Original Paper

Implementation of Sensor-Augmented Conversational Agent for Personalized Lifestyle Support in Older Adults With Mild Cognitive Impairment: 2-Week, Single Arm, Feasibility Study

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Abstract

Background: Early lifestyle interventions may reduce dementia-related cognitive decline, but individuals with cognitive impairment often face barriers to accessing and maintaining such interventions. Smartphone apps and wearables may offer low-burden, real-time support.

Objective: This study examined the feasibility and acceptability of a 2-week sensor-augmented just-in-time adaptive intervention (JITAI) delivered via smartphone-based conversational agents (CAs) and a wearable fitness tracker in older adults with mild cognitive impairment (MCI).

Methods: In this single-arm, feasibility study, 24 participants with MCI (mean age 75.9, SD 5.52 years) used the intervention with a rule-based CA delivering two daily JITAI interventions: (1) a sensor-informed primary physical-activity component, in which continuously collected step-count data from a wrist-worn fitness tracker (Garmin vivoactive 6 [AMIT International Group FZE]) were used to assess vulnerability against a personalized step goal and deliver tailored walking prompts; and (2) an ecological momentary assessment (EMA)–based secondary health-promoting component targeting one of six additional health domains (hydration, nutrition, cognitive exercise, sleep, social engagement, and movement), assessed via momentary self-report. Both components followed the same JITAI decision logic.

Results: Of the 336 scheduled afternoon prompts, response rates were 86.6% (291/336) for the primary physical-activity component and 84.2% (283/336) for the secondary health promoting activities component. Evening check-in response rates were 85.6% (95/111 receptive participant-days) for the former, and 79.3% (65/82 receptive participant-days) for the latter. Of all scheduled afternoon prompts, 38.7% (130/336) were classified as vulnerable for the primary physical-activity component, and 32.1% (108/336) for the secondary health promoting activities component. Among these vulnerable responses, 85.4% (111/130) and 75.9% (82/108), respectively, were receptive, and of these receptive responses, 76.6% (85/111) and 70.7% (58/82), respectively, resulted in adherence at the evening check-in. On days satisfying the full JITAI chain for physical activity (vulnerable, receptive, and completed the evening check-in), participants exceeded their personalized step goal, reaching a mean of 170% (SD 95%) of the goal and a mean evening step count of 7718 (SD 3453) steps. The wearable-based data acquisition pipeline was feasible and largely reliable under study conditions, with the Garmin device supplying step-count data in 80.8% (312/386) of decision points, the smartphone in 17.4% (67/386), and manual self-report required in only 1.8% (7/386) of cases. Participants rated the CA favorably across all technology acceptance and usability domains, with all mean

scores above the neutral midpoint on 7-point Likert scales. Qualitative analysis described an intervention both accessible and structured.

Conclusions: This pilot study supports the short-term feasibility and acceptability of integrating wearable-derived step data into a smartphone-based CA-delivered JITAI for older adults with MCI. Passive sensing may reduce reliance on self-report. Controlled studies with adaptive decision times, sensor-derived baselines, and more diverse samples are needed.

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Keywords: conversational agents; older adults; cognitive impairment; just-in-time adaptive intervention; sensor-based health care; digital health implementation; health intervention; mobile phone

Introduction

With an expected prevalence of 152 million patients worldwide in 2050, dementia is one of the most pressing global health challenges, and dementia prevention has become an urgent global health priority [1]. The underlying pathophysiological processes begin long before the onset of overt clinical symptoms and are understood as a continuum, progressing from subjective cognitive decline (SCD), where individuals report cognitive decline but still perform within the normal range on cognitive tests, through mild cognitive impairment (MCI), which is defined by objectifiable cognitive impairment that does not affect the ability to live independently, to manifested dementia. Despite accumulating evidence from randomized controlled trials (RCTs) demonstrating lifestyle interventions to preserve or enhance quality of life (QoL), attenuate cognitive decline, and even modulate epigenetic aging, public [2-4] awareness of dementia-preventive strategies remains strikingly limited. In Switzerland, approximately one-third of adults are unaware that lifestyle choices substantially decrease dementia risk [5], highlighting a critical gap and the urgent need for scalable, accessible preventive interventions that enhance health literacy and support sustainable behavior change toward a healthy lifestyle. In response, there is a need for scalable approaches that can support dementia-preventive lifestyle behaviors beyond conventional health care encounters, and a growing array of mobile and digital health interventions has emerged to target modifiable risk factors associated with cognitive decline [6,7]. Although these approaches have shown promise (eg, improving diet quality, physical activity, and cognition [8]), they are frequently static, requiring substantial user initiative and providing minimal real-time personalization or context-sensitive behavioral guidance [9]. A recent JMIR Aging scoping review further situates this work within a broad landscape of home-based technology-assisted physical activity interventions for older adults, including mobile apps, wearable devices, exergaming, and virtual reality systems, while emphasizing the importance of usability, adherence, and user experience [10]. Smartphone-delivered, just-in-time adaptive interventions (JITAIs) offer a compelling alternative: JITAIs are defined as interventions that dynamically adapt to an individual's current and evolving status and contextual circumstances, delivering support precisely when it is most needed [11]. By design, JITAIs target moments of vulnerability (eg, high-risk behaviors or inactivity), receptivity (eg, optimal readiness to engage), and adherence (eg, uptake and sustained use of support) [7,11]. In older adults, ecological momentary assessment (EMA)–assessed affective and motivational determinants have been associated with subsequent accelerometer-assessed physical activity across short time windows, supporting the rationale for using time-varying, person-specific information to identify moments when activity prompts may be most receptive [12]. Despite their theoretical potential, JITAIs remain underdeveloped and underevaluated in this population, and recent reviews identify them as a "significant missed opportunity" for advancing precision digital health interventions [9,13]. Further, although early evidence suggests that JITAIs can support lifestyle behavior change [14,15], most research has focused on young, cognitively healthy populations [16-18]. Their feasibility and acceptability in older adults with cognitive vulnerability remain underexplored, including addressing unique challenges such as reduced digital literacy and difficulties navigating complex apps [19-21]. This is particularly important because JMIR Aging scoping evidence indicates that older adults with MCI face distinct human-computer interaction challenges and value technologies that are useful, easy to use, reliable, secure, physically comfortable, convenient, personalized, and integrated into daily life [22]. The evidence base for conversational and virtual agents in people with memory problems is still small: a systematic review found generally positive usability in early studies but noted small samples, short interactions, and limited reporting of interaction quality, reinforcing the need for feasibility studies in cognitively vulnerable populations [23]. To address this gap and to inform the development of the present intervention, we previously conducted a 2-week proof-of-concept study delivering a smartphone-based, conversational agent (CA)–supported JITAI targeting multidomain lifestyle behaviors in older adults with SCD or MCI using self-reported EMA [24]. Participants (n=15, mean age 70.3 years, SD 5.01 years) engaged with the intervention at high rates (responsiveness of n=15, 81%, reported positive experiences, and, if vulnerable and receptive, n=15, 69% of participants reported adhering to the suggested health-promoting activity). This pilot study demonstrates that such adaptive digital interventions are feasible and well-accepted in cognitively vulnerable older populations, supporting their potential for scalable dementia-preventive strategies. However, this previous intervention relied exclusively on self-reported EMA data and did not integrate wearable-derived sensor data to inform intervention decisions.

Building on the results of our previous proof-of-concept study, the integration of wearable sensor technology represents a critical next step to further advance JITAI-based

interventions for cognitively vulnerable older adults. Reliance on self-reported behavior through EMA, while feasible, may increase participant burden and can be particularly challenging for individuals with MCI [25]. Wearable devices enable passive, continuous assessment of health-relevant behaviors, such as physical activity, providing more objective and temporally precise data while reducing user burden. Recent JMIR Aging evidence supports this rationale: in older adults with cognitive impairment, individualized walking prescriptions using mHealth technology effectively increased daily steps, underscoring the relevance of sensor-enabled, goal-based physical activity support for this population [26]. Sensor-derived data allows JITAIs to more accurately detect states of vulnerability in real time, enabling truly personalized, context-sensitive prompts while minimizing notifications and user input [11]. Thus, augmenting smartphone-based CAs with wearable sensing technology holds promise for delivering scalable, low-burden, and less biased lifestyle interventions that align with multidomain and patient-centered approaches to prevention of dementia and healthy aging [27].

Here, in the piloting and evidence generation of implementation, we pilot a sensor-augmented, smartphone-based, CA-delivered just-in-time adaptive lifestyle intervention in older adults with MCI in Switzerland. The intervention builds on the availability of smartphones and wearable technologies while addressing potential barriers in this population, including reduced digital literacy and difficulties navigating complex digital applications, through personalized and low-burden interactions designed to support integration into everyday life. Switzerland's national DigiSanté program [28] provides the broader policy context for digital transformation in health care, and although the present study is an independent research initiative, the intervention is consistent with its overarching objectives of advancing digitally enabled and patient-centered health services. The study evaluates (1) adherence to the intervention over 2 weeks, (2) perceived usability and acceptability of the system, and (3) the feasibility of using wearable-derived sensor data to inform adaptive intervention delivery. By addressing these questions, this work contributes to the emerging intersection of digital lifestyle interventions, JITAIs, CAs, and wearable sensing, providing critical insights into how these technologies can be adapted to support healthy aging in cognitively vulnerable populations.

Methods

Study Design

This 2-week feasibility study was designed as a pilot implementation to evaluate the acceptability, usability, and technical implementation of a smartphone-based digital lifestyle intervention augmented by wearable sensor data. The intervention was delivered via a rule-based CA and aimed to promote adherence to daily health-promoting behaviors among older adults with MCI. In contrast to the previous proof-of-concept study [24], this iteration incorporated passive step-count data via a wrist-worn Garmin vivoactive 6 wearable sensor and smartphone sensors to enhance real-time tailoring of JITAIs.

The primary outcome was feasibility of the sensor-augmented CA-delivered JITAI, assessed primarily through adherence to the intervention over the 14-day study period. This included response rates, vulnerability and receptivity classifications, and adherence to CA-suggested health-promoting activities across the primary physical-activity component and secondary health-promoting component.

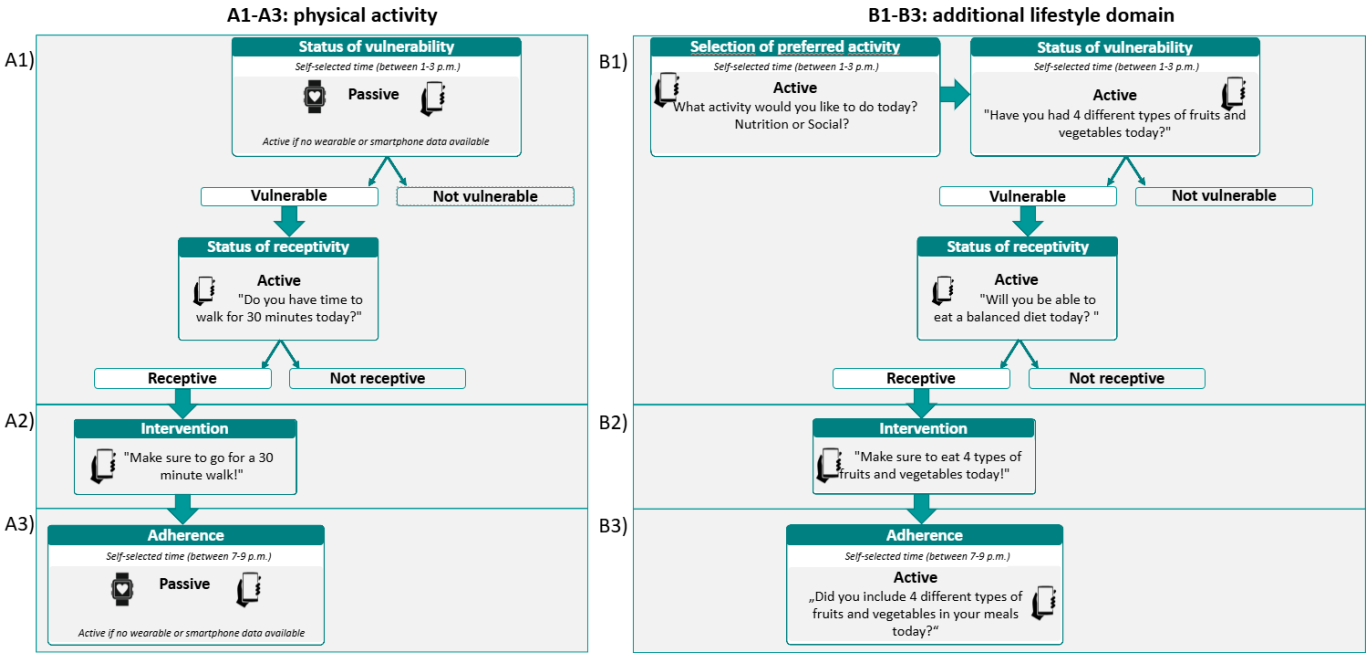
Secondary outcomes included perceived usability and acceptability, working alliance with the CA, and technical feasibility of the wearable-informed data acquisition pipeline for adaptive intervention delivery.

