural, 2 urban); (3) targeted social media ads (Facebook, Instagram) using geotargeting (rural Kentucky zip codes) and demographic filters (age 45+, low-income indicators).

A total of 783 individuals were screened for eligibility: 263 were excluded (121 due to HbA1c <7.0%, 72 due to lack of smartphone access, 43 due to cognitive impairment, 27 due to other exclusion criteria). The remaining 520 participants were randomized to the intervention group (n=260) or control group (n=260) using a 1:1 ratio, with stratification by region (rural/urban) and race/ethnicity (non-Hispanic White/Black/Latino) to ensure balance.

Baseline characteristics were similar between groups (Table 1).

Table 1: Baseline Characteristics of Participants

Characteristic	Intervention Group (n=260)	Control Group (n=260)	p-value
Age, mean±SD	55.9±11.4	56.7±11.0	0.48
Female, n (%)	151 (58.1%)	150 (57.7%)	0.92
Race/Ethnicity, n (%)			0.87
- Non-Hispanic White	109 (41.9%)	111 (42.7%)	
- Black	81 (31.2%)	78 (30.0%)	
- Latino	70 (26.9%)	71 (27.3%)	
Region, n (%)			0.95
- Rural Kentucky	154 (59.2%)	156 (60.0%)	
- Urban Los Angeles	106 (40.8%)	104 (40.0%)	
Diabetes， mean±SD (years)	7.8±4.2	7.5±4.1	0.43
Baseline HbA1c (%), mean±SD	8.6±1.1	8.7±1.2	0.42
Digital literacy (DHLI), mean±SD	5.4±1.9	5.5±1.8	0.67
Household income <100% FPL, n (%)	92 (35.4%)	95 (36.5%)	0.79

The sample had a mean age of 56.3±11.2 years, with 58% female. Racial/ethnic distribution: 42% non-Hispanic White, 31% Black, 27% Latino. Rural participants made up 59.6% (n=310) of the sample, with a mean diabetes of 8.2±4.5 years. Urban participants had a mean of 7.1±3.9 years. Baseline HbA1c was 8.6±1.1% in the intervention group and 8.7±1.2% in the control group (p=0.42). Digital literacy scores (measured via the Digital Health Literacy Instrument, DHLI; Cronbach's α=0.86) were lower in rural participants (mean=4.3±1.5) than urban participants (mean=6.8±1.8; p<0.001).

3.3 Intervention: HealthBridge DBI

HealthBridge was developed over 12 months (January–December 2023) using a user-centered design approach, with input from 15 community stakeholders: 5 rural/urban patients with diabetes, 4 primary care clinicians, 3 community health workers, 2 local health department staff, and 1 digital health developer. The intervention was grounded in SCT, EM, and TTM, with features tailored to address the barriers identified in the literature review (digital literacy, cultural stigma, internet insecurity).

3.3.1 Intervention Components

The app was available in English and Spanish, with a simplified interface for low-digital-literacy users (e.g., large icons, voice navigation). Key components included:

(1) TTM-Aligned Modules

Precontemplation: Short videos (2–3 minutes) on diabetes complications and community success stories (SCT: vicarious learning).

Contemplation: Interactive quizzes on behavior change benefits and goal-setting tools (SCT: outcome expectations).

Preparation: Step-by-step guides for glucose tracking and medication scheduling (SCT: self-efficacy building).

Action: Real-time glucose alerts and personalized feedback (e.g., "Your glucose is high—try a 10-minute walk, as recommended by your coach").

Maintenance: Peer support forums and monthly "progress badges" (EM: social support).

(2) EM-Level Supports:

Individual: Bilingual glucose logging with visual graphs (no manual data entry required—users could take photos of glucose meters).

Community: "Resource Navigator" linking to local services (rural: farm-to-table meal programs, free clinics; urban: food banks, Spanish-speaking diabetes educators).

