Exploring patient perceptions of artificial intelligence (AI) in diabetes self-management: foundations for an AI-integrated shared decision-making model

Nataly Martini, Navneet Dhaliwal, Elena Alipour, Shane Scahill, Laszlo Sajtos

Submitted to: JMIR Formative Research
on: August 26, 2025

Table of Contents

Exploring patient perceptions of artificial intelligence (AI) in diabetes self-management: foundations for an AI-integrated shared decision-making model

Nataly Martini[1] PhD; Navneet Dhaliwal[1] BPharm (Hons); Elena Alipour[1] BHSc/BSc; Shane Scahill[1] PhD; Laszlo Sajtos[2] PhD

[1]85 Park Road School of Pharmacy University of Auckland Auckland NZ
[2]85 Park Road Department of Marketing, Business School University of Auckland Auckland NZ

Corresponding Author:
Nataly Martini PhD
85 Park Road
School of Pharmacy
University of Auckland
Grafton
Auckland
NZ

Abstract

Background: Artificial intelligence (AI) offers new opportunities to support chronic disease self-management and expand shared decision-making (SDM) frameworks beyond the traditional patient-clinician dyad.

Objective: This study explored patient perceptions of AI across key diabetes self-management tasks and examined task-specific preferences for AI versus healthcare provider (HCP) involvement. The findings aim to lay the groundwork for future models integrating AI into SDM processes.

Methods: A cross-sectional online survey of adults with diabetes in New Zealand assessed preferences for AI or HCP support across seven diabetes self-management tasks. Participants rated perceived HCP involvement, perceived usefulness of AI, comfort with HCP use of AI, and their preference for AI versus HCP involvement for each task. Stepwise linear regression was used to examine predictors of AI preference for each task.

Results: Participants (N=48) rated HCP involvement as moderate to low across most self-management tasks. In contrast, AI was rated as moderately useful, especially for data-driven tasks such as tracking and interpreting health information, though actual usage remained limited. HCPs were preferred for tasks involving clinical judgment and personal reflection. Perceived usefulness of AI was a significant predictor of preference for AI involvement in self-management. Notably, participants rated HCP involvement in personal reflection as low but still strongly preferred HCPs over AI for this domain. Collaboration between AI and HCPs was not viewed as a key factor influencing preferences.

Conclusions: Patients demonstrate task-specific openness to AI involvement in diabetes management, particularly for structured, data-intensive activities. These findings lay a foundation for future development and evaluation of AI-integrated SDM models. A broader exploration of technology types, relationship dynamics, and collaborative decision-making will be essential as AI becomes increasingly embedded in chronic care management.

(JMIR Preprints 26/08/2025:83030)
DOI: https://doi.org/10.2196/preprints.83030

Preprint Settings

1) Would you like to publish your submitted manuscript as preprint?

✓ **Please make my preprint PDF available to anyone at any time (recommended).**
Please make my preprint PDF available only to logged-in users; I understand that my title and abstract will remain visible to all users.
Only make the preprint title and abstract visible.
No, I do not wish to publish my submitted manuscript as a preprint.

2) If accepted for publication in a JMIR journal, would you like the PDF to be visible to the public?

✓ **Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).**

Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain v

Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in <a href="http

No. Please do not make my accepted manuscript PDF available to anyone. I understand that if I later pay to participate in <a href="https:/

Original Manuscript

Exploring Patient Perceptions of Artificial Intelligence (AI) in Diabetes Self-Management: Foundations for an AI-integrated Shared Decision-Making Model

Abstract

Background: Artificial intelligence (AI) is increasingly being applied to chronic disease management, including diabetes, where it has the potential to support real-time data interpretation, improve clinical decision-making, and enhance patient engagement. While AI tools are often developed to increase efficiency and personalization, there is limited evidence on how patients perceive the role of AI in managing their condition—particularly in relation to shared decision-making (SDM) and the patient–provider relationship.

Objective: This study explored how people with diabetes perceive the usefulness of AI across key self-management tasks and examined their preferences for AI versus healthcare provider (HCP) involvement. It also assessed predictors of AI preference and proposed a conceptual foundation for integrating AI into a triadic SDM model involving patients, HCPs, and AI.

Methods: We conducted a cross-sectional online survey of adults with diabetes in New Zealand. Participants were asked to rate seven diabetes self-management tasks in terms of: (1) current HCP involvement, (2) perceived usefulness of AI, (3) comfort with HCPs using AI, and (4) their preference for AI, HCP, or both in completing each task. Tasks included data collection, data interpretation, medication adherence, treatment decision-making, lifestyle management, personal reflection, and evaluation of treatment options. Stepwise linear regression was used to identify predictors of AI preference for each task.

Results: Participants (N=48) rated HCP involvement as moderate to low across most self-management tasks. In contrast, AI was rated as moderately useful, especially for data-driven tasks such as tracking and interpreting health information, though actual usage remained limited. HCPs were preferred for tasks involving clinical judgment and personal reflection. Perceived usefulness of AI was a significant predictor of preference for AI involvement in self-management. Notably, participants rated HCP involvement in personal reflection as low but still strongly preferred HCPs over AI for this domain. Collaboration between AI and HCPs was not viewed as a key factor influencing preferences.

Conclusions: Patients demonstrate task-specific openness to AI involvement in diabetes management, particularly for structured, data-intensive activities. These findings lay a foundation for future development and evaluation of AI-integrated SDM models. A broader exploration of technology types, relationship dynamics, and collaborative decision-making will be essential as AI becomes increasingly embedded in chronic care management.

Keywords: Artificial intelligence; Diabetes self-management; Shared decision-making; Patient

preferences; Digital health; Chronic disease management

Introduction

Diabetes is one of the most significant global health challenges, with the number of adults affected projected to reach 783 million by 2045.[1] In 2021, it ranked among the top ten causes of mortality worldwide, contributing to 6.7 million deaths and healthcare costs nearing one trillion USD.[1] As the prevalence of diabetes continues to rise, effective care and management strategies are urgently needed.

Despite advances in diabetes care, many individuals struggle with poor glycemic control, increasing their risk of complications. In New Zealand, a review of over 3,500 individuals with type 2 diabetes found that more than half had uncontrolled diabetes.[2] Barriers include late diagnosis, inequitable distribution of medical resources, inadequate support for lifestyle changes, and weak therapeutic relationships between patients and healthcare providers (HCPs).[2,3] These compromise both clinical outcomes and patient engagement in care.

Shared decision-making (SDM) is a cornerstone of patient-centred care and is particularly important in chronic conditions such as diabetes, where daily self-management depends on aligning clinical guidance with the patient's goals, values and lived experience.[4,5] SDM fosters collaboration between patients and HCPs to select treatments and self-management strategies that reflect personal preferences and real-time health needs.[6,7] When effectively implemented, SDM builds trust, enhances confidence, and supports long-term self-efficacy.[8] However, SDM in practice is often constrained by time pressures, limited health literacy, and role confusion between patients and HCPs.[9–11] These barriers can result in mismatched expectations and leave patients to self-manage without meaningful collaboration, undermining the very goals of SDM.[7,12] Furthermore, while patients value active participation in decision-making,[13,14] evidence on how patients perceive SDM in their care remains scarce.[15]

Artificial intelligence (AI) has emerged as a potential enabler of more responsive, patient-centred diabetes care.[16] AI-powered technologies – such as continuous glucose monitors (CGMs), mobile health apps, smart insulin pumps, and image-based screening systems – can support real-time tracking, data interpretation,[3,17–21] and personalized feedback for dietary, exercise, and medication decisions.[22–26] These tools increase patients' capacity to manage their condition outside clinical settings, which is essential for sustained engagement and the prevention of long-term diabetes complications.[23] More importantly, AI holds promise in enhancing key components of the SDM process, such as simplifying complex medical information,[23,26,27] empowering patients to consider treatment options,[3,28] and generalizing personalized insights that can inform conversations between patients and HCPS. While these capabilities align with the goals of SDM—supporting informed, values-aligned decisions—they are rarely discussed in relation to the relational dynamics that SDM entails. Existing research tends to focus on AI's functionality in isolation, rather than its role in collaborative decision-making frameworks.

