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Role of Digital Health Technologies in Improving Chronic Disease Management: An Interdisciplinary Study of Clinical Care, Patient Behaviour and Healthcare Accessibility

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ABSTRACT: Background: Chronic diseases require continuous monitoring, adherence and regular clinical contact, which many patients, particularly rural patients, struggle to obtain.

Objective: This study examined how digital health technologies (DHTs) relate to clinical outcomes, patient behaviour and healthcare accessibility among adults with type 2 diabetes mellitus and/or hypertension.

Methods: A hospital-based analytical cross-sectional study was conducted among 420 adults using a structured questionnaire (eHealth Literacy Scale, perceived usefulness, perceived accessibility and Medication Adherence Report Scale) linked to clinical records of glycated haemoglobin (HbA1c) and blood pressure. Analyses included chi-square tests, Welch t-tests, ANOVA, correlation, linear and logistic regression and bootstrapped mediation.

Results: Overall, 60.5% of participants used at least one DHT. Use was lower among rural (45.6%) than urban (71.7%) patients, declined with age and rose with education and income (all $p < 0.01$). Users reported higher digital health literacy, perceived accessibility and medication adherence (Cohen's d 0.72–0.97) and had lower HbA1c (7.79% vs 8.27%, $p < 0.001$); the difference in systolic blood pressure was not significant ($p = 0.081$). High-intensity use independently predicted adherence ($\beta = 0.26$, $p < 0.001$). Adherence mediated 55% of the association between DHT use and HbA1c (indirect effect −0.288; 95% CI −0.430 to −0.164).

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Conclusions: DHTs appear to improve chronic disease control mainly through patient adherence and access, but benefits are unevenly distributed across the digital divide. [Simulated values — replace.]

INTRODUCTION

Chronic non-communicable diseases (NCDs), led by cardiovascular disease, diabetes, chronic respiratory disease and cancer, are the dominant cause of death worldwide. They accounted for an estimated 43 million deaths in 2021, about three-quarters of all non-pandemic deaths, and a disproportionate share occurred in low- and middle-income countries (WHO, 2024). India carries a particularly heavy and rising metabolic burden: the nationally representative ICMR–INDIAB study estimated that 11.4% of Indian adults have diabetes and 35.5% have hypertension, with substantial undiagnosed and uncontrolled disease (Anjana et al., 2023). Unlike acute illness, these conditions are managed over decades. Good outcomes depend less on episodic hospital encounters than on the day-to-day behaviour of patients, continuous monitoring of clinical markers, and timely adjustment of therapy by clinicians (Wagner, 1998).

Digital health technologies (DHTs) are a broad family that includes teleconsultation, mobile health (mHealth) applications, connected home-monitoring devices and automated text-message reminders. They have been promoted as a way to extend chronic care beyond clinic walls. The World Health Organization's *Global Strategy on Digital Health 2020–2025* frames DHTs as tools for universal health coverage (WHO, 2021). The COVID-19 pandemic then accelerated their adoption at a pace that would previously have taken years (Keesara et al., 2020). In India, the national telemedicine service eSanjeevani had served more than 10 crore (100 million) patients by early 2023 (PIB, 2023), operating under the national Telemedicine Practice Guidelines (MoHFW, 2020).

Evidence of clinical benefit is encouraging but uneven. Meta-analyses report modest but clinically meaningful reductions in HbA1c with mobile phone applications for diabetes (Hou et al., 2016; Kitsiou et al., 2017). Text-message interventions roughly double the odds of medication adherence in chronic disease (Thakkar et al., 2016), and self-monitoring of blood pressure lowers blood pressure when combined with co-interventions such as clinician-led titration (Tucker et al., 2017; McManus et al., 2018). Telehealth also appears to improve patient satisfaction and convenience (Kruse et al., 2017). However, large pragmatic trials in low-resource settings have not always reproduced these effects: the mWellcare cluster-randomised trial in India found no significant improvement in blood pressure or HbA1c with an mHealth decision-support system in primary care (Prabhakaran et al., 2019). A systematic meta-review likewise concluded that telehealth benefits depend heavily on the condition, the intervention components and the context of delivery (Hanlon et al., 2017).

Part of this inconsistency arises because the effect of a DHT is not purely technological. Whether a technology improves outcomes depends on at least three interacting domains, which are usually studied in isolation. (i) **Clinical care:** the capacity of DHTs to support monitoring, follow-up and treatment adjustment. (ii) **Patient behaviour:** whether patients have the digital health literacy (Norman and Skinner, 2006), perceived usefulness (Davis, 1989; Venkatesh et al., 2003) and self-efficacy (Bandura, 1977) to adopt DHTs and translate them into sustained self-management (Michie et al., 2011). (iii) **Healthcare accessibility:** whether DHTs reduce the geographic, financial and temporal barriers that determine whether care can be reached at all (Penchansky and Thomas, 1981; Levesque et al., 2013). Socio-technical frameworks such as NASSS further warn that technologies which work in one population may be abandoned or never adopted in another (Greenhalgh et al., 2017). This raises the risk that DHTs widen, rather than narrow, the gap between advantaged and disadvantaged patients.

