



Analysis of Participant-Level Characteristics Predicting Adherence to Long-Term EMA and Fitbit Monitoring in the 4HAIE Prospective Cohort Study

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Received: 29 September 2025 / Accepted: 29 December 2025

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Abstract

Background Ecological momentary assessment (EMA) and wearable devices provide valuable real-time data on health behaviors, but their utility depends on sustained participant adherence. Limited evidence exists on which individual characteristics predict adherence in long-term, large-scale studies.

Purpose This study examined participant-level factors associated with adherence to a 12-month monitoring protocol that combined wearable activity tracking and repeated mobile surveys in a prospective cohort of community-dwelling adults.

Methods A total of 1,314 adults from two regions in the Czech Republic (Moravia-Silesia and South Bohemia) wore a Fitbit activity tracker daily and completed EMA surveys during four two-week bursts across one year. Adherence was operationalized as the number of valid Fitbit monitoring days, completed time-based surveys, and completed weekly surveys. Bidirectional stepwise regression and random forest analyses identified predictors of adherence from demographic, psychological, motivational, and health-related characteristics assessed at baseline.

Results Adherence was generally high, with participants providing an average of 77% valid Fitbit-days. Older age, lower stress, greater life satisfaction, higher optimism, and stronger barrier self-efficacy predicted greater adherence. Conversely, poorer physical health, higher body mass index, and higher controlled regulation predicted lower adherence.

Conclusions Sustained long-term monitoring with mobile surveys and wearables is feasible in large cohorts. Adherence was lower among participants with poorer physical health, higher BMI, and stronger controlled motivation, suggesting that protocols which reduce burden, promote autonomous rather than externally driven motivation, and provide additional support for individuals with health-related barriers may help optimize adherence and data quality.

Keywords Adherence · Ecological momentary assessment (EMA) · Wearable devices · Fitbit · Longitudinal cohort study

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Introduction

Physical Activity (PA) is considered a dynamic and complex behavior that changes in people over time and across contexts [1]. Therefore, researchers place importance on intensive monitoring of PA [2]. Ecological Momentary Assessment (EMA) is a valuable research method that involves repeated, real-time assessments of participants' behaviors, emotions, and experiences in their natural environments [3–5]. Concretely, EMA enables a dynamic way to capture data via prompting schedules that vary based on time (so-called time-based triggers), specific occurrences (event-based triggers), or by passive or continuous sensing through a wearable device. EMA protocols thus typically specify the length of monitoring (e.g., days, weeks), frequency of sampling and the types of triggers to prompt either self-report or sensor-based assessment. For example, a study by Yang et al. [6] included a seven-day monitoring period with 8 time-based assessments throughout the day, when participants received notifications to bring awareness to a short questionnaire to be completed while continuously wearing an accelerometer to assess PA. Follow-up reminders were also given to participants who did not respond to the prompted surveys within a desired response timeframe [6]. EMA studies may also unfold in single or multiple measurement bursts, depending on whether short-term or long-term effects are of interest [2, 7]. The complexity and frequency of EMA prompts, as well as the perceived burden of participation, can influence adherence rates (i.e., dropout and response rates). Understanding these factors can help researchers design more effective EMA protocols that minimize participant burden and maximize adherence. Moreover, poor adherence can significantly impact study outcomes, leading to biased results and limiting the generalizability of findings and recommendations that would lead to better public health. The present study, therefore, focuses on assessing factors related to adherence in a 12-month EMA study of a large cohort ($N = 1,314$) with a multiple-burst design.