A formal implementation budget and total cost-of-ownership analysis were outside of the scope of this feasibility study. Itemized implementation costs such as technology licensing, change management, and user training were therefore not quantified. Further, a business or long-term sustainability model and institutionalization or exit strategy were not defined either.

Intervention Design

The intervention was developed within a JITAI framework, leveraging both self-report (EMA) and wearable sensor inputs to determine whether and when to prompt health-promoting behaviors. The target population consisted of older adults with MCI, who typically retain the capacity to provide structured momentary self-reports and to interact reliably with low-burden digital tools. Participants received daily prompts from the CA asking about their health behavior. The intervention consisted of 2 parallel components delivered each day: the first, a sensor-informed physical activity component, was triggered by continuously collected step-count data, drawn first from the Garmin software development kit (SDK), then from the smartphone (Apple HealthKit/Google Health Connect) if Garmin data were unavailable, and from EMA self-report only if neither sensor source was available; the second, an EMA-based lifestyle component, drew on momentary self-report and rotated across 6 additional health domains (cf. section Procedure). While the 2 components shared the same underlying JITAI logic (Figure 1), they differed in how vulnerability and receptivity were assessed: passively via wearable sensor data for physical activity, and actively via EMA for the lifestyle domains.

Figure 1. Decision tree illustrating the just-in-time adaptive intervention logic. For the primary physical-activity component, (A1) each day, participants are prompted at a self-selected time in the afternoon (between 1 and 3 PM) to assess vulnerability based on prior walking behavior, using both passive sensor data and active self-report. If classified as vulnerable, receptivity is then evaluated through a follow-up question about current availability. (A2) When participants are both vulnerable and receptive, a tailored intervention prompt is delivered. (A3) Adherence is assessed later in the evening at a participant-selected time (between 7 and 9 PM) via passive and active measures. For the secondary health-promoting activity component (B1), each day, participants can select from 2 suggested activities (ie, nutrition or social) at a self-selected time in the afternoon (between 1 and 3 PM). Vulnerability is assessed through active self-report. If classified as vulnerable, receptivity is then evaluated through a follow-up question about current availability. (B2) When participants are both vulnerable and receptive, a tailored intervention prompt is delivered. (B3) Adherence is assessed later in the evening at a participant-selected time (between 7 and 9 PM) via self-reported active measures.



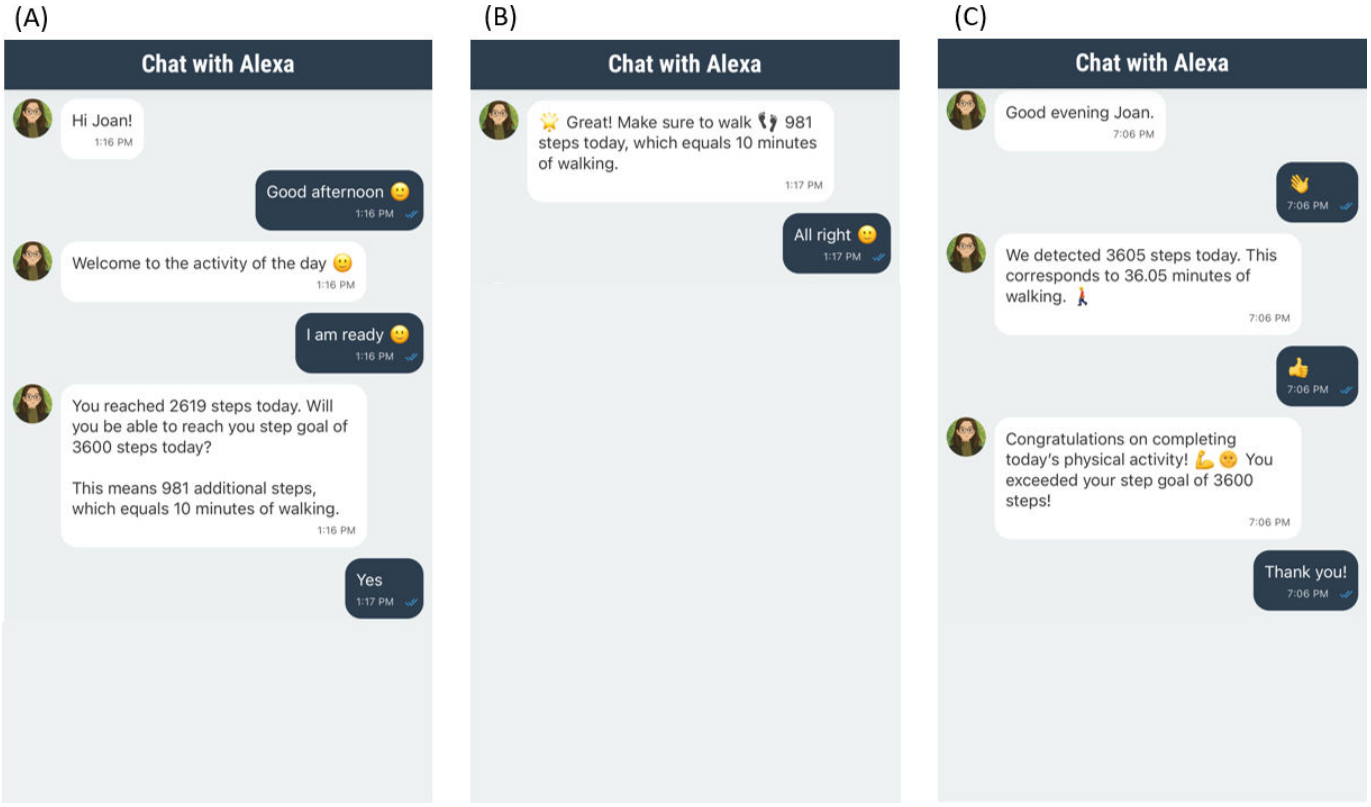
Technical Implementation

Overview

The smartphone-based JITAI was developed using a study-specific instance of the latest version of the MobileCoach software (version 1.4.2), hosted by Pathmate Technologies [29,30], which has already been used for various health interventions [31-38], including our 2025 proof-of-concept study on the usability of the EMA-based JITAI intervention [24], and was extended to include the Garmin Health SDK and the Apple HealthKit/Google Health Connect API for passive tracking and transmitting step counts from the wearable and the smartphone.

The study app was available for both Apple (iOS 15 or higher) and Android (Android 12 or higher) devices. Mobile Coach facilitates data collection (eg, via self-reports and interaction logs) and the delivery of JITAIs through a rule-based CA. The user interface follows the principles of messaging applications, but for usability purposes in our cognitively impaired population, the answer options were predominantly predefined. During onboarding, participants chose between 3 CAs (Alexa, Esther, Gianluca) to be their digital coach over the 2-week study period. The 3 key JITAI conversational turns (state of vulnerability, state of receptivity, and adherence to the CA-suggested health-promoting activity; Figure 1) are depicted in Figure 2A-C. The Garmin vivoactive 6 (software version 16.28) and the smartphone's built-in sensor were used to track participants' physical activity.

Figure 2. The physical activity conversational turns [(A) vulnerability and receptivity, (B) intervention delivery, and (C) adherence] with the conversational agent Alexa providing the just-in-time adaptive intervention in the 2-week, single-arm pilot study among older adults with mild cognitive impairment.



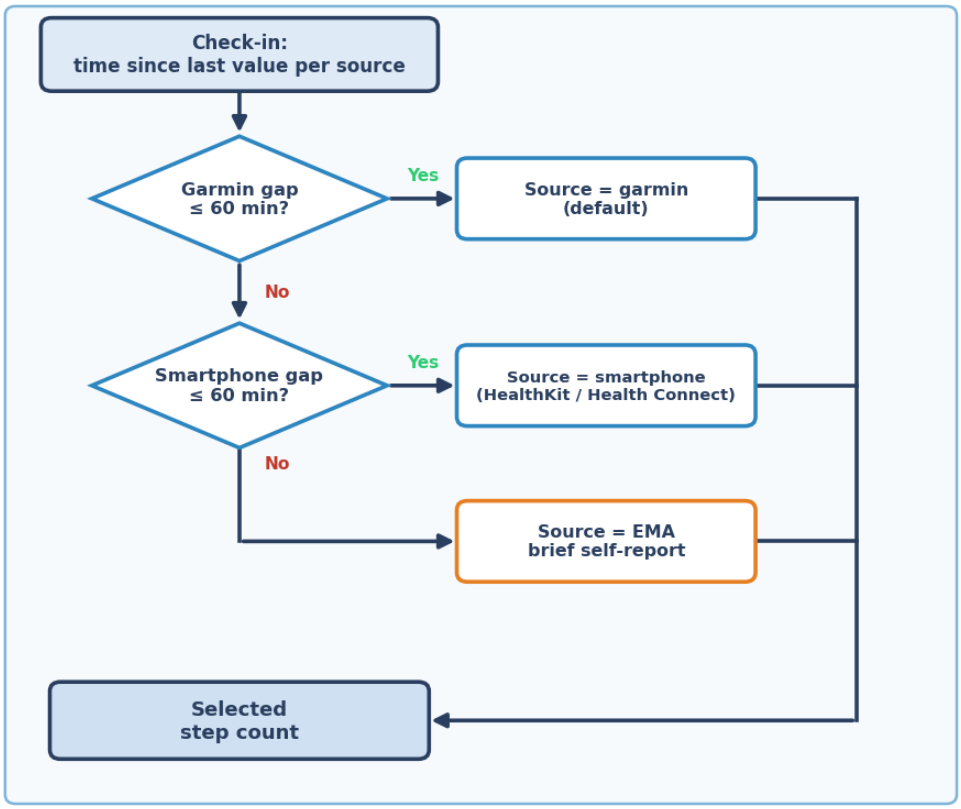
Data Hosting, Governance, and Security

All study data were collected and stored on a production server located in Switzerland, provided as cloud-based hosting by a supplier certified under ISO/IEC (International Electrotechnical Commission) 27001; a separate development server in Germany was used for testing only and held no participant data. The study team owns the data and retains full control over data handling. Data was not shared with third parties. No formal interoperability standard was applied; communication between the study app and the smartwatch used the proprietary Garmin SDK.