In this study, we aim to bridge that gap by exploring a patient-centred, triadic model of SDM that incorporates AI as a third actor alongside the patient and HCP. We adopt a broader view of SDM, recognizing that in chronic disease contexts like diabetes, decisions such as interpreting glucose data, adjusting behaviours, or understanding treatment options are made outside clinical consultations and increasingly involve digital tools. We argue that understanding how patients perceive the role of AI across these decision points, and how they distribute trust and responsibility between themselves, their HCP, and AI, is critical for future models of care.

This study contributes to the SDM literature in three ways. First, it disaggregates diabetes care into seven distinct self-management tasks, mapping patient preferences for AI versus HCP involvement in each. Second, it empirically tests how patient–HCP, patient–AI, and HCP–AI relationships influence these preferences. Third, it proposes a novel triadic SDM framework that reimagines decision-making as a distributed process involving human and digital actors, thereby expanding current conceptualizations of SDM beyond the consultation room. The novelty of this framework lies in examining patients' views on three dyadic interactions in SDM, and in assessing their relative importance in shaping preferences for either HCPs or AI at each step of the diabetes management process.

Conceptual Framework

Our proposed triadic model expands traditional SDM by incorporating AI as an additional decision partner (Figure 1). This model focuses on patient perceptions of three key relationships—Patient–HCP, Patient–AI, and HCP–AI—and how these shape preferences for decision support across specific diabetes self-management tasks.

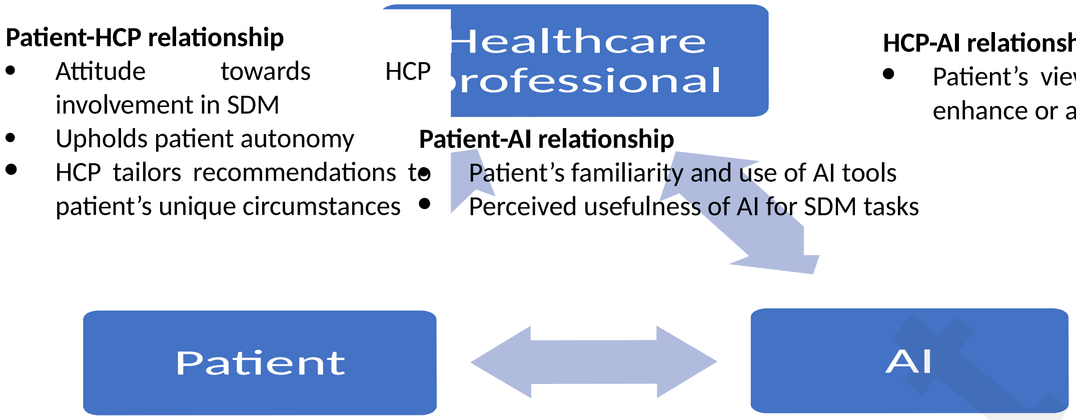


Figure 1: The triadic shared decision-making framework integrating AI in diabetes care

Patient-HCP relationship refers to the patient's perception of their HCPs' involvement in their care. As patients take on more responsibility for daily self-management, they rely on continuous support from HCPs to ensure that their decisions are aligned with long-term health goals.[5,28] Our research explores whether AI is likely to require HCPs to continue to support patients or, alternatively, whether it would allow patients to feel more autonomous and less reliant on their HCPs.

Patient-AI relationship refers to the patient's perceived usefulness of AI. AI provides personalized recommendations based on real-time data, enabling patients to make informed decisions about their care.[16,24,29] Our research examines whether a higher perceived usefulness of AI can, in fact, boost patients' preferences towards AI.

HCP-AI relationship refers to the patients' acceptance of HCPs using AI in their care. Current research suggests that HCPs remain the primary decision-makers for tasks requiring clinical judgment and empathy, particularly for complex cases where patients rely on their expertise.[21,29] Our research explores whether patients accept HCPs using AI in their treatment and for which tasks.

AI is not treated as a monolithic tool but conceptualized along a spectrum from passive (e.g. data collection) to active (e.g. predictive suggestions) to actively assistive (e.g. closed-loop insulin pumps). Each actor contributes to different phases of diabetes self-management, ranging from data tracking to contextualized decisions, depending on the nature of the task and the capabilities of the support system.

Bidirectional arrows between AI and patients/HCPs are used to represent perceived interactions, not literal reciprocity. While AI does not reciprocate relationships, it can offer feedback loops (e.g. data interpretation, tailored prompts) that patients experience as responsive or personalized. Similarly, HCPs may rely on AI insights to inform care decisions.

Self-management tasks

In this research, we focused on specific self-management tasks to address two overarching types of processes: data-driven tasks and contextualized decision-making tasks (Table 1).

Data-driven tasks include activities such as collecting health data, interpreting trends, and evaluating general treatment information. These tasks are supported by current AI technologies (e.g. CGMs, mobile health applications with predictive capabilities). Patients often perform these tasks independently, with AI enabling tracking, interpretation, and visualization of data. In this sense, AI acts as an enabler of self-efficacy, often facilitating early insights or triage that may later be shared with HCPs.

Contextualized decision-making tasks include clinical judgment (e.g. selecting treatment plans, medication adherence) and personal reflection (e.g. weighing personal pros and cons, aligning care with goals and values). We group them together to highlight a shared demand for understanding beyond data. These tasks rely on contextualized reasoning, relational trust, and emotional nuance. AI may support aspects of this domain through decision aids, reminders, or empathetic conversational agents, but cannot yet fully replicate the relational aspects of human care.

This classification draws on patient-centric categories in daily diabetes management.[30] It also reflects the fundamental functions of AI, which range from collecting and processing information (often referred to as big data approaches) to learning from this data through machine learning, and ultimately adapting and personalizing outputs to individual contexts.[31] Previous research highlights the value of AI-driven tools to enhance patient knowledge and tailor support to their real-time needs.[3]

Table 1. Patient’s diabetes self-management strategies and tasks associated with them

Data-Driven Tasks	Contextualized Decision-Making Tasks
Collecting and tracking health data (e.g., blood glucose levels and medical history): This involves the routine data capture and monitoring supported by	Personal reflection (i.e. sharing thoughts and feelings about personal circumstances, goals, beliefs, and values): Reflecting on personal health

wearables and sensors.	beliefs to weigh up personal pros and cons of treatment and lifestyle options.
Interpreting diabetes data (e.g. analysing blood sugar levels, recognising potential problems or complications that may arise): AI tools can detect patterns and provide alerts and/or predictions.	Lifestyle management (i.e. managing diet, exercise and lifestyle): Integrating healthy eating, physical activity, social and emotional support.
Evaluating medical information, including pros and cons of different treatments: Focuses on information retrieval and comparative decision support by identifying or summarizing research evidence (e.g. guidelines) to present evidence-based options.	Medication adherence (i.e. taking medications correctly): Following prescribed medication schedules and ensuring consistent use of medications. Requires a mixture of habit-forming and behavioural support.
	Seeking medical advice on how to manage diabetes/deciding on the best treatment plan: Involves seeking guidance and making informed decisions when encountering unexpected health issues or irregularities.