Background

The advancement in wearable and mobile technology has enabled the recording and monitoring of individuals' behavior within their everyday life for both short and long durations [8], allowing for easier and broader applications of EMA research of behaviors and contexts [9]. The use of EMA methodologies reduces recall biases while increasing the ecological validity of studies by collecting real-time behavioral data via constant or intermittent sampling of different aspects of a participant's life in a real-world

setting [4, 5, 10]. This enables researchers to study the dynamics of PA and related processes in various contexts (e.g., physical, psychological, and social), which provides valuable inputs for the design of more efficient interventions that can be tailored and personalized for a specific population, individual, and situation [2]. However, the full potential of EMA methodology is based on the assumption of user engagement and adherence to the monitoring [11, 12]. Thus, it is important to quantify adherence to EMA study protocols and monitoring, and to understand what predicts participants' adherence.

Selection Bias in EMA Studies

One of the primary challenges in EMA research is the initial selection bias. EMA studies are often demanding, requiring participants to respond to multiple prompts throughout the day over extended periods. This can lead to a self-selection bias, where individuals who agree to participate are typically those who are more motivated, have higher levels of interest in the study topic, or have more flexible schedules. For example, a systematic review by Perski et al. [9] highlighted that participants in EMA studies often exhibit higher levels of engagement and interest in health-related behaviors compared to the general population. This selection bias can limit the generalizability of the findings, as the sample may not accurately represent the broader population [11, 12]. Existing EMA studies in the PA domain, in particular, predominantly targeted younger, low-active adults or student samples [9, 13], limiting their generalizability to more habitually active populations. This concern is heightened in studies with small sample sizes, which unfortunately comprise the majority of existing EMA studies' assessments [13]. Therefore, it is crucial to understand the characteristics of the participants who choose to engage in EMA studies and explore how these characteristics relate to adherence. By identifying the characteristics of participants, researchers can tailor interventions and study designs to better suit the needs and preferences of different subgroups.

Participation in EMA Studies

Once participants are enrolled in an EMA study, a second challenge arises—ensuring consistent participation. It includes not only responding to prompts but also attending study sessions, completing surveys, and any other required activities [14]. The terms compliance and adherence both describe how well participants follow study protocols but differ in nuance. *Compliance*, a term historically rooted in medical contexts, implies that participants follow instructions given by healthcare providers or researchers, often in a relatively passive role [15, 16]. *Adherence*, in contrast, reflects a more active, voluntary, and collaborative role of

participants, suggesting that they engage with study procedures because they understand, agree with, and commit to them [17–19]. In the context of EMA and mHealth studies, study adherence encompasses two key aspects: (1) retention, or how many participants remain enrolled in the study, and (2) data provision, or the extent to which participants provide the intended amount of data. Data provision in EMA studies is often operationalized as the response rate, the proportion of answered assessments relative to the total number of scheduled assessments [13]. For example, if a participant responds to 8 out of 10 prompts, their response rate is 80%. It is a measure of how often participants provide the required data [20].

Beyond adherence and compliance, recent literature has emphasized the importance of *digital engagement*, which is a broader construct describing how individuals interact with and experience digital health tools. Engagement encompasses both behavioral components (e.g., frequency, duration, and depth of use) and experiential components such as interest, attention, and affective involvement [21, 22]. Whereas adherence refers to the extent to which participants complete study tasks or provide data as intended, engagement reflects the underlying quality, motivation, and sustained involvement in those behaviors.

Adherence to EMA Protocols

Adherence to EMA protocols can vary widely among participants, influenced by factors such as the frequency and timing of prompts, the perceived burden of participation, and individual differences in motivation and daily routines [9]. Poor adherence can lead to missing data, which can bias the results and reduce the statistical power of the study. For instance, Stinson et al. [23] found that adherence rates in EMA studies varied significantly, with some studies reporting adherence as low as 1.8%. This variability underscores the importance of designing EMA protocols that minimize participant burden and enhance engagement. This is especially important in light of evidence linking poor adherence to study outcomes [24].