Data Acquisition Pipeline

A hierarchical, layered data acquisition strategy was implemented to ensure reliable and continuous estimation of step counts for the primary physical-activity JITAI component. Step-count data were collected in the background from 2 passive sources. The Garmin vivoactive 6 continuously recorded physical activity throughout the day and transmitted step counts to the MobileCoach app through the Garmin Health SDK, while step counts from the smartphone's built-in sensor were obtained through Apple HealthKit on iOS and Google Health Connect on Android. Both sources required the app to run in the background, and neither updated when the app was closed. From the app, step counts were transmitted to and stored on the study-specific MobileCoach server hosted by Pathmate Technologies, where the source-selection logic was executed. For each source, we computed the time since the last received value and used it to select the active source (Figure 3): the Garmin by default, the smartphone when the most recent Garmin value exceeded 60 minutes (indicating a connectivity or transmission gap), and a brief self-report via EMA when both exceeded 60 minutes. By prioritizing passive sensing and resorting to active self-report only as a last resort, this layered approach ensured uninterrupted JITAI functionality, minimized participant burden, and increased the robustness of activity detection by reducing missing or biased inputs.

Figure 3. Decision tree illustrating the step data source logic for the physical activity components: At every check-in corresponding to A1 and A3 in Figure 1, the algorithm selects which device supplies the step count, prioritizing the most accurate source while falling back when its most recent value is no longer under the 60-minutes threshold. It first evaluates Garmin: if the time since the most recent Garmin value is within 60 minutes, Garmin is used (default). If the most recent Garmin value exceeded 60 minutes (indicating a connectivity or transmission gap), the algorithm checks the smartphone (Apple HealthKit/Android Health Connect); if the time since its most recent value is within 60 minutes, the phone is used. If the most recent value from both Garmin and the smartphone exceeded 60 minutes, the participant is prompted for a brief EMA self-report. The chosen source yields the selected step count used for the remainder of the just-in-time adaptive intervention logic. EMA: ecological momentary assessment.



Procedure

During the in-person onboarding session, demographic data and technology readiness (the duration, modality, and frequency of smartphone and smartwatch usage) were evaluated via questionnaires (Multimedia Appendix 1). After downloading the study app, participants familiarized themselves with the chat interface and were able to individualize their app's settings: they selected their virtual assistant, reported their typical daily level of physical activity (<10, 10, 30, 60, or 90 min), and specified their preferred walking duration strategy (either increasing their current activity level, corresponding to a +20% increase in walking duration, or maintaining their current level). Each self-reported daily walking duration was converted into a daily step count using a fixed walking cadence of 100 steps per minute (step count = walking duration in minutes × 100). The "<10 min" response was coded as a 10-min walking goal and therefore converted to a daily step goal of 1000 steps. Step goals were set once at onboarding and remained fixed for the entire 14-day intervention period; no recalibration occurred during the study. To limit the risk of inappropriate increases in activity, goals were capped at +20% above the self-reported baseline, and walking prompts were delivered only to participants classified as vulnerable who had confirmed their receptivity. In addition, participants chose their preferred notification times (Figure 1) for the daily interactions with the CA, selecting 1 afternoon time point (1:00, 2:00, or 3:00 PM) and 1 evening time point (7:00, 8:00, or 9:00 PM). Participants then received a smartphone-based JITAI over a 2-week period. At the individually preselected afternoon notification time, participants were prompted on 2 health-promoting activities: physical activity and additional lifestyle domains.

Regarding physical activity, the first JITAI component targeted physical activity (Figures 2A-2C) through step count and was informed by continuously collected step-count data obtained through a hierarchical, layered strategy that prioritized passive sensing: step counts were drawn from the Garmin wearable by default, from the smartphone's built-in sensor when Garmin data were unavailable, and from a brief self-report only when both passive sources failed. This data stream was used to evaluate the participant's physical activity level and served as the basis for JITAI-triggered prompts in the domain exercise. When step count remained below the individually predefined step goal threshold by early afternoon, the system classified the participant as physically inactive (=vulnerable), and asked for their status of receptivity; if receptive, the CA delivered a tailored prompt encouraging movement. At the participant's evening check-in time, adherence was then assessed by comparing the day's step count, drawn from the same layered data strategy, against the personalized step goal: participants who reached their

goal were classified as adherent and received confirmatory feedback, whereas those who fell short were classified as nonadherent and received a supportive, nonjudgmental message.

Regarding additional lifestyle domains, in parallel, participants received 1 daily just-in-time prompt from the CA targeting 1 of 6 other lifestyle domains: hydration, cognitive exercise, nutrition, sleep hygiene, social engagement, or movement (Figures 4A-4C). The domains were chosen based on evidence-based lifestyle components affecting positive health outcomes in the literature [39], and details can be found in Table 1. Each day, participants selected their preferred activity from a randomized subset of 2 domains. Each day, participants were offered 2 of the 6 domains and chose one. The daily pairs followed a predetermined, balanced rotation. The schedule was organized into blocks of 3 days, and within each block all 6 domains appeared exactly once (6 slots across 3 days) before the cycle reset, so no domain recurred within a block. The same schedule was applied to all participants. Because the 14-day period comprised 4 complete blocks and 1 partial block, 4 domains were offered 6 times and 2 (movement and hydration) 4 times over the study. For these domains, the CA relied on EMA to determine participants' state of vulnerability (ie, whether the behavior had already been performed) and receptivity (ie, willingness to perform the behavior later in the day). If both conditions were met, a tailored prompt was delivered to encourage engagement, and adherence was assessed in the evening interaction via EMA.

Figure 4. The additional lifestyle conversational ((A) selection of preferred activity; (B) vulnerability, receptivity, and intervention delivery; and (C) adherence) turns with the conversational agent Alexa providing the just-in-time adaptive intervention in the 2-week, single-arm pilot study among older adults with mild cognitive impairment.

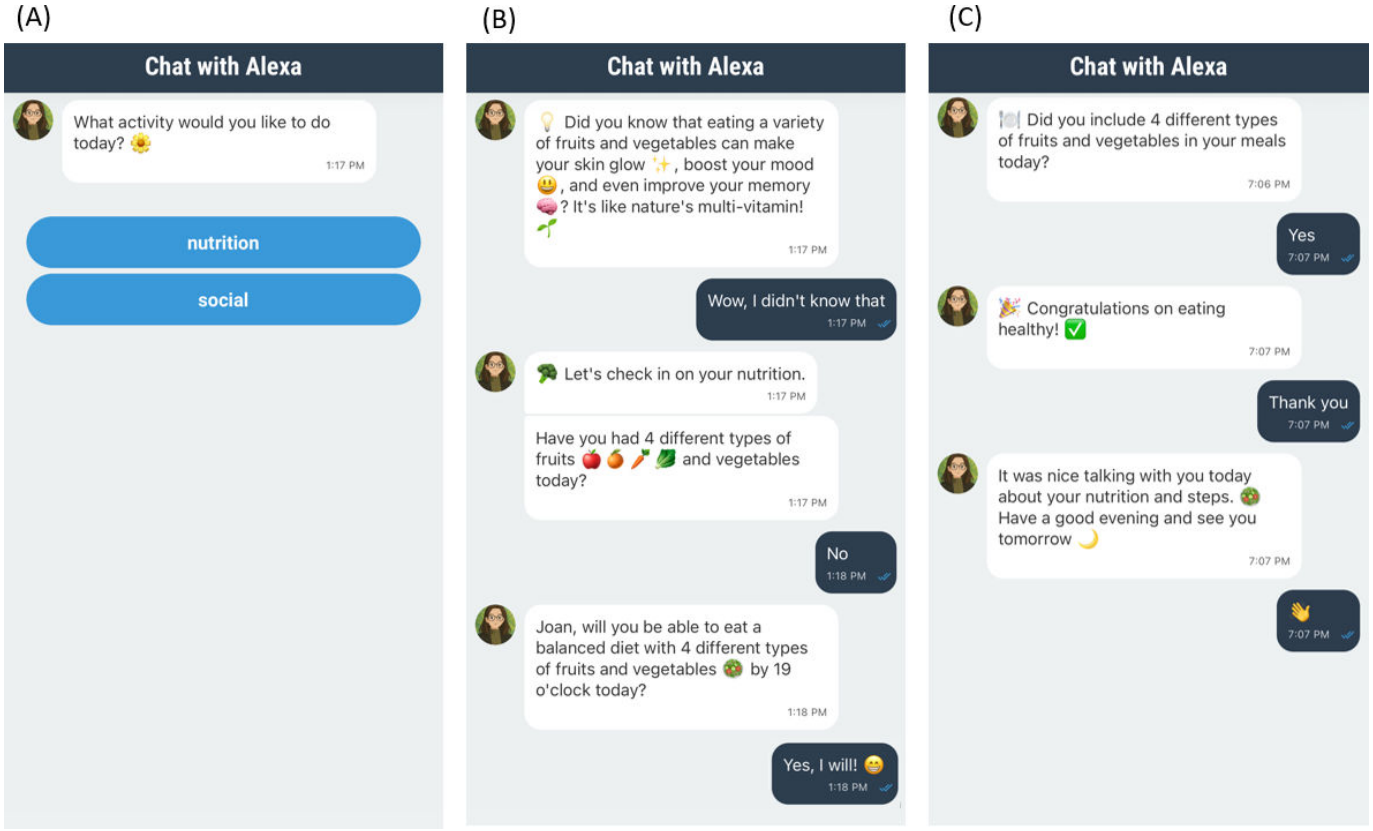


Table 1. An overview of the 6 secondary health-promoting activities prompted through the CAs[a] during the 2-week study.

Health domains	Example
Nutrition	Eating 4 different types of fruit and vegetables throughout the day
Sleep	Slept well last night and woke up refreshed; if not, nap for 25 minutes
Cognitive exercise	Crossword puzzle, Sudoku, Scrabble
Social engagement	Meet or call a close friend or relative
Hydration	Drinking 5 glasses (0.2 l each) of water
Movement	Cycling, work in the garden, yoga

[a]CA: conversational agent.

Following the JITAI logic (Figure 1), vulnerability (noncompletion of the activity) triggered an assessment of receptivity (availability to complete the activity later that day). If receptive, participants received a brief motivation prompt (Figures 2 and 4). Adherence was assessed in the evening via both passive sensor data and active EMA self-report. After the 14-day study period, an on-site follow-up visit was conducted to confirm study completion, collect feedback on app usage, and retrieve the smartwatch. Participants also completed a postintervention questionnaire and adverse events questionnaire (Multimedia Appendix 2).

Data Collection

Data were collected via the MobileCoach app, wearable fitness trackers, smartphone sensors, EMAs, and pre- and postintervention questionnaires (Multimedia Appendices 1 and 2). App-based data were collected in anonymized form using participant IDs and exported from MobileCoach for analysis of feasibility-related metrics.

Secondary outcomes included perceived usability and acceptability of the system, working alliance with the CA, and the technical feasibility of using wearable-derived sensor data to inform adaptive intervention delivery. Usability and acceptability were assessed with a postintervention questionnaire on prior work with CAs [38]. The questionnaire included constructs such as perceived ease of use (PEU), enjoyment, usefulness both as a reminder of the health-promoting behavior and as a motivator to complete the activity, perceived control over the CA, and intention to interact (ITI) with the CA again [40-42]. Working alliance, an important relationship quality previously shown to be associated with treatment outcomes [22,43-45], was measured using the 6-item Session Alliance Inventory [45]. All items were rated on a 7-point Likert scale ranging from 1=strongly disagree to 7=strongly agree.

The postintervention questionnaire also assessed smartwatch wearability and smartwatch handling and included qualitative open-ended questions covering CA interaction, smartwatch use, technical issues, and suggestions for improvement. The questions asked were the following: (1) What did you particularly like about the interaction with the CA? (2) What needs to be improved about the interaction with the CA? (3) Do you have any feedback on the smartwatch (usability, technical issues, etc)? (4) Do you have any further comments or suggestions for improvement? Additionally, participants were also provided with space to provide open feedback and details regarding their smartphone, smartwatch, and mobile OS.

Responsiveness to notifications was assessed using app interaction logs, including whether participants responded to scheduled prompts. Technical feasibility was evaluated based on the availability and reliability of step-count data from the Garmin wearable and smartphone sensors.