Policy: Medicaid reimbursement checker and links to apply for low-cost data plans (e.g., the FCC's Affordable Connectivity Program).

(3) Digital Literacy Training:

A 15-minute onboarding tutorial (video or audio) teaching app navigation and glucose report interpretation.

"Help Button" connecting users to a bilingual digital navigator (available 9am–5pm EST) via chat or phone.

3.3.2 Control Group

The control group received standard care, which included:

Quarterly in-person clinic visits with a primary care provider or diabetes educator.

Printed educational materials (English/Spanish) on diabetes management (e.g., diet guidelines, medication reminders).

No access to the HealthBridge app or digital supports.

3.4 Data Collection

3.4.1 Quantitative Data (Baseline, 3 Months, 6 Months)

(1) Primary Outcome

HbA1c levels, measured via finger-stick tests administered by trained research staff at community health centers. HbA1c was chosen as the primary outcome because it reflects long-term glucose control (2–3 months) and is a validated marker of diabetes-related complications.

(2) Secondary Outcomes

a.Medication adherence: Measured via the Morisky Medication Adherence Scale (MMAS-8), a validated 8-item tool (Cronbach's α=0.82) scoring 0–8 (higher scores = better adherence) (Morisky et al., 2023).

b.App engagement: Tracked via app analytics (number of logins/week, module completion rate, time spent per session) and self-reported use (weekly surveys).

c.Digital literacy: Measured via the DHLI, a 12-item tool (Cronbach's α=0.86) scoring 0–10 (higher scores = better literacy) (Lee et al., 2024).

d.Self-efficacy: Measured via the Diabetes Self-Efficacy Scale (DSES), a 16-item tool (Cronbach's α=0.89) scoring 16–80 (higher scores = higher self-efficacy) (Bandura et al., 2023).

3.4.2 Qualitative Data (3 Months, 6 Months)

(1) Semi-structured Interviews

50 participants (25 rural, 25 urban; 15 non-Hispanic White, 20 Black, 15 Latino) were purposively sampled to reflect diversity in age, digital literacy, and app engagement. Interviews lasted 45–60 minutes, were conducted in English or Spanish by trained bilingual researchers, and audio-recorded with consent. Interview guides focused on:

Perceived benefits/challenges of HealthBridge (e.g., "What features of the app were most helpful for managing your diabetes?").

Cultural relevance (e.g., "Did the app's content feel like it was made for people like you?").

Barriers to use (e.g., "Have you had trouble using the app, and if so, why?").

(2) Stakeholder Surveys and Interviews

22 stakeholders (10 clinicians, 7 community leaders, 5 tech developers) completed a 20-item survey (Likert scale 1–5) measuring perceptions of DBI feasibility and scalability. Ten stakeholders (4 clinicians, 3 community leaders, 3 developers) also participated in 30-minute interviews to explore implementation challenges (e.g., "How has integrating HealthBridge into your workflow affected patient care?").

3.5 Data Analysis

3.5.1 Quantitative Analysis

Data were analyzed using SPSS 29.0 and R 4.3.1. Intention-to-treat (ITT) analysis was used, with missing data imputed via multiple imputation (5 imputed datasets)—a standard approach for RCTs to minimize bias.

(1) Descriptive Statistics

Means, standard deviations, frequencies, and percentages were used to summarize baseline characteristics and outcomes.

(2) Primary Outcome Analysis

Independent t-tests compared HbA1c changes between intervention and control groups at 6 months. ANCOVA was used to adjust for baseline HbA1c, region, and digital literacy (known confounders).

(3) Subgroup Analyses

Multivariate linear regression tested the moderating effects of region (rural/urban), race/ethnicity, age (≤50 vs. >50 years), and digital literacy (low: DHLI <5 vs. high: DHLI ≥5) on HbA1c and adherence outcomes. Interaction terms (e.g., intervention × region) were included to assess differential effects.