Recently, Bittel et al. [10] completed a systematic review of the literature employing EMA methodology to study the social cognitive determinants of movement-related behaviors. Encouragingly, of the 24 studies included in the review, all have reported compliance rates, which ranged from 56.9% to 95%. Another systematic review and meta-analysis, specifically focused on methodology and compliance monitoring in EMA [13], reported that existing EMA studies lasted seven days on average and included six assessments per day with an overall adherence rate of 79% (with the majority of the studies reporting 80% adherence or higher). Across the 347 studies included, adherence (defined in terms of a response rate or % of prompts answered per day) did not

differ with the number of scheduled prompts per day, possibly as a result of pre-selection into the study or the tradeoff that researchers often made between the frequency of assessment and study length (longer studies typically included fewer prompts per day). Financial incentives were found to enhance adherence, with higher adherence rates observed in studies offering any monetary incentives versus none at all. Contrary to some other studies, the authors did not observe any systematic differences in adherence rates by sample characteristics such as age or health status, but adherence was higher in samples with a greater proportion of women (especially for studies with > 60 assessments). Importantly, less than one third of studies reported dropout rates and reasons for dropout [13]. The greater than 80% adherence rate in EMA studies is consistent with EMA research focused specifically on health behaviors with Perski et al. [9] reporting median adherence of 84% across five target behaviors (PA and sedentary behavior, dietary behavior, alcohol consumption, tobacco smoking, and sexual health behavior). Nearly 25%, or 157 out of the 633 studies assessed, did not report adherence data.

Notably, it is important to point out that adherence levels reported in EMA research (median \approx 80–84%; [9, 13]) compare favorably to adherence observed in traditional medical and behavioral regimens. Decades of research show that long-term adherence to prescribed treatments or medical advice typically ranges from 50–60% [19, 25]. This contrast underscores that EMA protocols, despite their intensity, can achieve adherence levels that exceed many other long-term health behaviors.

Adherence to Ambulatory Assessment

Oftentimes, EMA studies involve a wearable device such as a smartwatch, e.g., Fitbit, Apple Watches, or Garmin, or even waist-worn devices. Obtaining data from objective monitoring of PA provides an immense amount of information about an individual in their natural environments that is beyond the traditional healthcare setting, as well as aids in behavioral health research (Xu et al., 2018; see also Polgreen et al., 2018). Wearable devices also allow for low-cost, personalized, and attainable interventions for behavior change to be created for various populations (Polgreen, et al., 2018). Prior research has revealed that factors related to sample characteristics (e.g., age, gender, and baseline PA level) or study design (e.g., incentive structures, device type, and duration of monitoring) have an effect on adherence to behavior monitoring via wearables. In Paolillo's (2022) study, participants wore a Fitbit on average 89% of the days, and women were more adherent than men. When an incentive to wear a wearable device is no longer there, participants continued use decreases significantly (Polgreen et al., 2018). Also, newer technology (commercial-grade

wearables) is more appealing to participants aesthetically and more comfortable than previous accelerometers worn, allowing for greater adherence rates (Bedard et al., 2017). However, the use of consumer-grade devices also introduces potential device reactivity, whereby participants temporarily alter their behavior due to increased awareness of being monitored [26]. To mitigate such reactivity and ensure stable measurement, some authors recommend incorporating a run-in or familiarization period prior to formal data collection, allowing participants to adjust to device wear and identify early technical or motivational issues [27, 28]. Participant characteristics are, however, rarely investigated with respect to adherence with monitoring via wearables, with only a few studies reporting on reasons for non-adherence.