Data Analysis

Preintervention questionnaires were used descriptively to characterize the sample and assess baseline factors, including demographic information, prior smartphone and smartwatch use, and cognitive performance measured with the Montreal Cognitive Assessment (MoCA).

Based on the mobile app data collected by MobileCoach, metrics for vulnerability, receptivity, and both adherences (ie, CA-initiated conversational turns and CA-suggested health-promoting activity) could be analyzed. All JITAI-pathway metrics were computed at the participant-day level, where 1 participant-day corresponds to 1 participant's scheduled daily interaction with a given component (24 participants × 14 days = 336 participant-days per component).

For each participant-day, vulnerability was first determined at the time of the afternoon's CA-initiated notification. Participants were classified as not vulnerable if available activity data indicated that the target activity had already been completed before the afternoon notification. Participants were classified as vulnerable if the target activity had not yet been completed at that time. If no valid information was available from the layered data acquisition logic and the participant did not respond to the vulnerability prompt, the participant-day was classified as nonresponsive for this step.

Receptivity was assessed only among vulnerable participants, who were further categorized based on their intent to complete the activity. Participants were either classified as receptive (intended to complete the activity), not receptive (did not intend to complete the activity), or nonresponsive. Proportions were calculated by dividing the number of participants in each category by the total number of vulnerable participants.

Adherence to the CA-suggested health-promoting activity was assessed among vulnerable and receptive participants, using the layered data acquisition logic. At the evening check-in, each vulnerable and receptive participant-day was classified into 1 of 3 categories: adherent, nonadherent, or nonresponsive.

Missing data consisted of participant-days with no valid entry, either because the prompt was delivered but not answered or because the record was absent. Participant-days that were missing or nonresponsive at the vulnerability or receptivity stage were not carried forward to the subsequent stage. Adherence was calculated over all vulnerable and receptive participant-days, with evening nonresponses retained in the denominator and counted as nonadherence.

For the self-report items of the postintervention questionnaires, descriptive statistics were calculated to characterize participants' evaluations, including means, SDs, medians, and IQRs. Given the pilot nature of the study and the small sample size, these descriptive findings were considered the primary basis for interpretation. Shapiro-Wilk tests indicated that the self-report data were not normally distributed, and Wilcoxon signed-rank tests were conducted as exploratory analyses to assess whether responses differed from the neutral midpoint of 4 on the 7-point Likert scale. These analyses were not intended to provide confirmatory evidence of usability, acceptance, or working alliance, and P values were interpreted cautiously and considered secondary to the observed scores and their distributions. No adjustment for

multiple comparisons was applied because these analyses were exploratory. For the technology acceptance and working alliance section, an overall score for the 6-item session alliance inventory was computed by averaging the individual items. Internal consistency was high (Cronbach α=.89), supporting the use of a composite score [3]. Due to the limited number of items per construct in the smartwatch wearability and handling sections, no composite scores were calculated for these domains, and items were analyzed individually.

Open-ended responses from the postintervention questionnaire (translated into English) were analyzed using reflexive thematic analysis [46-48]. Coding was primarily inductive and undertaken at the semantic level, with latent interpretation where the data supported it, from an experiential orientation. Data were managed in MAXQDA Analytics Pro (version 26.2) [49]. Following the 6 phases of reflexive thematic analysis (ie, familiarization, coding, generating initial themes, developing and reviewing themes, refining and defining themes, and write-up), the full dataset was coded openly, with codes generated and refined iteratively rather than applied from a predetermined codebook. Codes were then collated into candidate themes using the Creative Coding tool and represented as a thematic map in MAXMaps (MAXQDA); candidate themes were reviewed against their coded extracts and the full dataset and defined around a central organizing concept, yielding 5 themes. Consistent with a reflexive approach, the analysis was led by 1 researcher (RV), coding-reliability statistics were not calculated, and a reflexive journal was maintained throughout to document interpretive decisions and the researcher's position.

Recruitment

Participants were recruited between February and June 2026 through the infrastructure of the Bern Memory Clinic [50] (ie, direct referrals via memory coaches in local cognitive training groups, newsletters, flyers, Facebook advertisements, and an existing participant pool). First, a short screening for a check of inclusion and exclusion criteria and a detailed explanation of the study was performed. An investigator explained the nature of the study, its purpose, the procedures involved (including the app and the smartwatch), the expected duration, the potential risks and benefits, and any discomfort it may entail. Participants were eligible if they were aged between 60 and 85 years, had cognitive decline classified as MCI, owned a smartphone (iOS or Android; for software details see "Technical Implementation"), were fluent in German, and were able to provide written informed consent. Exclusion criteria included severe psychiatric disorders or a history of substance use. In the absence of an official clinical diagnosis of MCI, cognitive status was determined using the MoCA, with scores between 18 and 25, meeting a MoCA-defined criterion for possible MCI [51,52].

Ethical Considerations

The study was approved by the local ethics committee in Bern (approval number 2024-00517). Data were pseudonymized at the point of collection, with directly identifying information replaced by participant IDs and access restricted to the core research team. For analysis and dissemination, data were fully anonymized, precluding identification of individual participants in the dataset, manuscript, or supplementary materials. Data collection, processing, and storage fully complied with Swiss legal and ethical regulations, including the Swiss Federal Act on Research Involving Human Beings (Human Research Act [HRA]) and the revised Federal Act on Data Protection (nFADP). Participants did not receive any compensation for their participation. No governmental body was involved in the development or implementation of the intervention at any stage. This research was cofunded by a University of Bern grant for digitalization projects within the framework of its "People in Digital Transformation" strategy and through institutional funds. Detailed study information and consent forms were provided to potential participants several days before the onboarding session. Participation in the study was voluntary. All participants gave written informed consent and could withdraw from participation at any time without giving an explanation.

Trial Registration

This was a single-arm feasibility study and was not designed to evaluate intervention efficacy but rather technical and patient-centered feasibility within a sample of participants with MCI. Therefore, trial registration was not undertaken. Future studies evaluating efficacy, particularly RCTs, should be prospectively registered in an appropriate clinical trial registry.

Results

Characteristics of the Study Population and Technology Readiness

The study was implemented as a monocentric feasibility study at the Bern Memory Clinic, Switzerland, and coverage was therefore regional. Participants were recruited by convenience sampling toward a predefined target of 24 participants; as this was a feasibility study, no fixed eligible-population denominator was defined, and recruitment stopped once the target sample was reached rather than aiming for population-level coverage. Of 73 people contacted, 36 passed the initial telephone prescreen (n=18 did not respond; n=15 declined; n=4 were interested but not available during the study's data collection period). Before intervention started, 2 withdrew for personal reasons, 4 were technically ineligible because their devices did not meet the operating-system requirements (Android 12 or iOS 15 or higher), and 2 did not meet the MoCA-based inclusion criterion during onboarding. Thus, 28 participants began the 14-day intervention. Four withdrew during the intervention and were not required to provide a reason for withdrawal in accordance with ethics approval. Therefore, the available data do not allow us to determine whether these withdrawals were related to technology-related burden, usability issues, personal reasons, or other factors. A total of 24 participants completed follow-up and were

included in the analysis. Completion among those who started was therefore 85.7% (24/28), and in-study withdrawal was 14.3% (4/28). All participants were assigned to the CA-delivered app intervention in this single-arm, feasibility study, and reporting followed the iCHECK-DH (Guidelines and Checklist for the Reporting on Digital Health Implementations) checklist (Checklist 1) and TIDieR (Template for Intervention Description and Replication) checklist (Checklist 2). See Multimedia Appendix 3 for a detailed participant flow diagram. The mean age of the sample was 75.9 (SD 5.52) years, with participants reporting an average of 14.4 (SD 2.62) years of education. All 24 participants who completed follow-up rated headache, dizziness, sleepiness, concentration problems, and the other symptom item as 0 (none) on the postintervention side-effects questionnaire. Adverse-event information was not collected from the participants who withdrew before completing the intervention. These findings describe symptoms reported by study completers and do not establish intervention safety. Cognitive performance measured by the MoCA averaged 23.2 (SD 1.92). The sample comprised 16 (66.7%) male and 8 (33.3%) female participants. In terms of smartphone usage, 13 (54.2%) participants used an Android device, and 11 (45.8%) participants used an Apple (iOS) device. Five (21%) of the participants owned a smartwatch. Technology readiness was assessed in the preintervention questionnaire for smartphone and smartwatch usage and is summarized in Tables 2 and 3. Participants used their phones most frequently for reading their emails (mean 4.04, SD 1.43, 14/24, 58% for several times a day) and least frequently for paying without contact (mean 2.04, SD 1.23, 12/24, 50%, for never) and listening to music (mean 1.92, SD 1.32, 13/24, 54%, for never).

Table 2. Smartphone- and smartwatch-related participant characteristics.

Smartphone OS	Participants, n/N (%)
Android smartphone	13/24 (54)
Apple iPhone	11/24 (46)
Frequency of carrying the smartphone	
Always (including at home)	14/24 (58)
When leaving the house	7/24 (29)
Only when needed	3/24 (13)
Smartwatch	
Yes	5/24 (21)
No	19/24 (79)
Frequency of carrying the smartwatch	
Always (including at home)	4/5 (80)
When leaving the house	1/5 (20)
Only when needed	0/5 (0)

Table 3. Using the smartphone (on a 5-point Likert scale, where 1 is “never” and 5 is “multiple times per day”).

Smartphone usage	Mean (SD)	Median (IQR)
Daily use for		
Reading emails	4.04 (1.43)	5 (1.25)
Researching information online	3.88 (1.36)	4.5 (2)
Chatting	3.67 (1.49)	4 (2)
Phone calls	3.62 (1.06)	3 (2)
Multiple times per week for		
Checking the weather	3.29 (1.23)	3 (1)
Writing emails	3.29 (1.49)	3.5 (3)
Taking pictures	3.12 (1.08)	3 (2)
Consulting their calendar	3.12 (1.65)	3.5 (4)
Tracking health-related data	2.88 (1.54)	3 (3)
Planning routes	2.5 (1.25)	2 (1.25)
Once per week		
Playing games	2.17 (1.58)	1 (3)
Paying without contact	2.04 (1.23)	1.5 (2)
Listening to music	1.92 (1.32)	1 (1)