Few studies from India have examined these three domains together, linked to objectively measured clinical outcomes, in the same patient population. The present study therefore adopted an interdisciplinary framework (Figure 1) with the following objectives: (1) to determine the extent and pattern of DHT use among adults with type 2 diabetes mellitus (T2DM) and/or hypertension, and its socio-demographic determinants; (2) to compare digital health literacy, perceived accessibility, medication adherence and clinical control between DHT users and non-users, and across levels of use intensity; (3) to identify independent predictors of medication adherence, accessibility and disease control; and (4) to test whether medication adherence mediates the association between DHT use and clinical outcomes. We hypothesised that DHT use would be associated with better adherence, accessibility and clinical control (H1); that these associations would follow a dose–response gradient with intensity

of use (H2); that adherence would mediate the association between DHT use and clinical outcomes (H3); and that DHT uptake would be socially patterned by age, residence, education and income (H4).

MATERIALS AND METHODS

Study Design and Setting

A hospital-based analytical cross-sectional study was conducted in the outpatient non-communicable disease clinics of [name of tertiary-care hospital] and [number] affiliated urban and rural primary health centres in [district, state], India, between [month year] and [month year]. The study is reported in accordance with the STROBE statement for observational studies (von Elm et al., 2007).

Participants and Sample Size

Adults aged 30 years or older with a physician-confirmed diagnosis of T2DM and/or hypertension for at least 6 months, receiving follow-up at the study sites, were eligible. Patients with type 1 or gestational diabetes, secondary hypertension, cognitive impairment that precluded interview, or acute illness requiring admission were excluded. The minimum sample size was calculated with Cochran's formula for a proportion (Cochran, 1977), $n = Z^2p(1 - p)/d^2$, assuming $p = 0.50$ (maximum variability for the unknown prevalence of DHT use), a 95% confidence level ($Z = 1.96$) and an absolute precision of 5%. This gave 384 participants, increased to 423 to allow for 10% non-response. A post hoc check in G*Power logic (Faul et al., 2007) confirmed that the analysed sample of 420 provides 91% power to detect a small effect ($f^2 = 0.05$) in a multiple regression with nine predictors at $\alpha = 0.05$; 322 participants would have been sufficient for 80% power. Participants were recruited by systematic random sampling (every [k]th eligible patient on the daily OPD register) until the target was reached.

Study Instrument

Data were collected by trained investigators through a face-to-face interview using a pre-tested, structured, bilingual ([English/regional language]) questionnaire (Appendix A), translated and back-translated and piloted on 30 patients who were excluded from the final analysis. The instrument had six parts:

(A) Socio-demographic and clinical profile: age, sex, residence (urban/rural), education, monthly household income category, condition (T2DM, hypertension or both), disease duration and smartphone ownership.

(B) DHT use: use in the preceding 6 months of four modalities, namely teleconsultation (video/audio), mHealth applications, connected remote-monitoring devices (glucometer/blood-pressure monitor) and SMS/WhatsApp medication or appointment reminders. Participants using any modality were classed as *DHT users*. Intensity of use was categorised as *none*, *low* (occasional use, less than weekly engagement with any modality) or *high* (at least weekly engagement, or use of a remote-monitoring device shared with the care team).

(C) Digital health literacy: the 8-item eHealth Literacy Scale, eHEALS (Norman and Skinner, 2006), scored 1–5 per item (total 8–40).

(D) Perceived usefulness of DHTs: 4 items adapted from the Technology Acceptance Model (Davis, 1989), scored 1–5 (total 4–20).

(E) Perceived healthcare accessibility: 5 items constructed from the patient-centred access framework of Levesque et al. (2013), covering ability to reach care, travel burden, cost, waiting time and continuity of contact, scored 1–5 (total 5–25).

(F) Medication adherence: the 5-item Medication Adherence Report Scale, MARS-5 (Chan et al., 2020), scored 1–5 (total 5–25; higher scores indicate better adherence). Participants also reported the one-way travel time to their usual clinic and the number of unplanned (unscheduled or emergency) health-facility visits in the previous 12 months.

Clinical Outcome Measures

The most recent HbA1c value (within the previous 3 months, measured by HPLC in the hospital laboratory) was abstracted from medical records for participants with T2DM. For participants with hypertension, blood pressure was measured by the investigator with a validated automated oscillometric device after 5 minutes of seated rest; the mean of two readings taken 1

minute apart was recorded. Glycaemic control was defined as HbA1c < 7.0% (ADA Professional Practice Committee, 2025), and blood-pressure control as < 140/90 mmHg (Williams et al., 2018).

Statistical Analysis

Data were entered in Microsoft Excel, double-checked, and analysed in [IBM SPSS Statistics version XX / R version X.X; the analysis script supplied with this manuscript reproduces every table in Python 3 with NumPy and SciPy]. Categorical variables are presented as frequencies and percentages; continuous variables as mean ± standard deviation (SD) or median (interquartile range, IQR) according to distribution. Internal consistency of each multi-item scale was assessed with Cronbach's α (Cronbach, 1951), with $\alpha \geq 0.70$ considered acceptable. Sampling adequacy and factorability were assessed with the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity (Kaiser, 1974).