Research Questions and Contribution

In summary, although EMA represents a powerful tool for capturing real-time data in naturalistic settings, researchers must be mindful of the challenges related to participant adherence. Identifying participant characteristics related to adherence represents an important intermediate step in helping researchers (1) design more effective participant engagement strategies essential for obtaining valid and reliable data in the context of EMA studies, and (2) identify subgroups (of low or non-adherers) in whom more personalized, tailored intervention designs are needed, to boost adherence. To date, most studies examining participant-level predictors of adherence have reported findings separately for EMA and wearable-sensor protocols. Only a small number of studies have reported adherence across **both** EMA and wearable sensor modalities within the same design. For example, Martinez et al. [29] found that in an observational sample of workers' characteristics and long-term compliance, demographic and personality characteristics explained ~19% of variance in wearable adherence and ~14% variance in EMA adherence. More recently, Holmqvist et al. [30] conducted a 4-week smartwatch + EMA feasibility trial in 44 older adults with mild cognitive impairment, reporting an average 21 h per day smartwatch wear time and 94% response rate to daily EMA surveys with age and race being significantly associated with adherence. Daniels et al. [31] reported ~67% EMA response rate alongside continuous wearable monitoring in older adults, nonetheless the focus of the study was not on participant-level predictors of adherence.

This current study, therefore, investigated participant-level factors predicting adherence to an EMA protocol and long-term PA monitoring via wearables in a large prospective cohort study of 1,314 community-dwelling adults residing in the Czech Republic. The existing reviews of EMA studies [9, 13, 23] suggest that the literature would benefit from more culturally diverse samples. Although the smartphone ownership penetration in the Czech Republic

is higher than the EU average (97% versus 80%) and digital skills are higher (69.1% versus 56%), some segments of the population lag significantly behind, with only 40% of adults aged 65 + considered to have basic digital skills [32, 33]. Including data from countries such as the Czech Republic can substantially enrich the current evidence base by capturing variability in socioeconomic, technological, and cultural factors that may shape participant engagement, thereby enabling a more nuanced understanding of the determinants that facilitate or hinder adherence in EMA and other forms of ambulatory assessment.

The primary aims of the current research study were to (1) identify participant-level factors that predict adherence to long-term monitoring of PA via a wearable device and (2) identify participant-level factors that predict overall adherence to EMA surveys within this prospective cohort study with four multiple bursts. Given the breadth of different assessments captured in the study, we have formulated a general research question: which demographics, psychological and motivational factors predict overall adherence to long-term monitoring of PA via a wearable and to EMA surveys?

To guide the selection of predictors of adherence, we drew on the Capability, Opportunity, Motivation–Behavior (COM-B) model [34], a widely used framework for understanding health-related behaviors. COM-B proposes that a behavior occurs when individuals have (1) capability (or the psychological and physical capacity to engage in the behavior), (2) opportunity (or external factors that enable or constrain behavior), and (3) motivation (the reflective and automatic processes that energize and direct behavior). Applied to adherence in EMA and wearable monitoring, the model suggests that individuals with greater psychological and physical capability, more favorable social and environmental opportunities, and more internalized or autonomous motivation are more likely to sustain participation over time. In line with the COM-B [34], we thus hypothesize that (H1) individuals with higher capability (e.g., lower anxiety, depressive symptoms, stress or better health status), (H2) opportunity (e.g., higher social support) and (H3) motivation (more autonomous motivation) have greater adherence. Additionally, in line with other evidence [9, 35], we hypothesize that (H4) women, younger participants and participants with higher education level and socioeconomic status exhibit higher adherence. Because adherence is shaped by both modifiable factors (e.g., stress, motivational quality, self-efficacy and non-modifiable factors (e.g., age, gender, we examined a broad set of participant-level characteristics, since non-modifiable factors can help identify subgroups at higher risk of low adherence, while modifiable factors may serve as potential targets for future engagement strategies.