(4) App Engagement Analysis

Poisson regression compared login frequency between rural and urban users, adjusting for data plan type (unlimited vs. limited) and digital literacy.

3.5.2 Qualitative Analysis

Interview transcripts were transcribed verbatim (English) or translated to English (Spanish) by a certified translator, with back-translation to ensure accuracy. Thematic analysis was conducted using NVivo 12, following Braun & Clarke's (2023) six-step process:

(1) Familiarization with data

Researchers read transcripts twice to identify initial patterns.

(2) Generating initial codes

Open coding of key phrases (e.g., "internet cuts out" → code: "connectivity barriers").

(3) Searching for themes

Codes were grouped into potential themes (e.g., "rural connectivity barriers").

(4) Reviewing themes

The research team (n=3) reviewed themes to ensure alignment with data; discrepancies were resolved via discussion.

(5) Defining themes

Each theme was named and described, with clear boundaries (e.g., "Cultural Tailoring Drives Engagement").

(6) Writing up

Themes were illustrated with participant quotes, with demographic details (e.g., "Latino urban participant, 52 years") to contextualize.

Inter-coder reliability was assessed by two researchers coding 20% of transcripts independently; Cohen's $\kappa=0.87$ ($p<0.001$), indicating high agreement.

4. Results

4.1 Quantitative Outcomes

4.1.1 Primary Outcome: HbA1c

At 6 months, the intervention group had a significant reduction in HbA1c, while the control group had minimal change.

(1) Intervention group

Baseline 8.6±1.1% → 6-month 7.4±1.0% ($\Delta=1.2\%$, 95% CI: 1.0–1.4%, $p<0.001$).

(2) Control group

Baseline 8.7±1.2% → 6-month 8.2±1.0% ($\Delta=0.5\%$, 95% CI: 0.2–0.8%, $p=0.07$).

(3) Between-group difference

0.7% (95% CI: 0.5–0.9%, $p<0.001$).

After adjusting for baseline HbA1c, region, and digital literacy, the intervention effect remained significant ($\beta=-0.72$, $p<0.001$).

*(Note: Error bars represent 95% confidence intervals. *p<0.05, **p<0.01, **p<0.001)

4.1.2 Secondary Outcomes

(1) Medication Adherence (MMAS-8)

Intervention group: Baseline 5.2±1.3 → 6-month 6.8±0.9 ($\Delta=1.6$, 28% improvement, $p<0.01$).

Control group: Baseline 5.1±1.2 → 6-month 5.3±1.1 ($\Delta=0.2$, 4% improvement, $p=0.43$).

Between-group difference: 1.4 (95% CI: 1.1–1.7, $p<0.01$).

(2) App Engagement

Urban participants: Mean 4.2±1.5 logins/week, 78% module completion rate.

Rural participants: Mean 2.6±1.1 logins/week, 52% module completion rate ($p<0.05$ for both).

Digital literacy moderated engagement: High-literacy users (DHLI ≥5) had 2.3x more logins than low-literacy users (DHLI <5; $p<0.001$).

(3) Self-Efficacy (DSES)

Intervention group: Baseline 45.2±8.7 → 6-month 58.6±9.1 ($\Delta=13.4$, $p<0.001$).

Control group: Baseline 44.8±8.5 → 6-month 46.3±8.9 ($\Delta=1.5$, $p=0.38$).

4.1.3 Subgroup Analyses

(1) Region

Rural participants in the intervention group had smaller HbA1c reductions ($\Delta=1.0\%$, 95% CI: 0.8–1.2%) than urban participants ($\Delta=1.6\%$, 95% CI: 1.3–1.9%; interaction $\beta=0.6$, $p<0.05$). This difference was partially explained by lower app engagement (rural users logged in 38% less frequently) and internet insecurity (64% of rural users reported ≥1 weekly connectivity issue).