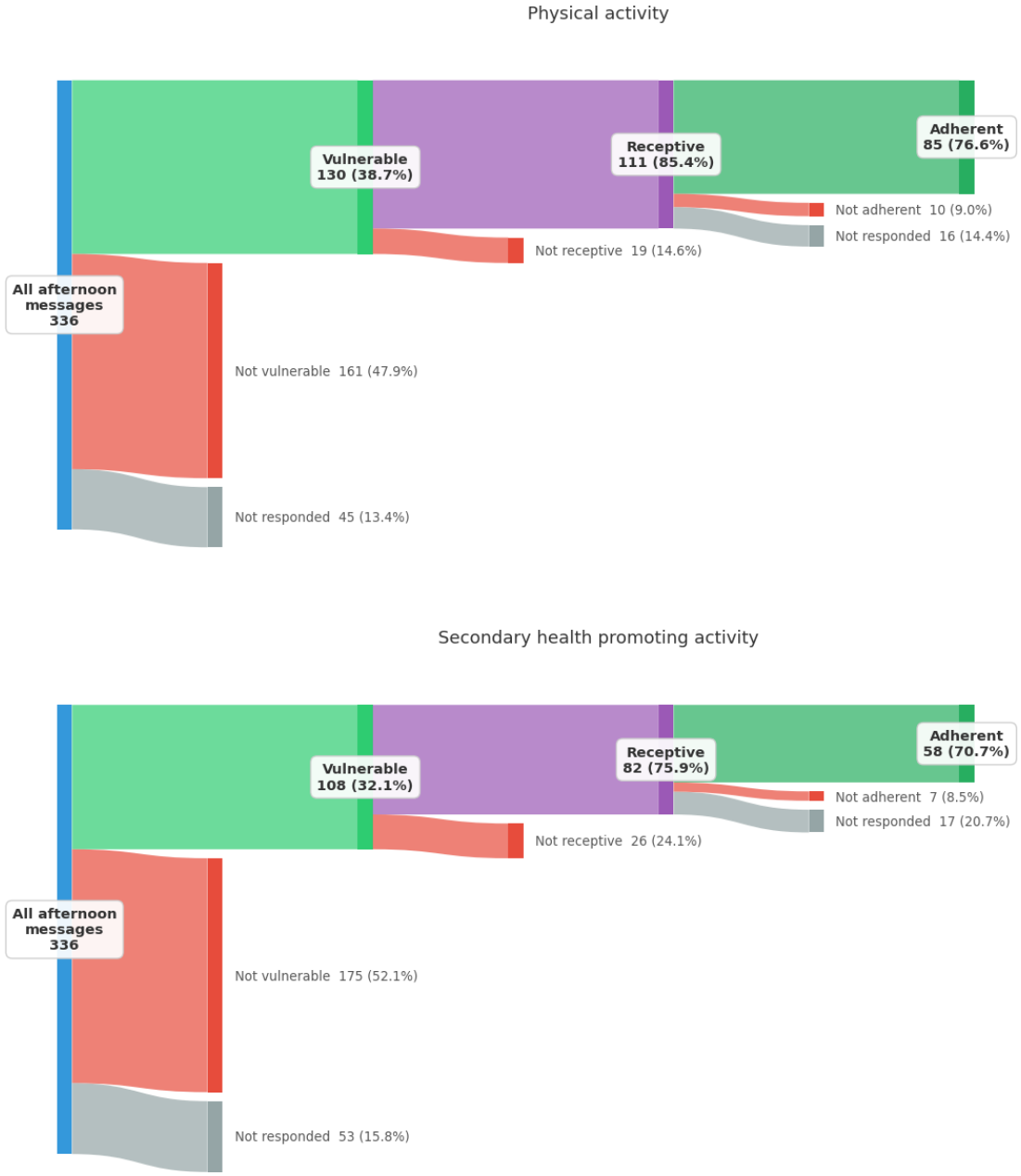
At baseline, participants reported an average daily step count of 3708 (SD 2156) steps, with 29.2% (7/24) choosing to maintain their current daily step goal and 70.8% (17/24) participants opting to increase their target over the

intervention period. The average daily step goal was 4192 (SD 2431) steps.

Responsiveness to the Notifications

Figure 5 presents the complete JITAI pathway for each component as a Sankey diagram, tracing the 336 scheduled afternoon messages through response, vulnerability and receptivity classification, evening response, and adherence at the evening check-in. Figure 5 shows the physical activity and the secondary health-promoting activity component.

Figure 5. Just-in-time adaptive intervention pathway from scheduled afternoon messages to adherence: physical activity component (top) and secondary health-promoting activity component (bottom). Sankey diagram showing prompt-level flow through the just-in-time adaptive intervention decision chain, from all scheduled afternoon messages (n=336 per component) through afternoon response, vulnerability, and receptivity classification to the evening check-in, where each vulnerable and receptive participant-day was classified as adherent, nonadherent, or nonresponsive. Percentages at each node are relative to the immediately preceding stage (eg, receptive as a share of vulnerable; adherent, nonadherent, and nonresponsive as shares of receptive); 24 participants.



Engagement with the CA was high across the 14-day study period and comparable across components at both daily check-ins. In the afternoon, 291 of the 336 (86.6%) scheduled messages were answered on the primary physical-activity component and 283 of 336 (84.2%) on the secondary health-promoting activity component. Engagement remained high at the evening check-in, where 85.6% (95/111) of evening messages were answered on the primary physical-activity component and 79.3% (65/82) on the secondary health-promoting activity component. Response rates were slightly higher on the physical-activity component than on the secondary health-promoting activity component at both

the afternoon and evening check-ins, with the larger gap emerging in the evening (6.3 percentage points difference) compared to the afternoon (2.4 percentage points difference).

Vulnerability, Receptivity, and Adherence to the JITAI

On the physical-activity component, participants were classified as vulnerable in 130 of the 336 (38.7%) afternoon messages and as not vulnerable in 161 (47.9%), with the remaining 45 (13.4%) unanswered; the corresponding figures on the secondary health-promoting activity component were 108 (32.1%), 175 (52.1%), and 53 (15.8%). All vulnerable responses were followed by a response at the receptivity stage on both components. Among vulnerable responses, 111 of 130 (85.4%) were classified as receptive on the physical-activity component and 82 of 108 (75.9%) on the secondary health-promoting activity component. Of these receptive responses, 85 of 111 (76.6%) resulted in adherence at the evening check-in on the physical-activity component and 58 of 82 (70.7%) on the secondary component. Of the remaining receptive responses, 10 of 111 (9%) on the physical-activity component and 7 of 82 (8.5%) on the secondary activity did not adhere, while 16 of 111 (14.4%) and 17 of 82 (20.7%), respectively, did not respond to the evening check-in.

Table 4 presents the JITAI pathway for each of the 6 domains on the secondary health-promoting activity component. The number of times each domain was selected ranged from 40 (movement) to 53 (nutrition). Vulnerability varied across domains: participants were classified as vulnerable most often for movement (24/41, 58.5% selections) and least often for social engagement (4/52, 7.7%), with cognitive exercise, hydration, and nutrition in between (22/47, 46.8%; 23/52, 44.2%; and 25/53, 47.2%, respectively) and sleep at 25% (10/40). Among vulnerable responses, receptivity was highest for hydration and social engagement, where all vulnerable responses were classified as receptive, and lowest for movement (15/24, 62.5%) and nutrition (16/25, 64%), with cognitive exercise (16/22, 72.7%) and sleep (8/10, 80%) intermediate. Adherence at the evening check-in, expressed as a proportion of receptive responses, was highest for cognitive exercise (13/16, 81.2%) and hydration (18/23, 78.3%) and lowest for social engagement (2/4, 50%) and movement (9/15, 60%); across domains, between 12.5% (n=2) and 50% (n=2) of receptive responses did not respond to the evening check-in, with the highest nonresponse again being for social engagement.

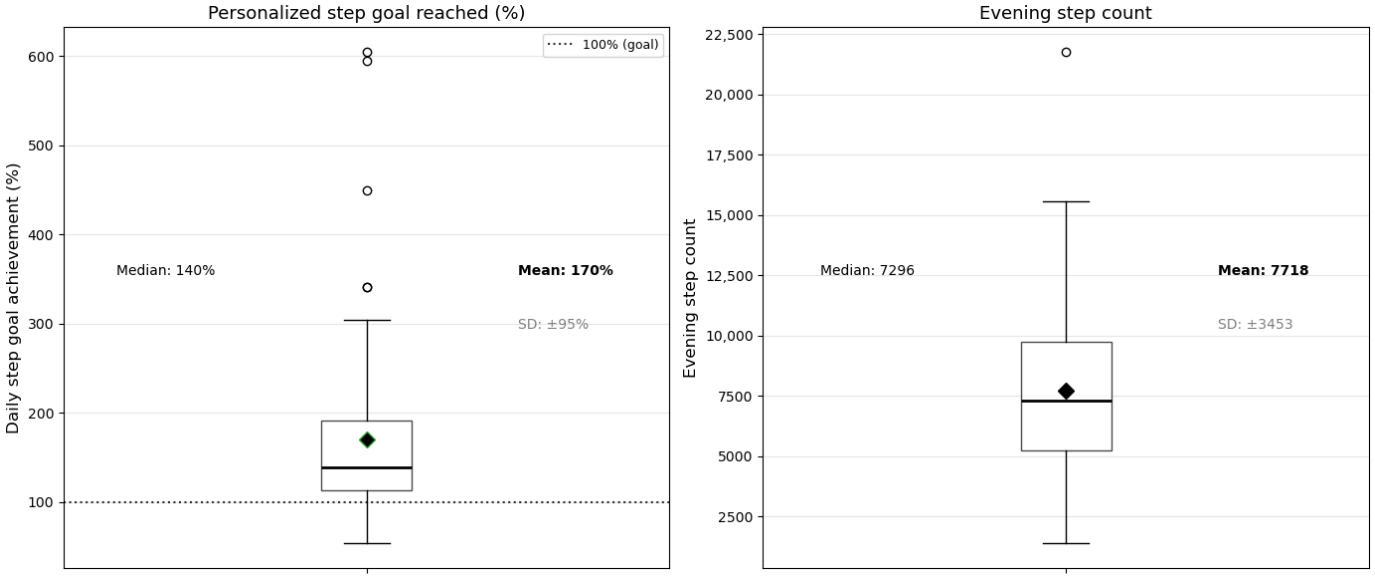
Table 4. JITAI[a] pathway by intervention domain on the secondary health-promoting activity component.

	Activity chosen, n	Vulnerability, n (%)			Receptivity, n (%)			Adherent, n (%)		
		Yes	No	No response	Yes	No	No response	Yes	No	No response
Domain										
Cognitive exercise	47	22 (46.8)	24 (51.1)	1 (2.1)	16 (72.7)	6 (27.3)	0 (0.0)	13 (81.2)	1 (6.2)	2 (12.5)
Hydration	52	23 (44.2)	28 (53.8)	1 (1.9)	23 (100.0)	0 (0.0)	0 (0.0)	18 (78.3)	1 (4.3)	4 (17.4)
Movement	41	24 (58.5)	17 (41.5)	0 (0.0)	15 (62.5)	9 (37.5)	0 (0.0)	9 (60.0)	3 (20.0)	3 (20.0)
Nutrition	53	25 (47.2)	28 (52.8)	0 (0.0)	16 (64.0)	9 (36.0)	0 (0.0)	11 (68.8)	1 (6.2)	4 (25.0)
Sleep	40	10 (25.0)	30 (75.0)	0 (0.0)	8 (80.0)	2 (20.0)	0 (0.0)	5 (62.5)	1 (12.5)	2 (25.0)
Social	52	4 (7.7)	48 (92.3)	0 (0.0)	4 (100.0)	0 (0.0)	0 (0.0)	2 (50.0)	0 (0.0)	2 (50.0)

[a]JITAI: just-in-time adaptive intervention.

Figure 6 shows daily step-goal achievement and evening step count on days that satisfied the full JITAI eligibility chain on the physical-activity component, computed at the participant-day level. Analysis was restricted to days that satisfied the full JITAI eligibility chain, that is, days on which the participant was classified as vulnerable at the afternoon check-in, was receptive to the intervention, and completed the evening check-in. This yielded 95 qualifying participant-days from 18 unique participants with a mean goal achievement of 170% (SD 95%), a median of 140% (IQR 113%-191%) and a median evening step count of 7296 (IQR 5200-9700), with a mean of 7718 (SD 3453) steps. Evening step count came from the highest-priority available source in the layered acquisition pipeline rather than exclusively from the wearable.

Figure 6. Physical-activity outcomes on days satisfying the full just-in-time adaptive intervention eligibility chain: that is, days classified as vulnerable and receptive at the afternoon check-in and with a completed evening check-in (n=95 qualifying participant-days from 18 unique participants out of 24 total participants). (A) Daily achievement of each participant's personalized step goal (%), where 100%=goal exactly met. (B) Evening step count. Boxes show the IQR, the line the median, the diamond the mean; whiskers extend to 1.5× IQR, and open circles are outliers.



Robustness of the Data Acquisition Pipeline

Across the 14-day study period, step-count data informing the physical-activity JITAI were obtained from the Garmin wearable in 80.8% (312/386) of cases, from the smartphone in 17.4% (67/386), and from self-reported manual entry in 1.8% (7/386). From smartphone observations, 9.6% (37/386) came from iOS devices and 7.8% (30/386) from Android devices. The source breakdown is illustrated in Figure 7.