Methods

The study used a cross-sectional survey design. Ethical approval was granted by the (*omitted for review purposes*) Human Participant Ethics Committee (Reference number 26326).

Recruitment

Participants were recruited via convenience sampling from New Zealand (NZ) diabetes organizations (Diabetes NZ, Manawatu Horowhenua Tararua Diabetes Trust, North Shore Diabetes Support Group, Diabetes Wellington, and Diabetes Trust Palmerston North) and diabetes Facebook groups and online communities. These organizations were contacted through email, telephone or private messaging to request their assistance and consent to advertise the questionnaire to their members through their channels. Inclusion criteria were New Zealand residents aged 18 and older who had been diagnosed with type 1 or type 2 diabetes. To participate, individuals were not required to have prior experience with AI.

Survey design

A cross-sectional survey was developed based on existing literature and expert consultation to explore participants' perceptions of AI in diabetes management and their preferences for AI versus HCP involvement across a range of self-management tasks (Supplementary file). It consisted of five sections:

(A) *Impact of diabetes and management behaviour*: This section assessed how diabetes affected participants’ daily lives (e.g. physical, emotional, social, financial), and what strategies they currently used to manage their condition (e.g. blood glucose monitoring, medication use, dietary changes, stress management).

(B) *Participants' motivation, knowledge, and perceived control of their diabetes*: Participants were asked how motivated they felt to manage their diabetes, how this motivation had changed over time, how knowledgeable they felt about their condition, and how much control they believed they had over their diabetes.

(C) *Importance of specific tasks and the current role of HCPs in managing these tasks*: Participants rated the importance of seven diabetes self-management tasks and the degree to which their HCP was currently involved in each. These tasks were presented with high-level descriptors. For example, “sharing your thoughts and feelings about your personal circumstances, goals, beliefs, and values” was used to represent the task we categorised as *personal reflection*.

(D) *Use and perception of AI:* Participants were provided with a definition of AI in the context of diabetes care:

> *“Artificial Intelligence (AI) is increasingly being used in healthcare to help people manage their diabetes. For instance, an app could use AI to analyse a person's diet, medication, exercise, and blood sugar levels, and then give personalised advice to help them control their blood sugar. Additionally, AI can be used in other ways, including wearable devices (e.g. smart watches), continuous glucose monitoring devices (e.g. Dexcom™, Freestyle Libre™), computerised insulin pumps, or diagnostic tools used by clinicians.”*

Participants were asked whether they currently used AI for each of the diabetes tasks (Yes/No), how useful they would find AI for those tasks, and how comfortable they were with their HCP using AI to assist in their care. The survey did not focus on specific AI technologies used.

(E) *Demographics:* Participants reported on age, gender, ethnicity, education level, and region of residence.

Data collection

The questionnaire was piloted with six people – three with type 2 diabetes – for clarity, structure, and flow of questions. Based on this feedback, jargon and ambiguous terminology were reworded, repetitive or obscure questions were removed, and further examples of AI were given to aid comprehension. Pilot survey results were excluded from the final dataset. Qualtrics® (Qualtrics, Provo, UT, USA) was used to create and distribute the questionnaire and manage data collection. The software afforded participants anonymity and allowed for convenient distribution. Consent was given via participants clicking a button to show they had understood and accepted participation in the study. Participants could enter a draw to win one of two NZ$150 supermarket vouchers to acknowledge their participation. Data were collected between the 1st and 30th of September 2023.

Statistical Analysis

While the survey included broader items on motivation and disease impact, the current study reports only on responses relevant to AI-supported care and SDM. Additional analyses will be reported in future publications.

Descriptive statistics (means, standard deviations, percentages) were used to summarize participant demographics and survey responses. For each self-management task, four key variables were derived:

(1) Perceived HCP's involvement (Patient-HCP) – rated on a 5-point Likert scale (1 = not at all, 5 = a great deal).
(2) Perceived usefulness of AI (Patient-AI) – rated on a 5-point Likert scale (1 = not at all, 5 = a great deal).
(3) Comfort with HCP using AI (HCP-AI)– rated on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).
(4) Preferences for a human HCP provider – rated on a 5-point scale (1 = HCP only, 3= AI and HCP equally, 5= AI only).

We used stepwise linear regression to measure participants' preferences for AI versus human HCPs for each task, focusing on the three key relationships (patient-HCP, patient-AI, and HCP-AI). The regression model assessed the impact of these relationships on preferences for either AI (coded as 5) or human HCPs (coded as 1). Data analysis was performed using SPSS (version 29), and statistical significance was set at $p < 0.05$. Adjusted R^2 values are reported to indicate model fit. Due to the modest sample size (N = 48), findings are interpreted as exploratory and hypothesis-generating.

Results

Participant Demographics

A total of 48 participants diagnosed with diabetes took part in the survey, the majority of whom had been living with diabetes for over 10 years (n=27; 54%), were female (n=38; 79.2%), between the ages of 26 – 45 (n=27; 56%) and European (n=36; 75%). A majority (n=26, 54%) had higher education qualifications and were distributed throughout New Zealand, with the highest concentration of participants located in Auckland and Coromandel (n=15; 31.3%) (Table 2).

Table 2. Participant demographics (N=48)

Characteristic	Number of participants (%)
Age	
18 to 25	9 (18.8%)

26 to 35	14 (29.2%)
36 to 45	13 (27.1%)
46 to 55	7 (14.6%)
56 to 65	2 (4.2%)
> 65	3 (6.3%)
Gender	
Female	38 (79.2%)
Male	8 (16.7%)
Ethnicity	
Asian	3 (6.3%)
Māori	4 (8.3%)
MELAA*	1 (2.1%)
European	36 (75%)
Pacific People	1 (2.1%)
Other	3 (6.3%)
Education	
Some secondary school	3 (6.3%)
Completed secondary school	8 (16.7%)
Technical certificate	10 (20.8%)
Bachelors degree	19 (39.6%)
Post-graduate degree	7 (14.6%)
Other	1 (2.1%)
Diabetes Diagnosis	
Less than a year	4 (8.3%)
1 – 5 years	10 (20.8%)
5 – 10 years	8 (16.7%)
> 10 years	26 (54.2%)
Region	
Northland	2 (4.2%)
Auckland and Coromandel	15 (31.3%)
Waikato	6 (12.5%)
Manawatu	4 (8.3%)
Bay of Plenty	1 (2.1%)
Hawkes Bay and Gisborne	1 (2.1%)
Wellington	9 (18.8%)
Canterbury	8 (16.7%)
Otago	1 (2.1%)
Southland	1 (2.1%)

* Middle Eastern, Latin American, African

AI use and perception in diabetes management

Participants’ ratings of their HCP’s involvement in diabetes management tasks were modest overall, with a mean of 2.82 on a 5-point scale (Table 3). Involvement was particularly low in tasks related to lifestyle management (M = 2.28) and personal reflection (M = 2.44). In contrast, participants rated AI as moderately useful, with an overall mean of 3.67 on a 5-point scale. AI was seen as particularly useful for collecting and tracking data (M = 4.23) and for interpreting diabetes data (M = 4.40). However, the actual use of AI across all tasks remained relatively low (mean usage rate of 31%), suggesting a gap between perceived usefulness and real-world adoption. AI use was most common for tasks involving health data tracking and interpretation, and least common for personal reflection.