Associations between socio-demographic characteristics and DHT use were tested with Pearson's chi-square test, with Cramér's V as the effect size. Continuous outcomes were compared between users and non-users with Welch's independent-samples *t*-test (not assuming equal variances), with Cohen's *d* as the effect size (Cohen, 1988); the skewed count of unplanned visits was compared with the Mann–Whitney *U* test. Differences across the three intensity groups were tested with one-way ANOVA, with Levene's test for homogeneity of variance, Tukey's HSD post hoc comparisons and eta-squared (η^2) as the effect size. Pearson's correlation, or Spearman's ϱ for the ordinal intensity variable, was used to examine bivariate relationships.

Multiple linear regression (enter method) identified independent predictors of medication adherence and perceived accessibility. Assumptions were checked with variance inflation factors (VIF < 5), the Durbin–Watson statistic and residual plots (Hair et al., 2019; Tabachnick and Fidell, 2019). Binary logistic regression estimated adjusted odds ratios (AORs) with 95% confidence intervals (CIs) for glycaemic control and blood-pressure control. Model fit was assessed with the likelihood-ratio χ^2, Nagelkerke R^2, the Hosmer–Lemeshow test and the area under the ROC curve (AUC) (Hosmer et al., 2013). Finally, a simple mediation model (Hayes, 2018; model 4) tested whether medication adherence mediated the association between DHT use and each clinical outcome, adjusting for age, disease duration and residence. The indirect effect was tested with 5,000 non-parametric bootstrap resamples and percentile 95% CIs, and was considered significant when the CI excluded zero. A two-tailed $p < 0.05$ was considered statistically significant throughout.

Ethical Considerations

The protocol was approved by the Institutional Ethics Committee of [institution] (approval no. [IEC/XXX/20XX], dated [date]) and conducted in accordance with the Declaration of Helsinki and the ICMR National Ethical Guidelines for Biomedical and Health Research Involving Human Participants (2017). Written informed consent was obtained from every participant (thumb impression with witness for non-literate participants). Data were anonymised at entry and stored on a password-protected computer.

RESULTS AND DISCUSSION

Participant Characteristics and the Digital Divide in DHT Uptake

A total of 420 participants were analysed (mean age 56.8 ± 10.6 years; 53.8% male; 42.9% rural). 155 (36.9%) had T2DM only, 127 (30.2%) hypertension only and 138 (32.9%) both conditions, giving 293 participants with T2DM and 265 with hypertension for the condition-specific analyses. Mean disease duration was 7.9 ± 5.4 years. Overall, 254 participants (60.5%) had used at least one DHT in the previous 6 months (Table 1).

DHT uptake showed a clear socio-economic and geographic gradient, supporting H4 (Table 1; Figure 2). Use was markedly lower among rural than urban participants (45.6% vs 71.7%; $\chi^2 = 28.26$; df = 1; $p < 0.001$; V = 0.26). It rose steeply with education, from 38.5% among those with primary schooling or less to 76.5% among graduates (V = 0.30), and with income (46.3% to 75.4%). It declined with age (74.1% below 45 years vs 50.9% at 60 years or older), and users were on average 4.2 years younger than non-users (Welch $t = 4.05$, $p < 0.001$). Smartphone ownership was among the strongest correlates (66.6% vs 28.4%; V = 0.28). Sex ($p = 0.972$) and type of chronic condition ($p = 0.529$) were not associated with uptake.

These patterns reproduce the 'digital divide' repeatedly described in the digital-health literature. The patients who stand to gain most from remote care, namely older, rural, less-educated and poorer patients, are the least likely to use it (Greenhalgh et al.,

2017; WHO, 2021). The finding matters for health equity: if uptake is left to individual initiative, DHTs could widen existing disparities in chronic disease control. It also justifies adjusting for these characteristics in the multivariable analyses below, because they confound the comparison between users and non-users.

Table 1. Socio-demographic and clinical characteristics of participants by DHT use (N = 420)

Characteristic	Total n (%)	DHT users n (row %)	Non-users n (row %)	χ^2 (df)	*p*	Cramér's V
Age group (years)						
<45	54 (12.9)	40 (74.1)	14 (25.9)	12.16 (2)	0.002	0.17
45–59	199 (47.4)	129 (64.8)	70 (35.2)			
≥60	167 (39.8)	85 (50.9)	82 (49.1)			
Sex						
Male	226 (53.8)	136 (60.2)	90 (39.8)	0.00 (1)	0.972	0.00
Female	194 (46.2)	118 (60.8)	76 (39.2)			
Residence						
Urban	240 (57.1)	172 (71.7)	68 (28.3)	28.26 (1)	< 0.001	0.26
Rural	180 (42.9)	82 (45.6)	98 (54.4)			
Education						
Up to primary	104 (24.8)	40 (38.5)	64 (61.5)	37.14 (2)	< 0.001	0.30
Secondary	167 (39.8)	100 (59.9)	67 (40.1)			
Graduate & above	149 (35.5)	114 (76.5)	35 (23.5)			
Monthly household income						
Low	177 (42.1)	82 (46.3)	95 (53.7)	27.57 (2)	< 0.001	0.26
Middle	129 (30.7)	86 (66.7)	43 (33.3)			
High	114 (27.1)	86 (75.4)	28 (24.6)			
Chronic condition						
T2DM only	155 (36.9)	91 (58.7)	64 (41.3)	1.27 (2)	0.529	0.06
Hypertension only	127 (30.2)	82 (64.6)	45 (35.4)			
T2DM + Hypertension	138 (32.9)	81 (58.7)	57 (41.3)			
Owns a smartphone						
Yes	353 (84.0)	235 (66.6)	118 (33.4)	32.82 (1)	< 0.001	0.28
No	67 (16.0)	19 (28.4)	48 (71.6)			
Age, mean ± SD (years)	56.8 ± 10.6	55.1 ± 10.7	59.3 ± 10.0	t = 4.05	< 0.001	
Disease duration, mean ± SD (years)	7.9 ± 5.4	8.1 ± 5.6	7.6 ± 5.2	t = 0.88	0.377	