Methods

Study Sample and Procedures

The cohort study, the Healthy Aging in Industrial Environment – Program 4 (4HAIE) study was a 12-month longitudinal study that focused on investigating the interactions between air pollution, biomechanical, physiological, psychosocial, and sociodemographic variables on PA, health and quality of life, and incidence of running-related injuries. The 12-month monitoring period was selected to align with the overarching aims of the 4HAIE cohort, which focused on the interplay between air pollution, PA, and health outcomes. Because air pollution levels exhibit strong seasonal variability, a year-long observation window was necessary to ensure that participants' behaviors and exposures were captured under diverse environmental conditions. The sample included participants ($N=1,314$) aged 18–65 who resided in two regions in the Czech Republic: the Moravian-Silesian Region [MSR] and Southern Bohemia Region [SBR], regions that differ in levels of ambient air pollution. The sample was recruited by a professional social science research and marketing company (FOCUS – Marketing & Social Research) which was granted full autonomy in designing and implementing the recruitment strategy. The agency drew on a variety of recruitment methods ranging from online recruitment (e.g., social media posts, online fora, job websites), recruitment in communities and at community events (e.g., sports clubs, mall stands), media ads (e.g., local newspapers, local transit, radio), recruitment through agency interviewer network, and by chain-referral. To ensure heterogeneity of the sample, recruitment followed non-probabilistic stratified quota sampling by location, age, gender, and PA status (for details, see [36]). Participants entered the study continuously, and the entire data collection period took place between April 2019 and August 2022.

In terms of PA status, the sample comprised active runners – that is, individuals who met the public health guidelines for PA of at least 150 min a week in moderate intensity PA or 75 min in high intensity PA or an equivalent combination [19], plus were running for six weeks or longer, with at least 10 km per week and planned to continue for another 12 months; and inactive individuals (i.e., those not meeting public health recommendations for PA but capable of PA, including running, meaning they were without limitations to PA imposed by a physician).

Eligible participants (see consort diagram in Fig. 1) were first required to complete two baseline surveys (socioeconomic [SES] and psychological) from home via the Qualtrics online survey platform and were also scheduled

for a 2-day laboratory assessment at the University of Ostrava. The 2-day laboratory assessment included psychological, physiological, biomechanical, anthropometric, cognitive, and magnetic resonance imaging (MRI) assessments. Participants were also required to complete two additional sets of questionnaires (PA and biomechanical) while in the laboratory. Selected measures from the baseline surveys were administered again online at months 6 and 12. For a list of all measures and study procedures, we refer to the respective protocol papers [36–38] or the study website <https://haie-lerco.cz/en/data-en/>.

All participants completed a written informed consent and all study procedures were approved by the Ethics Committee of the University of Ostrava.

PA Monitoring.

Participants were monitored for the following 12 months by a Fitbit Charge 3 (or, toward the later parts of the study, a Fitbit Charge 4 due to Charge 3 devices being no longer produced) and were required to wear the monitor all day, including while they slept, and when they were both sedentary and active. An exception to wearing the Fitbit was when there was a potential risk of injury (e.g., during contact sports). The data was downloaded from the Fitbit server to our study server via the HealthReact system (<https://www.healthreact.eu/>), used and described also in Vetrovsky et al. [39]. This study focused on adherence to wearing a Fitbit, defined as the number of valid days of monitoring (i.e., days with at least 10 valid hours of data per day during waking hours).

Ecological Momentary Assessments.

Participants completed brief surveys administered through their smartphones via the HealthReact platform and mobile app [39]. Participants completed surveys in four 2-week measurement bursts during a 12-month period (at baseline, month 4, month 8, and month 12). During each burst, participants were prompted on their smartphones four times per day for 2 weeks based on a semi-random schedule, with time-based surveys triggered during pre-defined assessment windows (8:00–11:59, 12:00–15:59, 16:00–19:59, 20:00–22:00) at least 90 min apart to assess momentary variability in affective states, stress, pain, and context. There were also two self-initiated surveys: PA report (episodes of intentional PA lasting at least 20 min and leading to an increase in breathing, sweating, and HR) and an injury report (when the injury involved the musculoskeletal system). Given the study's focus on musculoskeletal injury incidence, injury was also monitored prospectively via a time-based (weekly) survey distributed every Sunday between 16:00 and 20:00. Lastly, a context-triggered survey was triggered when a decrease in PA over the past seven days below the 90% confidence interval for the average weekly levels across the past month was indicated by the Fitbit data, possibly indicating an injury or other issue causing reduced PA.