Participants' comfort with HCPS using AI was high across all tasks (M = 5.27 on a 7-point scale), indicating general openness to AI-assisted care, especially when used by an HCP in their care. There was a noteworthy preference for AI where the utility was already recognized (Tasks 1 and 2).

Table 3: Mean scores (and standard deviation) of survey data related to diabetes management tasks and the use and perception of AI in these tasks.

	Patient-HCP Relationship	Patient-AI Relationship		HCP-AI Relationship	Patient's relationship with HCP & AI
Tasks	HCP's current involvement (1=Not at all; 3= Moderate; 5= A great deal)	AI Usefulness (1=Not at all; 3 = Moderate; 5=Extremely)	Current use of AI (0=No; 1=Yes)	Agree with HCP using AI (1=Strongly disagree; 5=Somewhat agree; 7=Strongly Agree)	Preference for 1=HCP only; 3=HCP & AI; 5=AI only
Task 1: Collecting and tracking health data	3.10 (1.15)	4.23 (1.06)	0.58	5.81 (1.23)	3.48 (0.85)
Task 2: Interpreting diabetes data	3.02 (1.19)	4.40 (0.87)	0.50	5.71 (1.27)	3.25 (0.81)
Task 3: Seeking medical advice and making treatment decisions	3.06 (1.21)	3.60 (1.17)	0.25	5.30 (1.69)	2.77 (1.04)
Task 4: Lifestyle management	2.28 (1.19)	3.52 (1.37)	0.21	4.98 (1.82)	3.26 (0.85)
Task 5: Medication adherence	3.00 (1.34)	3.83 (1.2)	0.32	5.42 (1.67)	2.90 (1.04)
Task 6: Personal reflection	2.44 (1.35)	2.61 (1.44)	0.09	4.33 (1.94)	2.54 (1.17)
Task 7: Evaluating medical information	2.83 (1.19)	3.52 (1.27)	0.23	5.35 (1.54)	2.88 (0.94)
Overall mean	2.82 (1.23)	3.67 (1.20)	0.31	5.27 (1.35)	3.01

Participant preferences for AI versus HCPs

When asked to choose between AI, HCPs, or both for completing specific tasks, participants demonstrated a clear task-specific preference pattern (Figure 2). They favoured AI for data-driven tasks, such as collecting and tracking data (M = 3.48, 50%) and interpreting data (M = 3.25, 33%), while HCPs were preferred for contextualized tasks involving clinical judgment (e.g. treatment decisions, M = 2.77, 35%) and personal reflection (M = 2.54, 48%).

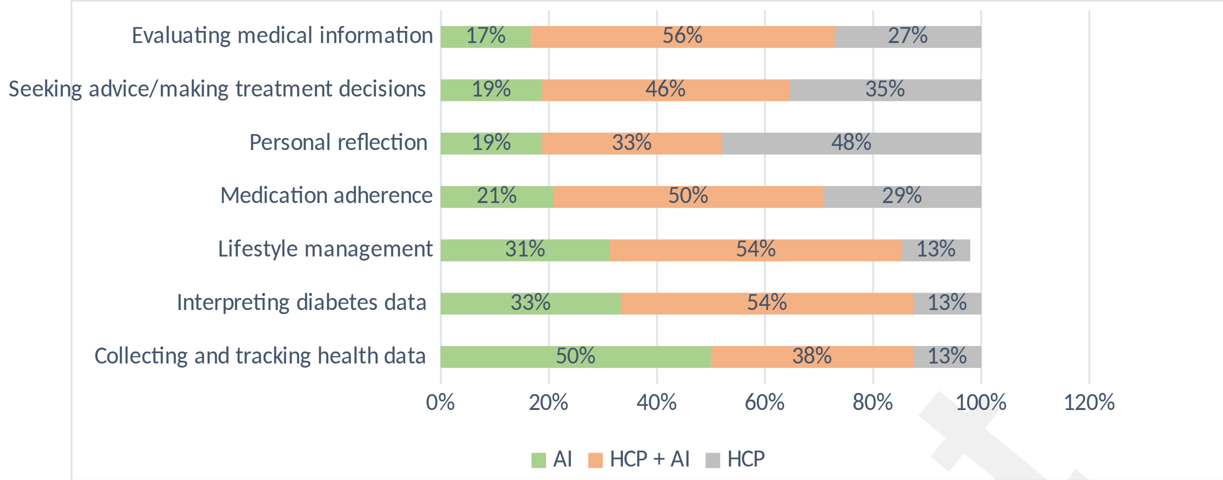


Figure 2: Bar graph showing the percentage of patients who preferred AI or healthcare providers for each diabetes task

The stepwise regression analysis (Table 4) revealed that participants' perceived usefulness of AI (the patient–AI relationship) was a significant positive predictor of AI preference across all tasks except one (evaluating treatment options). This indicates that patients with a stronger affinity for AI tend to favour AI-based solutions for data-driven tasks. Conversely, the perceived strength of the patient–HCP relationship negatively predicted AI preference in tasks involving treatment decisions and medication adherence. This suggests that a strong existing relationship with a human provider decreases the likelihood of patients preferring AI in these areas and increases their preference towards their HCP.

Interestingly, participants' views on the HCP–AI relationship (i.e. their comfort with clinicians using AI) did not significantly influence their task preferences, suggesting that while patients may be comfortable with AI-supported care in principle, their preferences are more strongly shaped by their direct perceptions of AI's value and their relationships with their HCPs.

Table 4: Stepwise regression results predicting participants' preferences toward AI vs HCP

	Task 1: Collecting and tracking	Task 2: Interpreting data	Task 3: Seeking medical advice/ making	Task 4: Lifestyle management	Task 5: Medication adherence	Task 6: Personal reflection

			treatment decisions			
Model summary	F(1,46)=8.56*** Adj R2=.14	F(1,46)=8.74*** Adj R2=.14	F(2,44)=6.9*** Adj R2=.2	F(1,43)=7.4** Adj R2=.13	F(2,44)=5.9*** Adj R2=.18	F(1,44)=6.99** Adj R2=.12
Patient-HCP	ns	ns	-.26(.12)**	ns	-.24(.11)**	ns
Patient-AI	.32(.11)***	.37(.13)***	.34(.12)***	.23(.09)**	.34(.12)***	.3(.11)**
HCP-AI	ns	ns	ns	ns	ns	ns
Gender (Inidicator category =Female, vs. else)	ns	ns	ns	ns	ns	ns
Age (indicator category = 36+, vs else)	ns	ns	ns	ns	ns	ns

** p< 0.05, *** p< 0.01, ns= non-significant

Discussion

Principle Results

This study explored how patients with diabetes perceive the role of AI in their self-management, focusing on task-specific preferences and perceived relationships with HCPs and AI systems. Participants generally rated their HCPs' involvement as moderate to low across most self-management tasks, especially for lifestyle support and personal reflection. In contrast, AI was rated as moderately useful, particularly for data-focused tasks like tracking and interpreting health data, although actual use of AI technologies remained limited. These results highlight a disconnect between perceived utility and real-world uptake, which may reflect accessibility, familiarity or trust in existing AI tools.