Row percentages are shown for users and non-users. χ^2, Pearson's chi-square test; t, Welch's t-test. Values derived from simulated data.

Reliability and Validity of the Measurement Scales

All four scales showed good internal consistency, with Cronbach's α ranging from 0.802 to 0.882 (Table 2), above the conventional 0.70 threshold. KMO values (0.795–0.927) indicated adequate to excellent sampling adequacy, and Bartlett's test was significant for every scale ($p < 0.001$), confirming factorability. The first factor explained more than 50% of item variance

in each scale, supporting a single underlying dimension, so summed scale scores were used in all subsequent analyses. The eHEALS reliability observed here is consistent with the original validation (Norman and Skinner, 2006).

Table 2. Reliability and sampling adequacy of the study scales

Scale	Items	Score range	Mean ± SD	Cronbach 's α	KMO	Bartlett's χ^2 (df)	Variance, factor 1 (%)
Digital health literacy (eHEALS)	8	8–40	24.51 ± 6.64	0.882	0.927	1388.2 (28)***	55.0
Perceived usefulness of DHT	4	4–20	12.10 ± 3.56	0.802	0.795	500.7 (6)***	62.7
Perceived healthcare accessibility	5	5–25	15.87 ± 4.12	0.808	0.825	633.8 (10)***	56.8
Medication adherence (MARS-5 type)	5	5–25	16.15 ± 4.28	0.819	0.842	660.7 (10)***	58.2

KMO, Kaiser–Meyer–Olkin measure of sampling adequacy. ***p < 0.001. Values derived from simulated data.

Pattern of DHT Use

Among the 254 users, SMS/WhatsApp reminders were the most common modality (74.4%), followed by teleconsultation (63.8%), mHealth applications (56.7%) and connected remote-monitoring devices (39.0%); users engaged with a mean of 2.34 modalities (Table 3). Rural users were less likely than urban users to use every modality. The difference was significant for SMS reminders, mHealth apps and remote monitoring (p = 0.045, = 0.031 and = 0.020, respectively) and borderline for teleconsultation (p = 0.058). The relative gap widened with technical demand: rural users were 84% as likely as urban users to use low-bandwidth SMS reminders, but only 63% as likely to use connected remote-monitoring devices, which require purchasing a device and reliable connectivity. This gradient suggests that device cost, connectivity and technical complexity, not willingness alone, shape which technologies reach rural patients, and that low-complexity channels may be the most equitable entry point.

Table 3. Modalities of DHT used among users (n = 254), overall and by residence

DHT modality	Users, n (%)	Urban users (%)	Rural users (%)	χ^2	p
SMS / WhatsApp reminders	189 (74.4)	78.5	65.9	4.02	0.045
Teleconsultation (video/audio)	162 (63.8)	68.0	54.9	3.60	0.058
Mobile health (mHealth) app	144 (56.7)	61.6	46.3	4.68	0.031
Remote monitoring device (glucometer/BP, connected)	99 (39.0)	44.2	28.0	5.42	0.020

Categories are not mutually exclusive. Values derived from simulated data.

Comparison of DHT Users and Non-users

DHT users scored significantly higher than non-users on digital health literacy (26.82 vs 20.98; d = 0.97), perceived usefulness (d = 0.87), perceived healthcare accessibility (17.23 vs 13.79; d = 0.91) and medication adherence (17.30 vs 14.40; d = 0.72), with moderate-to-large effect sizes (all p < 0.001; Table 4). They reported 26 minutes shorter travel time per visit (d = −0.75) and fewer unplanned visits in the preceding year (median 1 (1–2) vs 2 (1–3); p < 0.001).

Clinically, users with T2DM had a mean HbA1c 0.48 percentage points lower than non-users (7.79% vs 8.27%; t = −3.57, p < 0.001, d = −0.43). A larger proportion were at target (25.0% vs 9.1%; χ^2 = 10.92, p < 0.001). By contrast, the 3.1 mmHg lower systolic and 1.7 mmHg lower diastolic pressure among users with hypertension did not reach significance (p = 0.081 and p = 0.086), and neither did the difference in blood-pressure control (23.3% vs 16.7%; p = 0.253). H1 was therefore supported for the behavioural, access and glycaemic outcomes, but not for blood pressure.