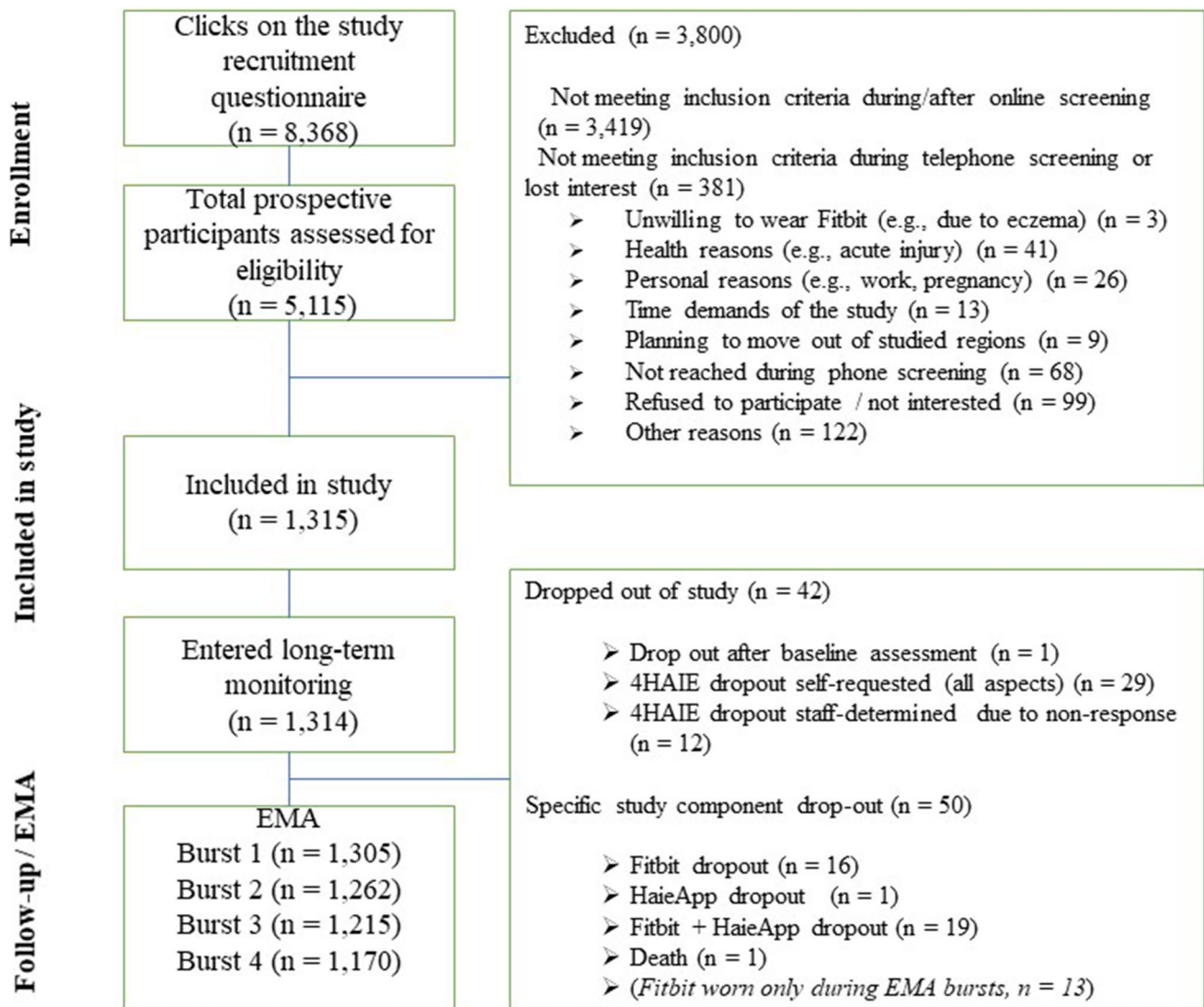


Fig. 1 The CONSORT diagram showing the flow of participants through the study and reasons for dropout.. *Note.* Participants were considered *dropouts* only if they formally withdrew from all aspects of the study or stopped providing any data (EMA, Fitbit, or online surveys) and did not respond to repeated contact attempts. Some participants discontinued specific components (e.g., EMA bursts) but