Comparison with Prior Work

When participants were asked to express their preferences for who should support various tasks (HCP, AI, or both), clear patterns emerged. AI was favoured for data-driven tasks such as data collection, tracking and interpretation, with over half of the participants using AI for these purposes. Regression analyses showed that patients who viewed AI as useful were more likely to prefer AI involvement in self-management tasks. While this may appear tautological, it reflects a meaningful relationship consistent with technology acceptance theory, where perceived usefulness is a strong driver of adoption.[32] Positive perceptions of AI usefulness also reflect a growing acceptance and trust in technologies like CGM devices, smartwatches, and smartphone applications in managing health data. These tools are valued for their efficiency, accuracy[29,33] and ability to provide real-time insights, excelling in areas requiring routine monitoring and pattern recognition—areas where human oversight may be more prone to errors or delays.[3,17,19,21,22] However, our findings also revealed that participants often rated AI as useful even when they were not currently using AI tools in their diabetes management. This may reflect positive attitudes toward the concept of AI, shaped by expectations rather than experience. For example, some participants may associate step tracking or glucose monitoring with AI, even when the device itself lacks predictive or adaptive features. Although the study used a broad, accessible definition of AI in the survey, AI capabilities vary widely, and the line between "monitoring" and "intelligent assistance" is often blurred.

In contrast, HCPs were preferred for tasks involving clinical judgment (e.g. medication and treatment decisions) and personal reflection (e.g. goal alignment), where relational trust, contextual awareness, and shared understanding are central. The negative association between the patient-HCP relationship and preferences for AI in these tasks highlights the importance of strong HCP-patient relationships in effective self-management.[34] While some studies suggest a strong, ongoing preference for HCPs over AI,[24,35] others highlight emerging support for a blended approach that combines the efficiency and analytical strengths of AI with the relational strengths of HCPs.[17,21,36] These mixed preferences are likely due to the still-evolving nature of AI applications and their ability to deliver contextually relevant recommendations. For instance, AI shows promise in improving the accuracy of dietary monitoring and enhancing patients' understanding of complex medical information tailoring,[3,37] but limited adoption may stem from challenges in addressing cultural and individual preferences.[35] In New Zealand, Māori and Pacific Peoples have shown a strong preference for human involvement in healthcare, reflecting cultural values that prioritize personal connections and face-to-face interactions in medical decision-making.[21] Importantly, our findings suggest that patients with weaker HCP relationships may view AI as a potential source of support where relational or clinical continuity is lacking. While this interpretation remains exploratory, it aligns with the broader aim of digital tools to enhance patient empowerment and self-engagement in care.[34] In cases where patients feel unsupported, AI may offer a sense of responsiveness or access. However, the diversity of AI tools in the marketplace is likely to contribute to varied levels of acceptance, reinforcing the need to assess AI preferences at a task and technology-specific level rather than assuming uniform acceptance or rejection.

An important finding in this study was the low perceived usefulness of AI for personal reflection, where participants overwhelmingly favoured HCPs. Interestingly, participants also rated their HCP's current involvement in personal reflection as below average, highlighting a broader gap in support for these more relational aspects of care. This contrasts with evidence showing that patients value opportunities to reflect on how diabetes affects their symptoms, daily lives, and treatment plans.[9,38] One possible explanation for this discrepancy is uncertainty about the relevance of personal reflection to SDM or limited prior experience with these conversations in routine care. Patients may also hesitate to express vulnerability to a non-human entity, given their reliance on HCPs for empathy, compassion, and trust to aid decision-making.[39] Given AI's current inability to replicate these human attributes fully, there are understandable doubts about its effectiveness in offering personal support or facilitating deeper patient-HCP relationships. However, recent developments in generative AI suggest this may be changing. Studies show that AI systems can exhibit empathetic tone and rapport that, in some cases, outperform physicians in perceived bedside manner.[40,41]

Chatbots have also shown promise in supporting mental health, particularly where users value guidance or non-judgmental listening.[42] Low perceived usefulness in our study may therefore reflect a lack of access or experience with these tools rather than inherent limitations.

Our results indicate that patients do not view collaboration between AI and HCPs as a decisive factor in their preferences for either. This suggests that while AI may have the potential to support SDM, its integration into clinical workflows may not yet be perceived as necessary for effective collaboration. Previous studies support the notion that patients are generally comfortable with AI technologies being used by HCPs for screening and diagnosis, particularly when clear physician oversight is maintained.[21,43] Such supervision provides reassurance, increasing patient confidence in AI outputs when mediated by their clinicians. For HCPs, delegating routine tasks to AI could theoretically free up time for higher-value interactions with patients, enhancing personalized diabetes care,[3] improving diagnostic accuracy, and reducing bias in treatment-related decisions.[21] However, the potential of AI in data collection and tracking remains underrecognized despite its demonstrated efficiency and utility in these tasks.[44,45]

Limitations

Several limitations should be considered when interpreting the findings of this study. While we propose a triadic AI–SDM model involving patients, HCPs, and AI tools, the regression analyses conducted in this study treated each relationship (patient–HCP, patient–AI, HCP–AI) as an independent predictor of AI preference. This statistical approach allowed exploration of relational perceptions individually, but did not fully capture the collaborative and interactive dynamics central to SDM. Furthermore, although the task preference measure was adapted from the Control Preferences Scale, it assessed which actor (AI, HCP, or both) participants preferred to perform each task, rather than the extent of collaboration or shared agency. As such, our findings reflect task assignment preferences rather than preferences for co-deliberation or shared decision-making processes.

Over half of our population had higher qualifications, and 75% were between 18 and 45 years old, with 66.7% living in larger cities in New Zealand, which can be attributed to the location of diabetes organizations that promoted the survey. Māori were underrepresented compared to national averages.[46] This skewed representation may limit the generalizability of our findings to older adults and rural or underrepresented ethnic groups. Methodologically, the self-selection bias of participants, many of whom were engaged with diabetes organizations or online communities, may have skewed the sample towards individuals with a greater interest or experience with technology. This suggests that our findings may overestimate the general population’s familiarity and comfort with AI. Additionally, the absence of qualitative data limits our ability to fully understand the motivations and preferences behind participants' attitudes toward AI and healthcare provider collaboration. Data-wise, the study's adjusted R^2 values ranged from 0.12 to 0.2, meaning our model explains only 12% to 20% of the variance in AI-related preferences, indicating that other unexplored factors, such as familiarity with technology or past experiences with AI, likely play a role in shaping preferences.

Implications for Healthcare

Integrating AI into diabetes care offers promising opportunity to address the challenges in primary care settings, including time constraints, limited staffing, and growing complexity of chronic disease management.[24,47] Our findings suggest that patients are most receptive to AI supporting data-driven, routine tasks where automation could relieve HCP workload and increase system efficiency. In contrast, clinical judgment, emotional reflection, or personalized goal-setting remain areas where human relationships and trust are paramount.