The size of the HbA1c difference is close to the pooled reductions of about 0.4–0.5 percentage points reported for mobile-phone interventions in randomised trials (Hou et al., 2016; Kitsiou et al., 2017). A reduction of this size is clinically meaningful at the population level. The absence of a significant blood-pressure difference agrees with trial evidence that self-monitoring alone produces little benefit unless it is coupled with active clinician-led medication titration (Tucker et al., 2017; McManus et al., 2018), and with the null blood-pressure result of the mWellcare trial in Indian primary care (Prabhakaran et al., 2019). In other words, DHTs that improve information flow without closing the loop to treatment adjustment are unlikely to move blood pressure. This is a clinical-care design problem rather than a technological one.

Table 4. Comparison of behavioural, access and clinical outcomes between DHT users and non-users

Outcome	Users, mean ± SD	Non-users, mean ± SD	Diff.	*t* / *U*	*p*	*d*
Digital health literacy (8–40)	26.82 ± 6.36	20.98 ± 5.40	5.84	10.08	< 0.001	0.97
Perceived usefulness (4–20)	13.24 ± 3.44	10.37 ± 3.01	2.87	9.01	< 0.001	0.87
Healthcare accessibility (5–25)	17.23 ± 3.62	13.79 ± 3.98	3.44	8.98	< 0.001	0.91
Medication adherence (5–25)	17.30 ± 4.20	14.40 ± 3.79	2.91	7.36	< 0.001	0.72
HbA1c (%)†	7.79 ± 1.11	8.27 ± 1.16	−0.48	−3.57	< 0.001	−0.43
Systolic BP (mmHg)‡	144.18 ± 13.86	147.28 ± 14.12	−3.10	−1.75	0.081	−0.22
Diastolic BP (mmHg)‡	87.78 ± 7.74	89.49 ± 7.92	−1.71	−1.73	0.086	−0.22
Travel time per visit (min)	59.25 ± 34.09	85.47 ± 36.57	−26.22	−7.38	< 0.001	−0.75
Unplanned visits, past 12 months§	1.62 ± 1.27	2.19 ± 1.46	−0.57	U = 16114	< 0.001	r = −0.21

Users n = 254, non-users n = 166. †T2DM subgroup (n = 293); ‡hypertension subgroup (n = 265). §Mann–Whitney U test with effect size r = Z/√N; median (IQR) 1 (1–2) vs 2 (1–3). Welch's t-test for all other outcomes; d, Cohen's d; Diff., mean difference (users − non-users). Values derived from simulated data.

Dose–response: Outcomes by Intensity of DHT Use

To test H2, outcomes were compared across the three intensity groups: none (n = 166), low (n = 119) and high (n = 135) (Table 5; Figure 3). Adherence rose stepwise from 14.40 to 16.12 to 18.35 ($F(2, 417) = 37.16$, $p < 0.001$, $\eta^2 = 0.151$), and every pairwise contrast was significant. Accessibility and digital health literacy followed the same monotonic gradient with large effects ($\eta^2 = 0.181$ and 0.200). HbA1c fell from 8.27% to 8.03% to 7.58% ($F = 10.04$, $p < 0.001$, $\eta^2 = 0.065$). Post hoc tests showed that only high-intensity users differed from non-users ($p < 0.001$) and from low-intensity users ($p = 0.025$); low-intensity use did not differ from non-use ($p = 0.289$). Systolic pressure showed a small, non-significant downward trend ($F = 1.89$, $p = 0.153$). Levene's test did not indicate heterogeneous variances for any outcome (all $p > 0.05$).

The dose–response pattern strengthens the case that the association is more than a marker of who chooses to adopt technology. The threshold pattern for HbA1c, with benefit confined to high-intensity use, is consistent with trial evidence that sustained engagement, not initial download, drives glycaemic benefit (Kitsiou et al., 2017). Occasional or passive use of DHTs appears insufficient to change metabolic control, and programmes should therefore measure and promote engagement, not merely enrolment.

Table 5. Outcomes by intensity of DHT use: one-way ANOVA with Tukey HSD post hoc comparisons

Outcome	None, mean ± SD	Low, mean ± SD	High, mean ± SD	*F*	*p*	η^2	Tukey pairs
Digital health literacy	20.98 ± 5.40	25.72 ± 6.29	27.79 ± 6.29	51.99	< 0.001	0.200	L–N, H–N, H–L
Healthcare accessibility	13.79 ± 3.98	16.55 ± 3.73	17.82 ± 3.41	46.19	< 0.001	0.181	L–N, H–N, H–L

Outcome	None, mean ± SD	Low, mean ± SD	High, mean ± SD	*F*	*p*	η^2	Tukey pairs
Medication adherence	14.40 ± 3.79	16.12 ± 3.83	18.35 ± 4.25	37.16	< 0.001	0.151	L–N, H–N, H–L
HbA1c (%)	8.27 ± 1.16	8.03 ± 1.17	7.58 ± 1.01	10.04	< 0.001	0.065	H–N, H–L
Systolic BP (mmHg)	147.28 ± 14.12	145.21 ± 14.20	143.37 ± 13.60	1.89	0.153	0.014	None

df = (2, 417) for scale outcomes, (2, 290) for HbA1c and (2, 262) for systolic BP. Tukey pairs lists significant contrasts ($p < 0.05$): H, high; L, low; N, none (no use). HbA1c analysed in the T2DM subgroup and systolic BP in the hypertension subgroup. Values derived from simulated data.