continued participating in others, such as wearing the Fitbit or completing follow-up questionnaires. These cases were treated as partial nonresponse rather than full dropout. As a result, the number of participants completing later EMA bursts is slightly lower than expected based on the total number of dropouts, reflecting typical patterns of intermittent participation in long-term digital monitoring studies

This floating algorithm was evaluated every day during early morning hours, and the survey asking for the context of the decrease was then sent to the respective participants in the morning. The EMA survey length varied based on the type of questionnaire and branching where relevant but morning (18–28 questions), daily 1 and daily 2 surveys (11–21 questions) took 1–2 min on average to complete, evening survey (21–43 questions) took 3 min on average to complete, and the weekly survey could take up to 3–4 min to complete due to branching in cases where injuries were reported. Finally, real-time data was collected on air quality from nearby air quality control stations based

on participants' locations (derived from the smartphone). This study focused on adherence to the common "core" EMA measures (i.e., response rates to the time-based surveys and weekly injury surveys).

Incentives.

Regarding incentives, participants received financial compensation for the baseline testing of ca. EUR 40 for MSR participants and ca. EUR 70 for SBR participants (to account for the extra travel time of about four hours by car one way; the transportation was provided). Participants also received results from several baseline assessments (e.g., graded exercise test) and a gift bag (about EUR 35 in value)

upon completion of the baseline testing. During each month of the 12-month monitoring period, participants were eligible to enter a lottery for one EUR 185 gift card. The number of entries in the lottery for each participant depended on completing the required aspects of the 12-month monitoring (e.g., wearing the Fitbit, completing smartphone surveys, and completing the questionnaires at months six and 12). At the end of the 12-month monitoring period, participants also received a personalized report based on the objectively measured data from Fitbit, responses to the EMA surveys, and air pollution data.

Adherence Monitoring.

The study staff ran frequent checks of adherence throughout the study. At the baseline testing, they made sure that both the HealthReact survey app (presented to participants under the name HAIEapp to build study identity) and the Fitbit app were running correctly on the participant's smartphone. Participants were instructed to check if the synchronization was working properly during the first weeks of the study. Subsequently, the study staff periodically monitored adherence via the HealthReact researcher interface and automated reports both in terms of wearing and syncing the Fitbit fitness bracelet and completing the EMA surveys in the survey app. When an issue was detected, participants were contacted by the study staff either by email, via a special smartphone survey reminder pushed by the HealthReact platform, by a text message, or by phone, depending on the issue and its severity in a systematic manner.

Study Dropout.

Despite our best efforts, we faced some level of dropout during the course of the 12-month-long study. We classified participants as dropouts when this circumstance was explicitly communicated between the participant and study staff or agreed upon by the study staff based on the missing data of a given participant and the failure to reach them. When communicating with participants, the study staff always tried to propose dropping out of only one element of the study, continuing with the other aspects. Dropout rates and reasons are presented in Fig. 1.

Measures

Baseline Characteristics and Predictors of Adherence.

Participant characteristics were assessed using an online questionnaire at baseline and also in the laboratory (body mass index or BMI, fitness status assessed via maximal graded exercise test). The sociodemographic variables included age, gender, socioeconomic status, and geographic location. To examine participant-level factors associated with adherence, we selected a comprehensive set of psychosocial, behavioral, and health-related predictors informed by the COM-B model. Capability-related factors included perceived stress, depressive and anxiety symptoms, sleep

quality, and physical health status, as these influence individuals' psychological and physical capacity to engage in EMA and long-term monitoring. Opportunity-related factors captured the role of the social environment, specifically social support for exercise. Motivation-related factors encompassed a broad range of constructs reflecting both reflective and automatic processes, including life satisfaction, self-esteem, neuroticism, optimism and pessimism, exercise identity, autonomous and controlled regulation of exercise, amotivation, confidence in overcoming barriers, and physical self-worth. Detailed descriptions of all measures, including scale characteristics, scoring procedures, and psychometric properties, are provided in the supplementary materials.