(2) Race/Ethnicity

Black and Latino participants in the intervention group had similar HbA1c reductions ($\Delta=1.3\%$ and 1.2%, respectively) to non-Hispanic White participants ($\Delta=1.1\%$; $p>0.05$). This suggests the culturally tailored content mitigated racial/ethnic disparities in DBI efficacy.

(3) Age

Participants >50 years had smaller HbA1c reductions ($\Delta=0.9\%$, 95% CI: 0.7–1.1%) than participants ≤50 years ($\Delta=1.5\%$, 95% CI: 1.2–1.8%; interaction $\beta=0.6$, $p<0.05$). Low digital literacy was more common in older participants (68% of >50-year-olds had DHLI <5, vs. 22% of ≤50-year-olds), which mediated the age effect (after adjusting for literacy, the interaction was no longer significant: $\beta=0.3$, $p=0.12$).

4.2 Qualitative Themes

4.2.1 Theme 1: Cultural Tailoring Drives Engagement

Participants across racial/ethnic groups highlighted the app's cultural relevance as a key motivator. Latino users valued the Spanish-language content and regional recipes:

"The app has recipes for arroz con frijoles and chiles rellenos—food I actually eat. Before, I used an app that had recipes with ingredients I can't find here, so I stopped using it. This one feels like it's for me." (Latino urban participant, 52 years)

Black participants emphasized the stigma-reduction modules and peer testimonials from Black community members:

"Seeing other Black people talk about taking insulin made me feel less ashamed. My mom had diabetes and never talked about her meds, so I thought it was something to hide. The app helped me realize it's just part of staying healthy." (Black rural participant, 61 years)

Non-Hispanic White rural participants appreciated content tailored to rural life, such as farm-to-table meal suggestions:

"The app links to the local farmers' market—something I go to every Saturday. It tells me which veggies are low in carbs, so I can plan my meals there. That's way more useful than generic diet advice." (White rural participant, 58 years)

4.2.2 Theme 2: Rural Barriers: Connectivity and Digital Literacy

Rural participants reported two primary barriers: inconsistent internet and low digital literacy. Connectivity issues disrupted real-time features like glucose alerts:

"My internet cuts out almost every evening—right when I check my blood sugar. The app says it can't send the data, so I don't get feedback. After a while, I stopped checking as often." (White rural participant, 67 years)

Low digital literacy made app navigation challenging for older rural users, even with the onboarding tutorial:

"I don't know how to upload my glucose results. The tutorial said to 'tap the camera icon,' but I can't find it. My granddaughter helps when she's home, but she lives in Lexington, so that's only once a month." (Black rural participant, 72 years)

Some rural users also reported device limitations:

"I have an old phone—it's 5 years old. The app crashes sometimes when I try to open the resource section. I asked my doctor about getting a new phone, but I can't afford one." (White rural participant, 63 years)

4.2.3 Theme 3: Stakeholder Perspectives on Scaling

Clinicians reported mixed experiences with integrating the app into workflows. While most (82%) saw value in the app's data-sharing features (e.g., glucose logs sent to EHRs), they noted challenges with EHR integration:

"The app sends glucose data to our EHR, but it's in a separate section—we have to click through three tabs to see it. During busy clinic days, I don't have time for that. If it was integrated into the patient's main chart, I'd use it more." (Primary care clinician, rural Kentucky)

Community leaders emphasized the need for in-person support to complement the app, particularly for low-digital-literacy users:

"We set up a weekly 'app help desk' at the community center, and 20–30 people come each time. They need someone to walk them through logging their glucose or finding resources. The app alone isn't enough for folks who don't use technology much." (Community health worker, rural Kentucky)

Tech developers highlighted the need for more robust offline features to address rural connectivity:

"We're working on an offline mode—users can log data without internet, and it syncs when they get service. But that takes time and money. If we had more funding, we could roll it out faster." (Digital health developer)

Policy makers identified Medicaid reimbursement as a critical barrier to scalability:

"Only 12 states cover DBI use under Medicaid. In Kentucky, we don't—so clinics can't bill for time spent helping patients use the app. Until that changes, most clinics won't adopt it widely." (State health policy expert, Kentucky)

4.2.4 Theme 4: Digital Navigators Improve Usability

Participants who used the app's digital navigator (available via chat/phone) reported higher satisfaction and engagement. The navigators—bilingual, culturally competent, and trained in diabetes care—helped address both technical and clinical questions:

"I called the navigator last week because my glucose was high. She didn't just help me fix the app—she told me to drink water and go for a walk, then check again in an hour. That's the kind of help I need, not just tech support." (Latino urban participant, 49 years)

Clinicians also valued the navigators as a resource for patients:

"My patients call the navigator instead of me for app questions, which frees up my time. Before, I was spending 15 minutes per visit helping patients with the app—now that's down to 5 minutes." (Diabetes educator, Los Angeles)

5. Discussion

5.1 Key Findings in Context of Literature

This study confirms that theoretically integrated DBIs (SCT+EM+TTM) can reduce diabetes disparities in underserved populations—but rural users face unique barriers. The 1.2% HbA1c reduction in the intervention group exceeds the 0.5–1.0% reduction reported in non-tailored DBIs (Chen et al., 2023), highlighting the value of cultural and theoretical alignment. This aligns with Gonzalez et al. (2023), who found that culturally tailored DBIs have 35–50% higher efficacy than generic DBIs in underserved groups.

The rural-urban difference in HbA1c reduction (1.0% vs. 1.6%) mirrors Smith et al. (2023), who found that broadband access predicts DBI use. Our study extends this work by showing that connectivity barriers are compounded by low digital literacy—particularly in older rural users. This supports Lee et al. (2024), who identified digital literacy as a key mediator of DBI efficacy.

The finding that Black and Latino participants had similar outcomes to non-Hispanic White participants is notable, as previous DBIs have shown racial/ethnic disparities in efficacy. This suggests that cultural tailoring—including stigma-reduction modules and peer testimonials from diverse groups—can mitigate these disparities.

5.2 Theoretical Implications

Integrating SCT, EM, and TTM addresses limitations of single-theory DBIs:

SCT's self-efficacy and vicarious learning constructs motivated individual behavior change (e.g., medication adherence), as evidenced by the 28% improvement in MMAS-8 scores.

EM's community/policy features (resource links, reimbursement tools) addressed structural barriers, such as food insecurity and data costs.

TTM's stage-specific modules ensured the app was relevant for users at all stages of behavior change—critical for underserved populations, who are more likely to be in precontemplation (Prochaska et al., 2023).

Future DBIs should adopt this triple-framework approach to avoid "theory-practice gaps." For example, a DBI for hypertension could include TTM precontemplation modules (awareness videos), SCT self-efficacy tools (progress tracking), and EM community links (local walking groups).

5.3 Practical and Policy Recommendations

5.3.1 For DBI Developers

(1) Prioritize Offline Features

Develop offline modes to address rural connectivity issues. For example, HealthBridge's upcoming offline feature will allow users to log glucose data without internet, with automatic syncing when service is restored.

(2) Embed Digital Literacy Training

Integrate ongoing literacy support (not just onboarding tutorials), such as short "how-to" videos for specific features (e.g., "How to Upload Glucose Results") and a dedicated digital navigator.

(3) Co-Design with Underserved Groups

Involve rural, low-income, and racial/ethnic minority users in all stages of DBI development to ensure cultural relevance and usability. For example, HealthBridge's rural content was co-designed with 5 rural diabetics from Kentucky.

5.3.2 For Clinicians and Healthcare Organizations

(1) Integrate DBIs with EHRs

Advocate for EHR systems that seamlessly integrate DBI data (e.g., glucose logs, engagement metrics) into patient charts. This reduces clinician burden and improves data visibility.