Correlations Among Study Constructs

DHT use intensity correlated positively with digital health literacy ($\varrho = 0.45$), accessibility ($\varrho = 0.42$), perceived usefulness ($\varrho = 0.40$) and adherence ($\varrho = 0.38$), and negatively with age ($\varrho = -0.18$) (Table 6). Adherence was most strongly associated with digital health literacy ($r = 0.42$). In the clinical subgroups, higher adherence was associated with lower HbA1c ($r = -0.41$, $p < 0.001$) and lower systolic pressure ($r = -0.21$, $p < 0.001$). All inter-construct correlations were below 0.50, arguing against multicollinearity among the regression predictors.

Table 6. Correlation matrix of study constructs (N = 420)

Variable	1	2	3	4	5	6
1. DHT use intensity	1					
2. Digital health literacy	0.45***	1				
3. Perceived usefulness	0.40***	0.41***	1			
4. Healthcare accessibility	0.42***	0.27***	0.23***	1		
5. Medication adherence	0.38***	0.42***	0.29***	0.16**	1	
6. Age	−0.18***	−0.25***	−0.14**	−0.07	−0.01	1

Spearman's ϱ for correlations involving DHT use intensity (0 = none, 1 = low, 2 = high); Pearson's r otherwise. *p < 0.05, **p < 0.01, ***p < 0.001. Values derived from simulated data.

Independent Predictors of Medication Adherence and Perceived Accessibility

The multiple regression model for medication adherence was significant ($F(9, 410) = 15.76$, $p < 0.001$) and explained 25.7% of its variance (adjusted $R^2 = 0.241$; Table 7). After adjustment, high-intensity DHT use was the strongest independent predictor (B = 2.38, β = 0.26, $p < 0.001$), followed by digital health literacy (β = 0.26, $p < 0.001$) and age (β = 0.10, $p = 0.027$). Low-intensity use ($p = 0.139$) and perceived usefulness ($p = 0.072$) were not independently significant once literacy was accounted for. Sex, residence, education and disease duration were not associated with adherence. VIFs were ≤ 1.81 and the Durbin–Watson statistic was 2.24, indicating no multicollinearity or autocorrelation.

The independent role of digital health literacy supports the behavioural domain of the framework. The technology is effective only in the hands of patients able to find, understand and act on digital health information, and literacy predicted adherence even among patients with similar levels of use. This is consistent with behaviour-change theory, in which capability is a precondition for sustained behaviour (Michie et al., 2011), and it implies that DHT programmes should build digital health literacy rather than assume it.

Table 7. Multiple linear regression: predictors of medication adherence (MARS-5 score)

Predictor	B	SE	β	*t*	*p*	VIF
(Constant)	7.643	1.598	—	4.78	< 0.001	—
DHT use: low (ref: none)	0.728	0.492	0.077	1.48	0.139	1.48

Predictor	B	SE	β	*t*	*p*	VIF
DHT use: high (ref: none)	2.383	0.513	0.260	4.64	< 0.001	1.73
Digital health literacy	0.169	0.037	0.263	4.60	< 0.001	1.81
Perceived usefulness	0.106	0.059	0.088	1.81	0.072	1.31
Age (years)	0.041	0.018	0.101	2.22	0.027	1.15
Female (ref: male)	−0.112	0.370	−0.013	−0.30	0.761	1.02
Rural (ref: urban)	−0.101	0.391	−0.012	−0.26	0.797	1.13
Graduate & above (ref: below)	0.721	0.464	0.081	1.56	0.121	1.49
Disease duration (years)	−0.048	0.034	−0.061	−1.41	0.161	1.03

$R^2 = 0.257$; adjusted $R^2 = 0.241$; $F(9, 410) = 15.76$, $p < 0.001$; Durbin–Watson = 2.24. B, unstandardised coefficient; SE, standard error; β, standardised coefficient; VIF, variance inflation factor. Values derived from simulated data.

For perceived healthcare accessibility (Table 8), both low-intensity (β = 0.21) and high-intensity DHT use (β = 0.33) were significant positive predictors (both $p < 0.001$). Rural residence (β = −0.23) and low income (β = −0.18) were independent negative predictors ($R^2 = 0.278$). Unlike adherence, accessibility improved even with low-intensity use, which makes sense because a single teleconsultation that replaces a long journey delivers an immediate access benefit. However, the rural and income penalties persisted after adjusting for DHT use: technology narrows access gaps but does not close them, echoing the multidimensional view of access in which geography and affordability remain distinct barriers (Levesque et al., 2013).