For healthcare providers considering the integration of AI into practice, several actionable recommendations emerge:

- Prioritize AI for backend data analysis, pattern recognition, and patient self-monitoring tools, where patient preference for automation is stronger. Use AI outputs to inform, but not replace, clinical conversations.
- HCPs should clearly explain to patients when and how AI tools are being used, especially in emotionally sensitive or decision-making contexts, to avoid undermining trust.
- Recognize that some patients place a high value on personal, face-to-face care. AI integration strategies should respect and adapt to these cultural expectations, ensuring that relational care is never sacrificed for technological efficiency.[48]

It is also important to recognize that AI tools are not without risk. Black-box AI systems lacking transparency erode patient trust and complicate informed decision-making.[28,49,50] While human-in-the-loop models offer oversight, they are not infallible and may still perpetuate bias or introduce complacency. Framing AI purely as a supportive tool without critical evaluation overlooks these challenges. Instead, AI should be incorporated through task-specific validation, transparent design, ethical oversight, and continuous evaluation of patient experience.

Given the modest sample size and exploratory nature of this study, further research is needed to understand better how different patient populations perceive and experience AI in care. Qualitative studies are especially necessary to explore patients' emotional safety, cultural expectations, and boundaries around AI use in relational care. Future work should also assess how specific AI tools impact trust, decision-making, and patient–HCP dynamics across diverse populations.

Conclusions

This study explored patient perception of AI across key self-management tasks and examined their preferences for AI versus HCP involvement. AI demonstrated strong utility in data-driven tasks such as collecting, tracking, and interpreting health data, where its accuracy and efficiency excel. However, tasks requiring contextual judgment, emotional support, or personal reflection remain firmly within the domain of human providers. These findings highlight the dual processes of diabetes self-management—adhering to data-informed rules and creating personalized, contextual knowledge—illustrating the complementary strengths of AI and HCPs.

These findings offer early empirical support for a triadic AI–SDM model in which AI, HCPs, and patients each contribute to decision-making according to the nature of the task. However, the results also emphasize that patient preferences are nuanced and shaped by prior experiences, personal values, and relational expectations, with AI–HCP collaboration not viewed as a decisive factor. While AI has the potential to enhance SDM, its integration must respect the relational core of person-centred care.

Given the exploratory nature of this study and the modest, demographically specific sample, findings should be interpreted cautiously. Nonetheless, they provide foundational insights to guide task-specific AI integration into diabetes care. Future research should prioritize qualitative inquiry to explore emotional safety, trust boundaries, and culturally appropriate models of AI use in chronic disease management. A broader exploration of technology types, relationship dynamics, and collaborative decision-making will be essential as AI becomes increasingly embedded in chronic care.

Acknowledgements

Financial support for this study was provided by the School of Pharmacy, the University of Auckland. The funding agreement ensured the authors' independence in designing the study, interpreting the data, writing, and publishing the report.

Conflicts of Interest

None declared.

Abbreviations

AI Artificial intelligence
HCP Healthcare professional
SDM Shared decision-making

References

1. International Diabetes Federation. IDF Diabetes Atlas 2021. ed), International Diabetes Federation, Brussels, Belgium 2021. https://diabetesatlas.org/atlas/tenth-edition/. Accessed October 16, 2024.

2. Chepulis L, Morison B, Cassim S, et al. Barriers to Diabetes Self-Management in a Subset of New Zealand Adults with Type 2 Diabetes and Poor Glycaemic Control. *J Diabetes Res*. 2021;2021(1):5531146. doi:10.1155/2021/5531146

3. Guan Z, Li H, Liu R, et al. Artificial intelligence in diabetes management: Advancements,

opportunities, and challenges. *Cell Rep Med*. 2023;4(10):101213. doi:10.1016/j.xcrm.2023.101213

4. Elwyn G, Frosch D, Thomson R, et al. Shared decision making: a model for clinical practice. *J Gen Intern Med*. 2012;27(10):1361-1367. doi:10.1007/s11606-012-2077-6

5. Tamhane S, Rodriguez-Gutierrez R, Hargraves I, Montori VM. Shared Decision-Making in Diabetes Care. *Curr Diab Rep*. 2015;15(12):1-10. doi:10.1007/s11892-015-0688-0

6. Barry MJ, Edgman -Levitan Susan. Shared Decision Making — The Pinnacle of Patient-Centered Care. *N Engl J Med*. 2012;366(9):780-781. doi:10.1056/NEJMp1109283

7. Légaré F, Witteman HO. Shared Decision Making: Examining Key Elements And Barriers To Adoption Into Routine Clinical Practice. *Health Aff (Millwood)*. 2013;32(2):276-284.

8. Vaskouei-Eshkevarei K, Hajinabi K, Riahi L, Maleki M. Developing a Shared Decision-Making Model for Diabetic Patients: A Qualitative Study. *Galen Med J*. 2020;10:e1735. doi:10.31661/gmj.v10i0.1735

9. Czuba K, Owens R, Brown P, Apaapa-Timu T, Strother R, Radecki R. Patients' and clinicians' views on shared decision making in cancer care: a qualitative study of Aotearoa New Zealand patients' and clinicians' perspectives. *PubMed*. 2023. https://pubmed.ncbi.nlm.nih.gov/37619224/. Accessed November 28, 2024.

10. Joseph-Williams N, Elwyn G, Edwards A. Knowledge is *not* power for patients: A systematic review and thematic synthesis of patient-reported barriers and facilitators to shared decision making. *Patient Educ Couns*. 2014;94(3):291-309. doi:10.1016/j.pec.2013.10.031

11. Steenbergen M, de Vries J, Arts R, Beerepoot LV, Traa MJ. Barriers and facilitators for shared decision-making in oncology inpatient practice: an explorative study of the healthcare providers' perspective. *Support Care Cancer*. 2022;30(5):3925-3931. doi:10.1007/s00520-022-06820-1

12. Peek ME, Quinn MT, Gorawara-Bhat R, Odoms-Young A, Wilson SC, Chin MH. How is shared decision-making defined among African-Americans with diabetes? *Patient Educ Couns*. 2008;72(3):450-458. doi:10.1016/j.pec.2008.05.018

13. Thiruvengadam SK, Ashvetiya T, Stone NJ, Blumenthal RS, Martin SS. Shared Decision-Making and Patient Empowerment in Preventive Cardiology. *Curr Cardiol Rep*. 2016;18(5):1-7. doi:10.1007/s11886-016-0729-6

14. Weingart SN, Zhu J, Chiappetta L, et al. Hospitalized patients' participation and its impact on quality of care and patient safety. *Int J Qual Health Care*. 2011;23(3):269-277. doi:10.1093/intqhc/mzr002

15. Tichler A, Hertroijs DF, Ruwaard D, et al. Treatment decisions among individuals with type 2 diabetes | PPA. https://www.dovepress.com/preferred-conversation-topics-with-respect-to-treatment-decisions-amon-peer-reviewed-fulltext-article-PPA. Accessed November 28, 2024.

16. Triberti S, Durosini I, Pravettoni G. A “Third Wheel” Effect in Health Decision Making Involving Artificial Entities: A Psychological Perspective. *Front Public Health*. 2020;8. https://www.frontiersin.org/article/10.3389/fpubh.2020.00117. Accessed March 16, 2022.