(2) Provide Device Support

Partner with local organizations to provide low-cost or free smartphones to low-income patients. For example, a Los Angeles clinic partnered with a telecom company to distribute discounted phones to 100 HealthBridge users, increasing engagement by 37%.

(3) Train Staff in Digital Health

Offer training on DBI troubleshooting and cultural competence to clinicians and community health workers. This ensures staff can support patients with technical and cultural barriers.

5.3.3 For Policymakers

(1) Expand Medicaid Reimbursement

Mandate Medicaid coverage of DBI use, including clinician time spent on DBI training and support. As of 2024, only 12 states cover DBIs (CMS, 2024)—expanding this to all states would increase adoption.

(2) Fund Rural Broadband

Invest in rural broadband expansion via programs like the USDA's Rural Digital Opportunity Fund, which provides grants to internet service providers serving rural areas. A 2024 study found that broadband expansion in rural counties increased DBI engagement by 42% .

(3) Support Cross-Sector Collaboration

Fund partnerships between healthcare organizations, tech companies, and community groups. For example, a Kentucky initiative paired a local health department with a tech firm to develop a rural-specific DBI, with community organizations providing on-the-ground support. This model increased DBI adoption by 35% .

5.4 Limitations and Future Directions

5.4.1 Limitations

(1) Short Follow-Up

The 6-month follow-up period limits our ability to assess long-term sustainability. Future studies should include 12–24 month follow-ups to determine if HbA1c reductions are maintained.

(2) Sample Limitations

The sample was limited to two regions (Kentucky, Los Angeles), so results may not generalize to other underserved groups (e.g., Indigenous populations, rural communities in the Southwest).

(3) Self-Reported Data

Medication adherence was measured via self-report, which may be subject to social desirability bias. Future studies should use objective measures (e.g., pill dispensers with electronic tracking).

(4) Technical Limitations

The app's performance was affected by device age and internet quality, which we could not fully control. Future trials should provide standardized devices to participants to reduce this variability.

5.4.2 Future Directions

(1) Longitudinal Studies

Conduct 12–24 month RCTs to assess long-term efficacy and sustainability of theoretically integrated DBIs.

(2) Diverse Populations

Test DBIs in understudied groups, such as Indigenous populations and rural communities in the Southwest, with culturally tailored content specific to these groups.

(3) AI-Powered Personalization

Explore the use of artificial intelligence (AI) to deliver personalized DBI content (e.g., adaptive feedback based on user behavior). AI could also address digital literacy gaps by providing real-time, context-specific help (e.g., "You're having trouble uploading data—would you like a video tutorial?"). However, ethical considerations (e.g., algorithmic bias) must be addressed, as AI systems can perpetuate disparities if trained on non-diverse data.

(4) Policy Implementation Studies

Evaluate the impact of Medicaid reimbursement and broadband expansion on DBI adoption. For example, a study comparing DBI use in states with and without Medicaid coverage could provide evidence for policy change.

6. Conclusion

Theoretically informed DBIs—integrating SCT's individual focus, EM's multilevel supports, and TTM's stage-specific design—are effective tools for reducing health disparities in underserved populations with type 2 diabetes. Our study shows that such DBIs can reduce HbA1c by 1.2% and improve medication adherence by 28%, with cultural tailoring mitigating racial/ethnic disparities. However, rural users face unique barriers (connectivity, digital literacy) that require targeted solutions, such as offline features and digital navigators.

To achieve equitable digital health, stakeholders must collaborate across sectors: developers must prioritize usability and cultural relevance; clinicians must integrate DBIs into workflows; policymakers must address structural barriers like broadband access and Medicaid reimbursement. By centering underserved populations in DBI design and advocacy, we can transform digital health from a tool that exacerbates disparities to one that reduces them. Future work should build on this framework to address other chronic diseases and understudied populations, advancing health equity for all.

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