Table 8. Multiple linear regression: predictors of perceived healthcare accessibility

Predictor	B	SE	β	*t*	*p*	VIF
(Constant)	16.105	1.465	—	11.00	< 0.001	—
DHT use: low (ref: none)	1.879	0.456	0.206	4.12	< 0.001	1.43
DHT use: high (ref: none)	2.897	0.468	0.329	6.19	< 0.001	1.61
Rural (ref: urban)	−1.905	0.369	−0.229	−5.16	< 0.001	1.13
Low income (ref: middle/high)	−1.498	0.390	−0.180	−3.84	< 0.001	1.25
Age (years)	−0.011	0.017	−0.029	−0.64	0.522	1.14
Digital health literacy	0.015	0.031	0.025	0.50	0.619	1.42

$R^2 = 0.278$; adjusted $R^2 = 0.268$; $F(6, 413) = 26.52$, $p < 0.001$; Durbin–Watson = 2.13. Values derived from simulated data.

Determinants of Glycaemic and Blood-pressure Control

In unadjusted logistic regression, DHT users had higher odds of glycaemic control (crude OR = 3.33; 95% CI 1.64–6.78; $p < 0.001$). After adjustment for adherence and covariates (Table 9; Figure 4), this association was attenuated and became borderline (AOR = 2.29; 95% CI 1.00–5.25; $p = 0.050$), while each one-point increase in adherence score independently raised the odds of glycaemic control by 20% (AOR = 1.20; 95% CI 1.09–1.32; $p < 0.001$). The model was significant (likelihood-ratio $\chi^2 = 43.76$, $p < 0.001$), fitted well (Hosmer–Lemeshow $p = 0.371$) and discriminated acceptably (AUC = 0.770; Nagelkerke $R^2 = 0.225$). For blood-pressure control, DHT use was not associated with control (AOR = 0.90; 95% CI 0.42–1.93; $p = 0.792$); adherence (AOR = 1.11; 95% CI 1.02–1.20; $p = 0.014$) and younger age (AOR = 0.97 per year, $p = 0.048$) were significant (Hosmer–Lemeshow $p = 0.307$; AUC = 0.689).

The attenuation of the DHT–glycaemic association once adherence enters the model is itself informative: it suggests that much of the benefit of DHTs runs *through* adherence rather than alongside it. This was tested formally below.

Table 9. Binary logistic regression: adjusted odds ratios for glycaemic and blood-pressure control

Predictor	Glycaemic control: AOR (95% CI)	*p*	BP control: AOR (95% CI)	*p*
DHT user (ref: non-user)	2.29 (1.00–5.25)	0.050	0.90 (0.42–1.93)	0.792
Medication adherence (per point)	1.20 (1.09–1.32)	< 0.001	1.11 (1.02–1.20)	0.014
Age (per year)	1.02 (0.99–1.05)	0.270	0.97 (0.94–1.00)	0.048
Female (ref: male)	0.75 (0.39–1.46)	0.401	0.86 (0.46–1.61)	0.629
Rural (ref: urban)	0.78 (0.38–1.62)	0.502	1.40 (0.73–2.72)	0.313
Disease duration (per year)	0.94 (0.88–1.01)	0.086	1.01 (0.95–1.08)	0.664
Graduate & above (ref: below)	1.35 (0.68–2.69)	0.391	1.91 (0.96–3.78)	0.063

Glycaemic control: T2DM subgroup (n = 293; 54 controlled). Blood-pressure control: hypertension subgroup (n = 265; 55 controlled). Model fit, glycaemic: LR $\chi^2(7) = 43.76$, p < 0.001, Nagelkerke $R^2 = 0.225$, Hosmer–Lemeshow p = 0.371, AUC = 0.770. Blood pressure: LR $\chi^2(7) = 17.71$, p = 0.013, Nagelkerke $R^2 = 0.101$, Hosmer–Lemeshow p = 0.307, AUC = 0.689. AOR, adjusted odds ratio. Values derived from simulated data.

Mediating Role of Medication Adherence

Consistent with H3, DHT use was associated with higher adherence (path $a = 2.88$, $p < 0.001$), and higher adherence with lower HbA1c (path $b = -0.100$, $p < 0.001$) (Table 10; Figure 5). The total effect of DHT use on HbA1c ($c = -0.52$, $p < 0.001$) became non-significant once adherence was controlled (direct effect $c' = -0.23$, $p = 0.106$). The bootstrapped indirect effect was significant (−0.288; 95% CI −0.430 to −0.164), accounting for 55% of the total effect, a pattern consistent with full mediation. For systolic pressure the indirect effect through adherence was also significant (−1.86 mmHg; 95% CI −3.53 to −0.50), even though the total effect was not ($p = 0.067$). This indicates that DHTs influence blood pressure through adherence, but that the effect is too small, or offset by other pathways, to produce a detectable overall difference in this sample.

The mediation results bring the interdisciplinary framework together. DHTs appear to act on clinical outcomes principally through a behavioural mechanism, better medication-taking, which is itself enabled by digital health literacy and by the improved continuity of contact that DHTs provide. Reminder-based and teleconsultation interventions have long been shown to improve adherence (Free et al., 2013; Thakkar et al., 2016); the present analysis links that behavioural gain to measured HbA1c in the same patients. Because the design is cross-sectional, however, the mediation is statistical rather than causal, and reverse causation (for example, already-adherent patients being more likely to adopt DHTs) cannot be excluded.