17. Braun M, Hummel P, Beck S, Dabrock P. Primer on an ethics of AI-based decision support systems in the clinic. December 2021. doi:10.1136/medethics-2019-105860

18. Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. *Future Heal J*. 2019;6(2):94-98. doi:10.7861/futurehosp.6-2-94

19. Kumar Y, Koul A, Singla R, Ijaz MF. Artificial intelligence in disease diagnosis: a systematic literature review, synthesizing framework and future research agenda. *J Ambient Intell Humaniz Comput*. 2022;14(7):8459-8486. doi:10.1007/s12652-021-03612-z

20. Sauerbrei A, Kerasidou A, Lucivero F, Hallowell N. The impact of artificial intelligence on the person-centred, doctor-patient relationship: some problems and solutions. *BMC Med Inform Decis Mak*. 2023;23(1):1-14. doi:10.1186/s12911-023-02162-y

21. Yap A, Wilkinson B, Chen E, et al. Patients Perceptions of Artificial Intelligence in Diabetic Eye Screening. *Asia-Pac J Ophthalmol*. 2022;11(3):287-293. doi:10.1097/APO.0000000000000525

22. Contreras I, Vehi J. Artificial Intelligence for Diabetes Management and Decision Support: Literature Review. *J Med Internet Res*. 2018;20(5):e10775. doi:10.2196/10775

23. Ellahham S. Artificial Intelligence: The Future for Diabetes Care. *Am J Med*. 2020;133(8):895-900. doi:10.1016/j.amjmed.2020.03.033

24. King DK, Toobert DJ, Portz JD, et al. What patients want: relevant health information technology for diabetes self-management. *Health Technol*. 2012;2(3):147-157. doi:10.1007/s12553-012-0022-7

25. Lauffenburger JC, Barlev RA, Sears ES, et al. Preferences for mHealth Technology and Text Messaging Communication in Patients With Type 2 Diabetes: Qualitative Interview Study. *J Med Internet Res*. 2021;23(6):e25958. doi:10.2196/25958

26. Prinjha S, Ricci-Cabello I, Newhouse N, Farmer A. British South Asian Patients’ Perspectives on the Relevance and Acceptability of Mobile Health Text Messaging to Support Medication Adherence for Type 2 Diabetes: Qualitative Study. *JMIR MHealth UHealth*. 2020;8(4):e15789. doi:10.2196/15789

27. Sze WT, Kow SG. Perspectives and Needs of Malaysian Patients With Diabetes for a Mobile Health App Support on Self-Management of Diabetes: Qualitative Study. *JMIR Diabetes*. 2023;8:e40968. doi:10.2196/40968

28. Rahimi SA, Légaré F, Sharma G, et al. Application of Artificial Intelligence in Community-Based Primary Health Care: Systematic Scoping Review and Critical Appraisal. *J Med Internet Res*. 2021;23(9):e29839. doi:10.2196/29839

29. Pelayo C, Hoang J, Mora Pinzón M, et al. Perspectives of Latinx Patients with Diabetes on

Teleophthalmology, Artificial Intelligence-Based Image Interpretation, and Virtual Care: A Qualitative Study. *Telemed Rep*. 2023;4(1):317-326. doi:10.1089/tmr.2023.0045

30. Moser A, van der Bruggen H, Widdershoven G, Spreeuwenberg C. Self-management of type 2 diabetes mellitus: a qualitative investigation from the perspective of participants in a nurse-led, shared-care programme in the Netherlands. *BMC Public Health*. 2008;8(1):91. doi:10.1186/1471-2458-8-91

31. Krafft M, Sajtos L, Haenlein M. Challenges and Opportunities for Marketing Scholars in Times of the Fourth Industrial Revolution. *J Interact Mark*. 2020;51(1):1-8. doi:10.1016/j.intmar.2020.06.001

32. Davis FD. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Q*. 1989;13(3):319-340. doi:10.2307/249008

33. Keel S, Lee PY, Scheetz J, et al. Feasibility and patient acceptability of a novel artificial intelligence-based screening model for diabetic retinopathy at endocrinology outpatient services: a pilot study. *Sci Rep*. 2018;8(1):4330. doi:10.1038/s41598-018-22612-2

34. Madanian S, Nakarada-Kordic I, Reay S, Chetty T. Patients' perspectives on digital health tools. *PEC Innov*. 2023;2:100171. doi:10.1016/j.pecinn.2023.100171

35. Tran VT, Riveros C, Ravaud P. Patients' views of wearable devices and AI in healthcare: findings from the ComPaRe e-cohort. *Npj Digit Med*. 2019;2(1):1-8. doi:10.1038/s41746-019-0132-y

36. Bergenstal RM, Johnson M, Passi R, et al. Automated insulin dosing guidance to optimise insulin management in patients with type 2 diabetes: a multicentre, randomised controlled trial. *The Lancet*. 2019;393(10176):1138-1148. doi:10.1016/S0140-6736(19)30368-X

37. Alotaibi MM, Istepanian R, Philip N. A mobile diabetes management and educational system for type- 2 diabetics in Saudi Arabia (SAED). *mHealth*. 2016;2(8). doi:10.21037/mhealth.2016.08.01

38. Entwistle V, Prior M, Skea ZC, Francis JJ. Involvement in treatment decision-making: Its meaning to people with diabetes and implications for conceptualisation. *Soc Sci Med*. 2008;66(2):362-375. doi:10.1016/j.socscimed.2007.09.001

39. Kerasidou A. Artificial intelligence and the ongoing need for empathy, compassion and trust in healthcare. *Bull World Health Organ*. 2020;98(4):245-250. doi:10.2471/BLT.19.237198

40. Ayers JW, Poliak A, Dredze M, et al. Comparing Physician and Artificial Intelligence Chatbot Responses to Patient Questions Posted to a Public Social Media Forum. *JAMA Intern Med*. 2023;183(6):589-596. doi:10.1001/jamainternmed.2023.1838

41. Tu T, Schaekermann M, Palepu A, et al. Towards conversational diagnostic artificial intelligence. *Nature*. April 2025:1-9. doi:10.1038/s41586-025-08866-7

42. Siddals S, Torous J, Coxon A. "It happened to be the perfect thing": experiences of generative AI chatbots for mental health. *Npj Ment Health Res*. 2024;3(1):1-9. doi:10.1038/s44184-024-

00097-4

43. Jutzi TB, Krieghoff-Henning EI, Holland-Letz T, et al. Frontiers | Artificial Intelligence in Skin Cancer Diagnostics: The Patients' Perspective. 2020. doi:10.3389/fmed.2020.00233

44. Mackenzie SC, Sainsbury CAR, Wake DJ. Diabetes and artificial intelligence beyond the closed loop: a review of the landscape, promise and challenges. *Diabetologia*. 2023;67(2):223-235. doi:10.1007/s00125-023-06038-8

45. Vettoretti M, Cappon G, Facchinetti A, Sparacino G. Advanced Diabetes Management Using Artificial Intelligence and Continuous Glucose Monitoring Sensors. *Sensors*. 2020;20(14):3870. doi:10.3390/s20143870

46. Health New Zealand Te Whatu Ora. Virtual Diabetes Register and web tool. https://www.tewhatuora.govt.nz/our-health-system/digital-health/virtual-diabetes-tool. Accessed August 25, 2022.