Across the same 14-day period, data synchronization delay, defined as the time elapsed between the last successful step-count transmission from each source and the moment the JITAI queried it, was characterized. The Garmin device yielded a mean delay of 3 (SD 8) minutes, whereas the smartphone yielded a mean delay of 23 (SD 17) minutes. Within the smartphone subset, iOS devices accounted for a mean delay of 29 (SD 14) minutes, while Android devices accounted for a mean delay of 15 (SD 17) minutes. The 4 distributions are illustrated in Figure 8.

Figure 7. Distribution of step-count data sources across afternoon and evening interventions. The choice of the data source is based on the synchronization time delay. The Garmin was the default data source choice. If the last step count received from the Garmin was more than 60 minutes ago, the data source was changed to the smartphone. If the last step count received from the smartphone was also more than 60 minutes ago, the data source was set to manual, and an explicit question about the step count reached is sent.

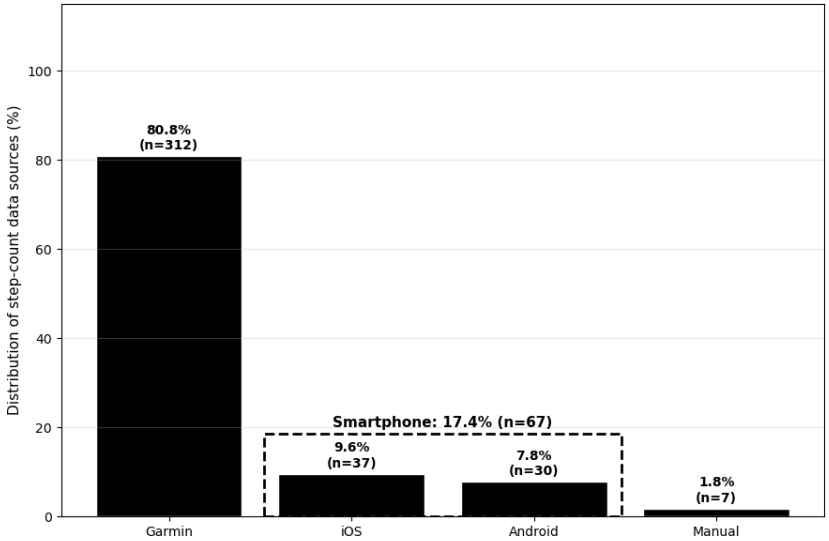
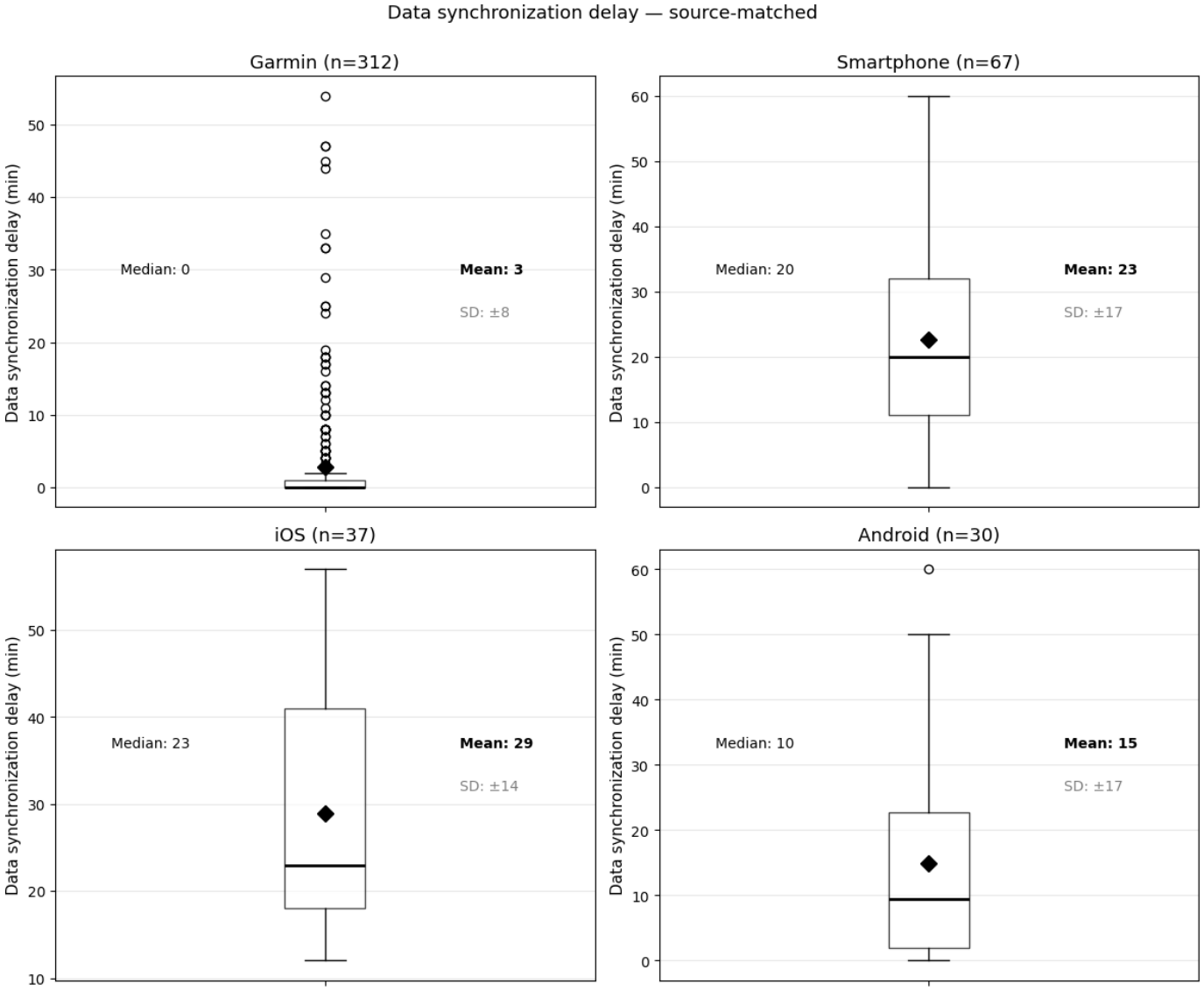


Figure 8. Data synchronization delay by data source. Box plots show the transmission delay, defined as the time elapsed (in minutes) between the most recent step-count update from a given source and the moment a just-in-time adaptive intervention prompt queried it, separately for each automated data source: the Garmin wearable (top left; n=312 decision points), the smartphone overall (top right; n=67), and the smartphone subset split by OS, iOS (bottom left; n=37) and Android (bottom right; n=30).



Technology Acceptance and Working Alliance Assessment

No item-level missing data were present; therefore, data from all participants were available for each item. Overall, participants evaluated the CA favorably after the interactions. Mean ratings were above the neutral midpoint of 4 for all constructs, indicating that participants generally perceived the CA as easy to understand (PEU: mean 6.75, SD 0.61), useful for working on the intervention (perceived usefulness [PU1]: mean 5.62, SD 1.64), motivating for performing the exercises (PU2: mean 6.12, SD 1.57), enjoyable to use (perceived enjoyment [PEN]: mean 5.71, SD 1.65), and controllable during the interaction (perceived control: mean 6, SD 1.67). Participants also reported a positive session alliance, with the overall perceived session alliance (PSA) score above the neutral midpoint (mean 5.79, SD 1.18). In the present study, the PSA score should be interpreted as capturing participants' perceived relational quality during interaction, rather than as evidence of a therapeutic alliance in the clinical sense, as they are interacting with a nonadaptive, rule-based CA. Intention to continue interacting with the CA was also above the neutral midpoint, although comparatively lower than the other ratings (ITI: mean 4.83, SD 1.99). These findings suggest that participants generally evaluated the CA positively, while their intention to continue interacting with it was more moderate.

Given the small feasibility sample, these descriptive results were considered the primary basis for interpretation. Wilcoxon signed-rank tests were conducted as exploratory analyses to examine whether ratings differed from the neutral midpoint of 4. These exploratory tests were not considered confirmatory evidence of technology acceptance or working alliance. The results are displayed in Table 5.

Table 5. Postintervention questionnaire of 24 participants on PEU[a], PU[b], PEN[c], perceived control, ITI[d], and PSA[e]. Seven-point Likert scales were used, ranging from strongly disagree (1) to strongly agree (7).

Construct	Item	Mean (SD)	Median (IQR)	Range[f]	95% CI	V[g]	*P* value
PEU	I thought the response from the CA[h] was easy to understand.	6.75 (0.61)	7 (0)	5-7	6.49-7.01	300.0	<.001
PU1	I found it useful to work on the intervention with the CA.	5.62 (1.64)	6 (2)	1-7	4.93-6.32	207.0	.0013
PU2	I found the CA motivated me to perform the exercises.	6.12 (1.57)	7 (1.25)	1-7	5.46-6.79	258.5	<.001
PEN	I had fun using the CA.	5.71 (1.65)	6.5 (2.25)	1-7	5.01-6.41	194.5	<.001
Perceived control	I was able to control the interaction with the CA.	6 (1.67)	7 (2)	1-7	5.30-6.70	216.0	<.001
ITI	I would continue interacting with the CA.	4.83 (1.99)	5 (3.25)	1-7	3.99-5.67	142.5	.05
PSA	I felt that the CA and I respected each other.	6.12 (1.26)	7 (2)	4-7	5.59-6.66	190.0	<.001
PSA	I felt that the CA appreciated me.	6.00 (1.29)	6.5 (1.25)	3-7	5.46-6.54	208.0	<.001
PSA	I felt that the CA cared about me even when I did things it did not approve of.	5.62 (1.31)	6 (3)	3-7	5.07-6.18	169.0	<.001
PSA	I felt that the CA and I are working towards mutually agreed upon goals.	5.75 (1.96)	7 (3)	1-7	4.92-6.58	185.0	.0014
PSA	I felt that the CA and I agree on what is important for me to work on.	5.83 (1.58)	7 (2)	1-7	5.17-6.50	196.0	<.001
PSA	I believe the way the CA and I are working with my problem is correct.	5.42 (1.21)	5.5 (2.25)	4-7	4.90-5.93	136.0	<.001
PSA	(Overall)	5.79 (1.18)	6.25 (2.12)	3.5-7	5.29-6.29	267.0	<.001

[a]PEU: perceived ease of use.
[b]PU: perceived usefulness.
[c]PEN: perceived enjoyment.
[d]ITI: intention to interact.
[e]PSA: perceived session alliance.
[f]Minimum to maximum.
[g]V is the test statistic of the Wilcoxon signed-rank test with test value 4.
[h]CA: conversational agent.

Smartwatch Wearability and Handling

No item-level missing data were present; therefore, data from all participants were available for each item. Overall, participants evaluated smartwatch wearability and handling favorably. Mean ratings for positively worded items were above the neutral midpoint of 4, indicating that participants generally found the smartwatch comfortable (mean 5.67, SD 1.81), easy to use (mean 6.5, SD 0.72), socially acceptable (mean 6.04, SD 1.57), and helpful for noticing notifications (mean 5.38, SD 1.74) and daily activity goals (mean 6, SD 1.69). The negatively worded items assessing interference with daily life (mean 6.46, SD 1.06) and technical problems (mean 5.92, SD 1.82) suggest low perceived burden and few technical difficulties. Wilcoxon signed-rank tests were conducted as exploratory analyses only and were not considered confirmatory evidence of smartwatch wearability or handling. The results are displayed in Table 6.

Table 6. Postintervention questionnaire of 24 participants on smartwatch wearability and handling. Seven-point Likert scales were used, ranging from strongly disagree (1) to strongly agree (7). Higher scores consistently reflect more positive evaluations. The interference and technical-problems items were reverse-coded as 8 minus the original response; higher displayed scores therefore indicate less interference and fewer technical problems.