Table 10. Mediation analysis: indirect effect of DHT use on clinical outcomes through medication adherence

Path	Coefficient	SE	*p*	Bootstrap 95% CI
Outcome: HbA1c (%) — T2DM subgroup (n = 293)				
a: DHT use → adherence	2.876	0.519	< 0.001	—
b: adherence → outcome	−0.100	0.015	< 0.001	—
c: total effect	−0.519	0.145	< 0.001	—
c′: direct effect	−0.232	0.143	0.106	—
a × *b*: indirect effect	−0.288	0.068	—	−0.430 to −0.164
Proportion mediated (%)	55.4			
Outcome: systolic BP (mmHg) — hypertension subgroup (n = 265)				
a: DHT use → adherence	2.946	0.543	< 0.001	—
b: adherence → outcome	−0.630	0.207	0.003	—
c: total effect	−3.384	1.842	0.067	—

Path	Coefficient	SE	*p*	Bootstrap 95% CI
c′: direct effect	−1.528	1.913	0.425	—
a × *b*: indirect effect	−1.856	0.784	—	−3.533 to −0.501
Proportion mediated (%)	54.8			

DHT use coded 1 = user, 0 = non-user. All paths adjusted for age, disease duration and residence. Percentile bootstrap CI from 5,000 resamples (Hayes, 2018, model 4). Values derived from simulated data.

Interdisciplinary Synthesis and Implications

Taken together, the findings describe DHTs as enablers whose clinical value depends on patient behaviour and access, rather than as stand-alone clinical tools. Three implications follow, one for each domain of the framework.

For **clinical care**, the glycaemic benefit was concentrated among high-intensity users and mediated by adherence, while blood pressure did not improve. Services should therefore integrate DHT data into clinical decision-making, for example with remote readings that trigger clinician-led dose titration, and should not treat DHTs as an add-on communication channel. For **patient behaviour**, digital health literacy emerged as an independent predictor of adherence, which argues for structured digital-literacy support, including caregiver-assisted use for older patients, as part of diabetes and hypertension education. For **healthcare accessibility**, DHT use was associated with shorter travel time, fewer unplanned visits and better perceived access, but rural and low-income patients still reported worse access and were far less likely to use DHTs at all. Low-bandwidth channels such as SMS, assisted teleconsultation through health and wellness centres and community health workers, and device-lending schemes are practical ways to extend the benefits to those currently excluded (WHO, 2021; PIB, 2023).

Strengths and Limitations

The study's strengths include the joint measurement of clinical, behavioural and access outcomes in one population; objective clinical end-points (laboratory HbA1c and standardised blood pressure); validated instruments with good reliability; adjustment for key confounders; and formal testing of mediation with bootstrapped confidence intervals. Several limitations must be acknowledged. First, the cross-sectional design precludes causal inference, and self-selection into DHT use may bias the user–non-user comparison despite adjustment. Second, adherence, DHT use and accessibility were self-reported and are subject to recall and social-desirability bias. Third, recruitment from hospital-linked clinics may under-represent patients with no contact with formal care, who may be the least digitally connected. Fourth, intensity of use was categorised from self-report rather than from device or platform logs. Finally, the findings come from [one district/state] and may not generalise to other health systems. Longitudinal and randomised designs, ideally using platform-level engagement data, are needed to confirm the causal pathway suggested here.

CONCLUSION

In this interdisciplinary study of adults with type 2 diabetes and/or hypertension, DHT use was associated with better digital health literacy, perceived access to care, medication adherence and glycaemic control, with a dose–response gradient favouring high-intensity use. The association with HbA1c operated largely through improved medication adherence, whereas no overall effect on blood pressure was detected. Uptake was strongly patterned by age, rural residence, education, income and smartphone ownership. DHTs can therefore strengthen chronic disease management, but only when they are embedded in clinical workflows, matched to patients' digital capability, and deliberately extended to rural and disadvantaged groups. Without such measures, digital health risks widening the inequalities it is intended to reduce. [Conclusions based on simulated data — rewrite after analysis of real data.]

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The authors declare no conflict of interest. [Each author to complete the ICMJE disclosure form.]

ETHICS STATEMENTS

The study was approved by the Institutional Ethics Committee of [institution] (approval no. [XXX], dated [date]), and written informed consent was obtained from all participants.

AUTHOR CONTRIBUTIONS

[Author 1]: conceptualisation, methodology, data collection, writing – original draft. [Author 2]: formal analysis, visualisation, writing – review and editing. [Author 3]: supervision, validation, writing – review and editing. All authors read and approved the final manuscript.

DATA AVAILABILITY STATEMENT

The de-identified dataset and the analysis script used to generate all tables and figures will be made available [as supplementary material / in a public repository, with DOI] in line with the journal's data-transparency policy.

DECLARATION ON THE USE OF GENERATIVE AI

[Disclose any use of AI-assisted tools in drafting the manuscript or code, as required by the journal's policy on generative AI. The authors take full responsibility for the content.]

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