47. Ashrafzadeh S, Hamdy O. Patient-Driven Diabetes Care of the Future in the Technology Era. *Cell Metab*. 2019;29(3):564-575. doi:10.1016/j.cmet.2018.09.005

48. Sajtos L, Martini N, Scahill S, Edwards H, Biasiny-Tule P, Rangi HT. Delivering Culturally-Appropriate, Technology-Enabled Health Care in Indigenous Communities. *J Law Med Ethics*. 2023;51(2):322-331. doi:10.1017/jme.2023.62

49. Molnár-Gábor F. Artificial Intelligence in Healthcare: Doctors, Patients and Liabilities. In: ; 2019. doi:10.1007/978-3-030-32361-5_15

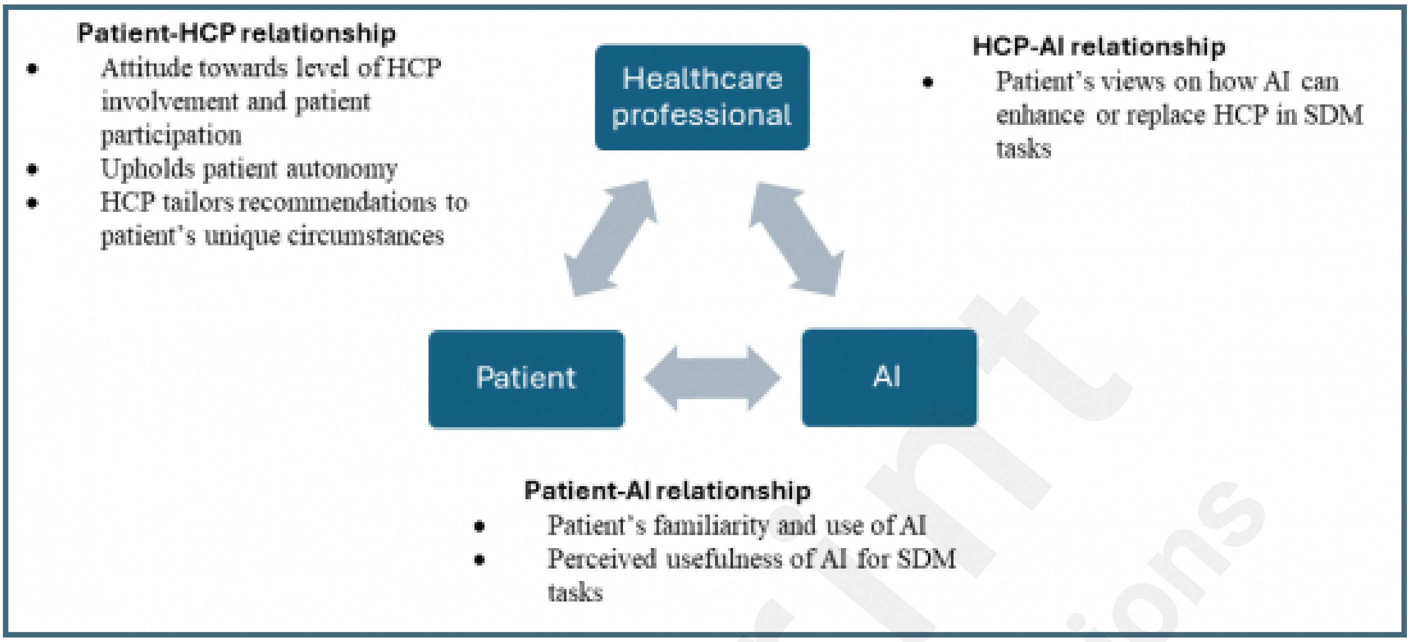
50. Carter SM, Rogers W, Win KT, Frazer H, Richards B, Houssami N. The ethical, legal and social implications of using artificial intelligence systems in breast cancer care. *The Breast*. 2020;49:25-32. doi:10.1016/j.breast.2019.10.001

Supplementary Files

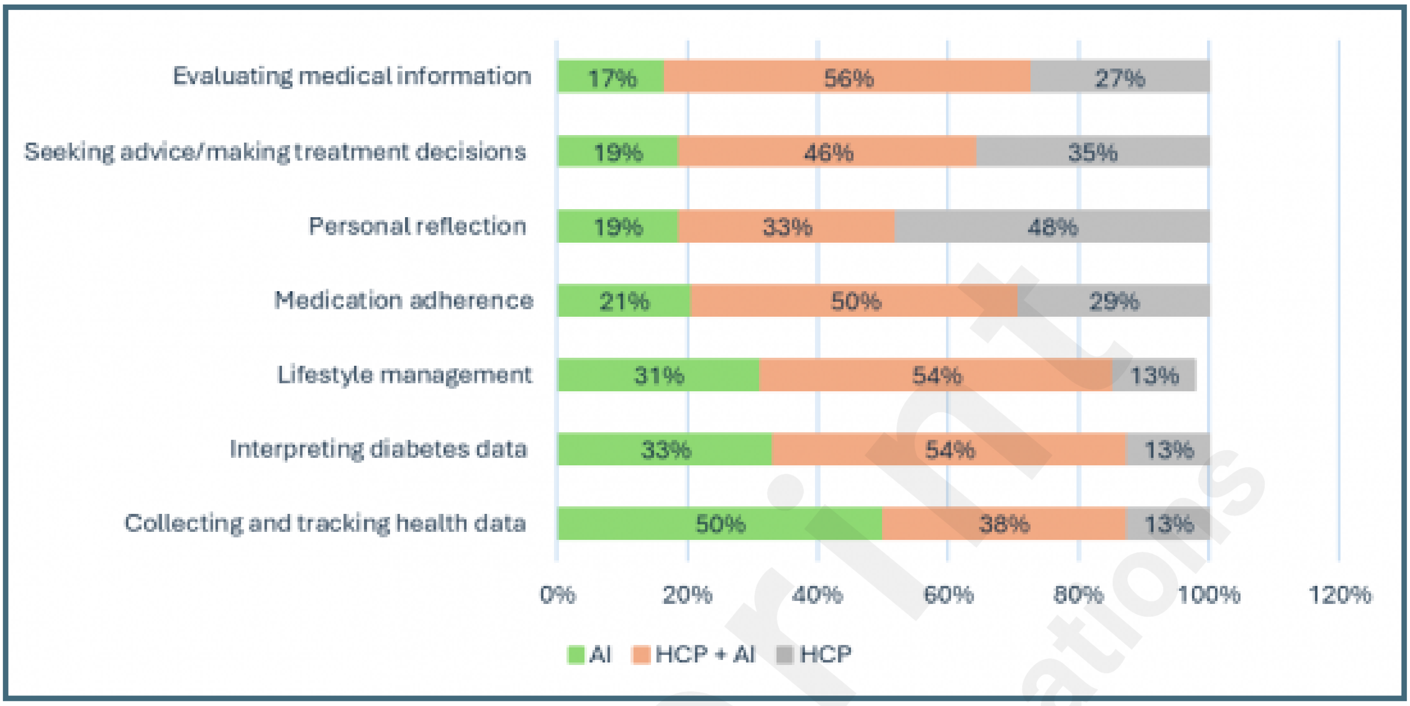
Untitled.
URL: http://asset.jmir.pub/assets/9100cd3e8257dcb1a01671b4cb205b33.docx

Figures

The triadic shared decision-making framework integrating AI in diabetes care.



Bar graph showing the percentage of patients who preferred AI or healthcare providers for each diabetes task.



Multimedia Appendixes

Supplementary data.
URL: http://asset.jmir.pub/assets/df0087631b6f9f8c020a37c651c0ee0f.docx