Item	Mean (SD)	Median (IQR)	Range[a]	95% CI	V[b]	*P* value
I found wearing the smartwatch comfortable.	5.67 (1.81)	7 (3)	1-7	4.90-6.43	157.0	.001
The smartwatch helped me notice notifications.	5.38 (1.74)	6 (3)	1-7	4.64-6.11	136.0	.004
The smartwatch interfered with my daily life.	6.46 (1.06)	7 (0.25)	4-7	6.01-6.91	231.0	<.001
I experienced technical problems with the smartwatch.	5.92 (1.82)	7 (1.5)	2-7	5.15-6.68	222.0	<.001

Item	Mean (SD)	Median (IQR)	Range[a]	95% CI	V[b]	*P* value
I was able to use the smartwatch without difficulty.	6.12 (1.54)	7 (1.25)	1-7	5.47-6.78	218.0	<.001
I found the appearance of the smartwatch appealing.	6.12 (1.33)	7 (1.25)	2-7	5.56-6.69	247.0	<.001
Simply wearing the smartwatch reminded me to perform the suggested activities.	5.12 (1.83)	5.5 (3)	1-7	4.35-5.90	204.5	.01
I found wearing the smartwatch socially acceptable.	6.04 (1.57)	7 (1.25)	1-7	5.38-6.71	198.5	<.001
The smartwatch helped me achieve my daily activity goal.	6 (1.69)	7 (1)	1-7	5.28-6.72	274.5	<.001
The smartwatch reminded me of my daily goals.	6.12 (1.19)	7 (2)	4-7	5.62-6.63	210.0	<.001
I found the smartwatch easy to use.	6.5 (0.72)	7 (1)	5-7	6.19-6.81	300.0	<.001
The smartwatch was easy to charge.	6.79 (0.66)	7 (0)	4-7	6.51-7.07	276.0	<.001
I enjoyed wearing the smartwatch.	5.96 (1.40)	7 (2)	3-7	5.37-6.55	226.0	<.001
I would continue to wear the smartwatch in the future to more easily achieve my activity goals.	4.71 (2.01)	5 (2.25)	1-7	3.86-5.56	120.5	.14

[a]Minimum to maximum.
[b]V is the test statistic of the Wilcoxon signed-rank test with test value 4.

Qualitative Findings

Reflexive thematic analysis of the open-ended responses generated 5 themes (Table 7), describing an intervention experienced as accessible and structured, with clear promise, but one that participants wanted to feel more personal and to do more.

Table 7. Themes from the qualitative analysis with illustrative quotes.

Theme	Central organizing concept	Illustrative quote
Simplicity and accessibility	Approachability made engagement possible: simple, clear, easy to use	"Simple and easy to understand" (ABLE205)
Structure you can lean on	The intervention's value lay in giving daily life dependable shape	"I could structure my day better" (ABLE219)
Whose motivation is it, and who is supported?	Motivation as externally prompted vs internally owned, and the value of support	"My own motivation drives me to act" (ABLE225)
Not met as a person, run through a script	Tension between standardized delivery and individual cognitive exercise	"Repeats itself over and over" (ABLE229)
A promising tool, not yet realized	Belief in the technology's potential held against present limitations	"The watch's potential is not being utilized" (ABLE229)

Underpinning engagement was the intervention's simplicity and accessibility: clear language and ease of use made it approachable, with participants valuing that the questions were "simple and easy to understand" (ABLE205). Much of its value then lay in the structure you can lean on*:* the dependable daily rhythm and timing gave shape to the day, such that 1 participant felt able to "structure [their] day better" (ABLE219).

Participants differed in where they located the drive to act (Whose motivation is it, and who is supported?). For some, prompts and encouragement were motivating forms of support; for others, motivation was internally owned: "my own motivation drives me to act" (ABLE225), indicating that external prompting suited some better than others. A central tension concerned being recognized as an individual rather than processed by a script (not met as a person, run through a script): participants experienced the coach as repetitive, noting that it "repeats itself over and over" (ABLE229), and wished for "a more personal/individual approach" (ABLE228) and greater freedom to respond. Finally, the technology was seen as a promising tool, not yet realized: belief in its potential sat alongside a wish for it to do more, with 1 participant observing that "the watch's potential is not being utilized" (ABLE229), and concrete frictions such as inaccurate step counts and short battery life were noted.

Across the themes, participants portrayed an accessible, structure-giving tool with genuine promise that they nonetheless wanted to feel more personal and more capable. Multimedia Appendix 4 includes a list of all participant quotes according to the open-ended postintervention questionnaire.

Discussion

Principal Results

Overview

This 2-week feasibility study evaluated the acceptability, usability, and adherence of a sensor-augmented, CA-delivered JITAI in older adults with MCI. The intervention builds on the established tradition of JITAIs and CAs and on our own EMA-only proof-of-concept in this population [24], which relied entirely on self-report and identified wearable

integration as the key next step. To our knowledge, this is the first study to use passive wearable sensing to drive a CA-delivered JITAI in older adults with MCI. Prior JITAIs in this population have used self-report alone, consistent with reviews noting a lack of lifestyle JITAIs for older adults at risk of dementia [9,13], whereas JITAIs that use passive step-count data to tailor physical-activity prompts have been tested only in younger, cognitively healthy adults (eg, the JustWalk JITAI [53]). Two design choices distinguish the present intervention: (1) physical activity was tracked passively and continuously through a wrist-worn fitness tracker (Garmin vivoactive 6), and (2) walking prompts were tailored in real time to the gap between each participant's current step count and their personalized daily step goal.

Adherence to the Intervention Over 2 Weeks

Our first research question asked whether older adults with MCI would adhere to a sensor-augmented, CA-delivered JITAI over 14 days. The findings indicate that they did.

Response rates to the afternoon messages exceeded 84% across both intervention components. These engagement levels were comparable to the 81% responsiveness observed in the EMA-only predecessor study [24], suggesting that augmenting the intervention with wearable-derived sensor data did not introduce additional burden that eroded participation. This addresses a concern raised in the broader JITAI literature, where the addition of sensing technology has been hypothesized to increase complexity and reduce user engagement, particularly in populations with limited digital experience [9,13].

Engagement extended beyond responsiveness to the full JITAI decision chain. Once a vulnerable state had been identified, the majority of participants went on to adhere by the evening check-in, with over 70% (235/336) of receptive states on both components resulting in completion of the suggested activity by the evening. The low dropout at each successive stage indicates that the complete JITAI sequence could be sustained in a cognitively vulnerable population over 2 weeks.

Two patterns in adherence are worth examining closely. First, the primary physical-activity component consistently outperformed the secondary health-promoting activity component across all stages of the JITAI chain. This advantage may reflect 2 design asymmetries. Physical activity was assessed passively through the wearable, removing the need for active input, and it was prompted with personalized, concrete goals rather than generic information, consistent with the principle that specific, attainable goals are more motivating than vague directives [54]. The health-promoting activity component, by contrast, relied entirely on active self-report and generic prompts. The finding that passive sensing supports higher engagement aligns with behavioral models emphasizing that reducing the effort required to act increases the likelihood of follow-through [55], and suggests that extending sensor-informed personalization to additional lifestyle domains represents a key design priority for future iterations. Second, adherence varied substantially across lifestyle domains, with movement responses showing the highest vulnerability but lowest receptivity, and social engagement showing the reverse pattern. This variation is consistent with the JITAI framework's recognition that states of vulnerability are inherently behavior-specific [11], and with behavioral models indicating that the effort required by a suggested activity shapes willingness to act [55]. The implication for intervention design is that a uniform prompting strategy across domains may be suboptimal; future systems should consider domain-specific timing, tailoring, and goal calibration to match the distinct behavioral profiles of each lifestyle target.

Finally, on eligible participant-days, mean step-goal achievement was 170% (SD 95%). Several factors may explain this overshoot. First, the goal may have been calibrated too conservatively. Goals were derived from self-reported walking duration and represented either maintenance or a 20% increase over baseline. Because self-reported physical activity is known to diverge from sensor-measured activity [56], the initial calibration may have underestimated participants' true capacity. Second, the system provided no real-time notification when participants reached their personalized step goal; achievement was fed back only at the evening check-in, so participants received no in-the-moment cue that the target had been met and may simply have continued walking. Taken together, the overshoot may therefore reflect a measurement difference between self-reported and sensor-based activity, an underestimated baseline, a real increase in activity, or a combination of these factors. It does not establish an intervention effect.

Feasibility of Using Wearable-Derived Sensor Data to Inform Adaptive Intervention Delivery

Our findings support the feasibility of the sensor-augmented approach. These findings are consistent with JMIR Aging evidence showing that older adults can achieve high daily adherence to wearable monitoring, while consecutive-day adherence and data consistency remain important implementation challenges that require simplified protocols and engagement support [57]. We found that passive sources supplied the step count informing the JITAI at the large majority of decision points, whereas the manual self-report fallback, the highest-burden option for this population, was needed only rarely. The layered pipeline therefore worked as designed and degraded gracefully: when 1 preferred source was unavailable, the system fell back to the next rather than failing, so the JITAI almost always had data to act on and intervention decisions were rarely skipped for lack of input. More importantly, this supports the central premise of the study: that for physical activity, passive sensing can take over the role played by self-report in our EMA-only predecessor [24]. The intervention ran predominantly on the objective signal it was built around rather than on the burdensome input it was meant to replace, asked little of a population for whom active input is hardest, and based its vulnerability classifications on objective rather than self-reported behavior. These findings provide empirical evidence that a JITAI can be driven predominantly by passive data in cognitively

vulnerable older adults, the population in which sensing had been expected to add complexity [9,13].

Attrition also informs the feasibility of the sensor-augmented approach. Of 36 people passing telephone prescreening, 8 did not start the intervention (2 withdrew, 2 did not meet the MoCA criterion, 4 were technically ineligible). Losses between prescreening and the analytic sample thus reflected several unrelated processes rather than a single attrition mechanism. Technical ineligibility, due to smartphone OSs too outdated to support the study app and wearable integration, affected 4 of 36 (11.1%) prescreened individuals. In-study withdrawal itself was modest: of the 28 who started, 24 (85.7%) completed follow-up, and 4 (14.3%) withdrew. The available data do not establish whether these withdrawals were related to technology burden or usability. Broader device compatibility or study-provided hardware may reduce preintervention exclusions. We found that the synchronization delay data explains why the wearable was the most suitable primary source. The Garmin transmitted step counts well within the window required for just-in-time decision-making, whereas the smartphone lagged noticeably further behind when it was the active source. Latency also varied between OSs, indicating that smartphone-based sensing alone cannot be assumed to deliver data of consistent timeliness across devices. These findings indicate that interventions requiring just-in-time decision-making may benefit from a dedicated wearable rather than relying on smartphone sensing alone.

Perceived Usability and Acceptability of the System

The descriptive findings suggest that a smartwatch- and CA-delivered JITAI can be implemented in a way that is acceptable and low burden for participants with MCI. Recent JMIR Aging feasibility work on a rule-based and large language model (LLM)–supported voice assistant for cognitive exercise in older adults similarly found favorable PEU, usefulness, enjoyment, and working alliance, while also identifying personalization and response quality as targets for improvement [58]. This is an important consideration for interventions targeting vulnerable populations, where engagement may be limited by cognitive demands [59]. The generally favorable ratings of both the CA and smartwatch suggest that participants did not perceive substantial barriers to use during the study period. Participants' responses further suggest that the simple design and clear instructions were generally perceived as supportive of use.

At the same time, the results point to a central tension. The structured, rule-based nature of the intervention likely contributed to its accessibility, but it may also have constrained the extent to which participants experienced the CA as personally responsive. Qualitative feedback describing the CA as repetitive and insufficiently individualized suggests that low-burden design should not be equated with overly standardized delivery [56,60]. This aligns with *JMIR Aging* design work showing that CAs for people with early-stage dementia and caregivers should enhance accessibility, provide simplified and tangible activities, and support guidance and personalization rather than relying on overly generic interaction flows [61]. For JITAIs, this is particularly relevant because timely support may be most effective when it is not only easy to receive but also perceived as personally and contextually appropriate [62].

The findings also indicate that motivational support should be adaptable rather than uniform. While some participants appeared to value reminders and encouragement, others located motivation primarily internally. This suggests that future interventions should allow users to personalize motivational prompting. Such tailoring may help preserve autonomy while still providing support for those who benefit from external prompts [11].

Finally, the smartwatch results suggest that perceived acceptability may depend not only on wearability, but also on whether the technology reliably supports intervention logic. Although the device was generally well accepted, comments on inaccurate step counts, battery life, and underused functionality show that technical limitations can weaken the perceived value of a JITAI. Future iterations should therefore focus on using smartwatch data more meaningfully and reliably, while maintaining the minimal burden that participants valued.

Overall, the study provides preliminary support for the feasibility of a low-burden CA- and smartwatch-supported JITAI. However, the next step is not simply to make the intervention more intensive, but to make it more adaptive: preserving simplicity and structure while increasing personalization [63].

Limitations and Future Research Directions

Several limitations should be considered when interpreting these findings.

First, this was a single-arm, monocentric feasibility study with a 2-week follow-up. The design does not permit causal attribution of the observed step counts or engagement to the adaptive or personalized components of the intervention. Participants' behavior may also have been influenced by wearing a fitness tracker, receiving daily attention, viewing activity-related feedback, or knowing that their behavior was monitored. Although responsiveness was comparable to that observed in the preceding EMA-based pilot study, this comparison cannot substitute for a concurrent control group because the 2 studies differed in their samples, intervention structure, target population, and measurement procedures. Furthermore, the brief study period cannot establish whether engagement would persist after novelty diminished or whether notification fatigue, device nonwear, or habituation would emerge during longer use. Therefore, future research should include longer intervention periods to examine habituation, device wear, and sustained activity.

Second, the personalized step goals may have been imperfectly calibrated. The reliance on self-reported activity to calibrate personalized goals is particularly problematic in older adults with MCI, in whom recall error might be elevated and self-reported physical activity is known to

diverge from sensor-measured activity [56]. In addition, the conversion of self-reported daily walking duration into a step-count baseline assumed a fixed walking cadence of 100 steps per minute, which does not account for individual differences and may have introduced further calibration error. Miscalibrated baselines can yield goals that are systematically too easy or too demanding, with implications for both engagement and safety, a concern amplified by the fact that goals, once set at onboarding, remained fixed for the entire 14-day period, so any initial miscalibration persisted uncorrected throughout the study. Although no adverse events were reported for headache, dizziness, sleepiness, concentration problems, or any other symptom, the system provided no real-time goal-achievement alert; in a population that includes individuals with chronic health conditions, activity sustained beyond the target could contribute to inappropriate increases in activity. Future studies should therefore address these fixed design elements. The self-reported baseline and fixed +20% rule should be replaced with goals derived from recent sensor-measured activity, mobility constraints, prior goal success, and day-specific context. Daily step goals should be recalibrated adaptively over the intervention period rather than remaining fixed after onboarding. The fixed walking-cadence should be replaced by individually measured cadence. Last, sensor-based run-in periods should be implemented to collect activity data before intervention delivery to estimate each participant's typical activity. Finally, a real-time goal-achievement alert should be included, providing positive feedback upon reaching the goal.

Third, the intervention used participant-selected but still fixed decision times for the 2-week intervention period. The large differences in vulnerability across lifestyle domains suggest that this timing did not identify comparable intervention opportunities for all behaviors. Activities such as movement may commonly have been completed before the check-in, whereas social engagement remained actionable later in the day. However, these differences may also reflect heterogeneous behavioral definitions and participant self-selection of domains. Future systems should therefore learn domain- and person-specific decision times from prior behavior, daily routines, and contextual information rather than apply the same decision window across activities.

Fourth, passive sensor integration was limited primarily to physical activity. Vulnerability, receptivity, and adherence for the remaining lifestyle domains continued to rely on self-report and were therefore susceptible to recall error, social-desirability bias, and differences in participants' interpretation of whether a behavior had been completed. Receptivity also represented stated willingness of anticipated availability rather than objectively observed capacity to act. In addition, step count is only a proxy for physical activity and does not capture intensity of nonambulatory activities such as cycling, swimming, or resistance exercise.

Fifth, although the layered data-acquisition system minimized complete data loss, the 3 data sources were not interchangeable. The wearable, smartphone, and manual reports may differ in measurement algorithms and accuracy. Smartphone-derived values were particularly limited by transmission latency, especially on Android devices, and may consequently have underestimated activity at the moment of decision-making. Delayed data could lead to false vulnerability classification and unnecessary prompts. Moreover, transmission failures may not have occurred randomly; they may have been associated with participants not carrying their phones, leaving home, device-management difficulties, or actual activity without their phones. The findings therefore support the feasibility of the Garmin-centered pipeline used in this study but do not yet demonstrate a reliable, device-agnostic fallback architecture.

Sixth, the interpretation of the postquestionnaire findings is subject to limitations related to the small feasibility sample and the exploratory nature of the statistical analyses. Although Wilcoxon signed-rank tests were used to examine whether responses differed from the neutral midpoint, these analyses were not intended to provide confirmatory evidence of technology acceptance, working alliance, or smartwatch wearability and handling. No adjustment for multiple comparisons was applied, and the statistical results should therefore be interpreted as exploratory, with the observed scores providing the primary basis for interpreting participants' experiences. Moreover, comparisons with a neutral midpoint may be of limited interpretive value for highly skewed or ceiling-prone ratings, particularly when participants tend to provide favorable responses. Future studies with larger samples should confirm these findings using adequately powered designs and more comprehensive assessments of usability, acceptance, and technology engagement.

Finally, several factors may have introduced selection bias and limit the generalizability of the findings. Recruitment from a single center and the small sample size (n=24), which included 66.7% (n=16) men and participants with relatively high educational attainment, may have resulted in a sample that is not representative of the broader population with MCI. In addition, the study included participants mostly based on the MoCA cutoff score, and an MCI diagnosis has not been independently confirmed, nor was a comprehensive neuropsychological assessment performed; consequently, the sample may include people with normal age-related cognitive change or early dementia. The findings should therefore be interpreted as applying to the MoCA-defined feasibility sample, not to all clinically diagnosed MCI. Recruitment also required smartphone ownership (exclusively Android or iPhone), willingness to use an app and wear a fitness tracker, capacity to attend onboarding, and ability to provide repeated responses. The sample may consequently overrepresent participants with greater digital literacy, motivation, functional independence, and interest in health-promoting behavior. The intensive onboarding and technical assistance available in the study may also exceed the support available in routine care. Generalizability to individuals with lower digital literacy, greater cognitive impairment, physical or sensory limitations, limited socioeconomic resources, or a need for caregiver assistance is therefore uncertain. Future studies should recruit larger and more diverse samples across multiple centers, with greater representation of women and

individuals with different educational and socioeconomic backgrounds. Studies should also include individuals with lower digital literacy and more varied cognitive functions with clinically established MCI diagnoses, supported by comprehensive neuropsychological assessment to examine generalizability and improve the specificity of cognitive status classification. Future research should also evaluate more scalable onboarding and technical support approaches that better reflect routine clinical care. Further, caregiver-assisted or voice-based pathways for those unable to manage the system independently should be included in the future. The study assessed short-term feasibility and acceptability and therefore cannot establish sustained behavior change, cognitive benefit, improved QoL, or dementia-preventive effects.

Conclusions

This 2-week pilot study demonstrates the short-term feasibility and acceptability of integrating wearable-derived step data into a smartphone-based, CA-delivered JITAI for older adults with MCI. Participants showed high engagement with the intervention, generally positive evaluations of the technologies, and frequent completion of suggested health-promoting activities. The Garmin-centered data pipeline provided step-count information for most decision points, supporting the potential of passive sensing to reduce reliance on self-report and inform personalized intervention delivery. However, limitations related to goal calibration, sensor latency, fixed intervention timing, the short single-arm design, and the selected sample preclude conclusions regarding efficacy or sustained behavioral change. Longer controlled studies using sensor-derived baselines, adaptive decision times, and more diverse populations are needed to determine whether sensor-augmented personalization produces meaningful and lasting benefits beyond monitoring and generic daily prompting.

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Generative AI Use

During the preparation of this manuscript, the authors made use of large language model–based AI tools (Claude from Anthropic) to assist with language refinement and manuscript polishing, code generation for data analysis pipelines, and proofreading. All AI-assisted outputs were critically reviewed, verified, and revised as necessary by the authors, who bear full responsibility for the integrity and accuracy of the reported content.

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Data Availability

All anonymized data that were collected as part of this study are presented in the main manuscript or additional supporting files.

Authors’ Contributions

Conceptualization: EB (lead), RV (supporting), MN (supporting), TK (supporting), SK (supporting)
Formal analysis: EB (lead), AH (supporting), AdTdM (supporting), RV (supporting)
Investigation: EB (lead), AH (supporting)
Methodology: EB (lead), TK (supporting), SK (supporting)
Software: AdTdM
Writing - original draft: EB (lead), AH (supporting), AdTdM (supporting), RV (supporting)
Writing - review & editing: RV, MN

Conflicts of Interest

AdTdM, RV, MN, and TK are affiliated with the Centre for Digital Health Interventions (CDHI), a joint initiative of the Institute for Implementation Science in Health Care, University of Zurich; the Department of Management, Technology, and Economics at ETH Zurich; the Institute of Technology Management and School of Medicine at the University of St. Gallen; and the School of Health Sciences at the Eastern Switzerland University of Applied Sciences. CDHI is funded in part by a Swiss health insurer and the Austrian health care provider Mavie Next. TK is also a cofounder of Pathmate Technologies, a university spin-off company that creates and delivers digital clinical pathways. However, neither the health insurer nor Mavie Next were involved in this study. Furthermore, TK has neither shares of Pathmate Technologies nor any formal role in the company. All other authors declare no conflict of interest related to this study.

Author note

This was a single-arm feasibility study and was not designed to evaluate intervention efficacy but rather technical and patient-centered feasibility within a sample of participants with mild cognitive impairment. Therefore, trial registration was not undertaken. Future studies evaluating efficacy, particularly randomized controlled trials, should be prospectively registered in an appropriate clinical trial registry.

Multimedia Appendix 1

Preintervention questionnaire.
[DOCX File (Microsoft Word File), 81 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Postintervention questionnaire.
[DOCX File (Microsoft Word File), 93 KB-Multimedia Appendix 2]

Multimedia Appendix 3

CONSORT flowchart.
[DOCX File (Microsoft Word File), 60 KB-Multimedia Appendix 3]

Multimedia Appendix 4

Participant quotes.
[DOCX File (Microsoft Word File), 34 KB-Multimedia Appendix 4]

Checklist 1

iCHECK-DH Checklist.
[DOCX File (Microsoft Word File), 38 KB-Checklist 1]

Checklist 2

TIDieR Checklist.
[DOCX File (Microsoft Word File), 39 KB-Checklist 2]

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Abbreviations

CA: conversational agent
EMA: ecological momentary assessment
HRA: Human Research Act
iCHECK-DH: Guidelines and Checklist for the Reporting on Digital Health Implementations
IEC: International Electrotechnical Commission
ITI: intention to interact
JITAI: just-in-time adaptive intervention
LLM: large language model
MCI: mild cognitive impairment
MoCA: Montreal Cognitive Assessment
nFADP: revised Federal Act on Data Protection
PEN: perceived enjoyment
PEU: perceived ease of use
PSA: perceived session alliance
PU: perceived usefulness
QoL: quality of life
RCT: randomized controlled trial
SCD: subjective cognitive decline
SDK: software development kit
TIDieR: Template for Intervention Description and Replication

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