Adherence Indicators.

Descriptive data are provided for completion rates of online surveys and availability of Fitbit data, both in terms of valid days of monitoring as well as Fitbit sleep data. The number of self-initiated PA and injury reports through the HealthReact app are also reported. As indicators of adherence (and dependent variables in regression models), we calculated the following statistics: (1) *EMA-time-based*—number of EMA time-based surveys with more than one question answered (maximum of 56 surveys across the four 2-week measurement bursts); (2) *EMA-weekly*—number of EMA-weekly surveys completed with more than one question answered across the 12 months of monitoring (maximum of 52 surveys); (3) *Fitbit-days*—number of days of valid PA monitoring via Fitbit (maximum 365 days). A valid day of PA monitoring was defined as a day with 10 or more hours of valid wear time.

Analytical Approach

Pre-processing of the Fitbit Data.

Several decisions were made in the process of aggregating and exporting the Fitbit data. First, the Fitbit PA data was aggregated to minute-level values for the individual variables (e.g., steps, heart rate [HR], active minutes). We also created indicators of valid Fitbit wear during a specific minute. Based on the available heart rate (HR) and step data, we coded each minute according to the presence of valid sensor signals: 0 = no HR and no steps, 1 = non-zero steps but missing HR, and 2 = HR available (with or without steps). For the purpose of identifying valid wear time, a minute was considered valid if it contained either a HR reading or a non-zero step count (i.e., a value of 1 or 2). This approach captures all periods during which the device was worn, recognizing that temporary loss of HR data can occur despite continuous wear (e.g., due to a loose wrist fit, movement artifacts, or brief skin-sensor disconnection). Daily wear time was calculated by summing the number of valid minutes during waking hours (excluding Fitbit-defined sleep

periods). A valid wear day was defined as one with at least 10 h of valid waking wear time, following standard conventions in wearable research. This variable (wear_time_steps) was used to quantify adherence for the current analyses.

Variable Selection for Adherence Modeling.

To identify the variables that most significantly influence adherence, we employed two distinct approaches: bidirectional stepwise regression [40] and a random forest analysis [41]. The following variables were examined:

- Capability (anxiety, perceived stress, depressive symptoms, sleep quality, mental health status, physical health status, PA self-regulation, barrier self-efficacy, satisfaction with life, self-esteem, physical self-worth, body mass index, body fat percentage, cardiorespiratory fitness—assessed as maximum oxygen uptake or $\text{VO}_2\text{-max}$)
- Opportunity (general social support, social support for exercise)
- Motivation (amotivation, autonomous motivation, controlled motivation, exercise identity)
- Behavior (self-reported PA level)
- Other covariates (age, gender, location, activity status, education, socioeconomic status, neuroticism, pessimism, optimism)

The bidirectional stepwise regression begins with a basic linear model that includes only the intercept parameter for the adherence variable. Variables are then sequentially added to the model based on their ability to minimize the Akaike Information Criterion (AIC) [42]. Once no additional variables can be added to further reduce the AIC, a deletion cycle is initiated, in which previously added variables are evaluated for removal to achieve a lower AIC. The final model is established once no further variable removal can decrease the AIC.

The random forest method [43] was used to model adherence from the available independent variables. Variable importance was evaluated using the node purity measure, which reflects how much each variable contributes to reducing impurity across the decision tree splits in the forest. For each independent variable, the aggregated increase in node purity serves as an estimate of its predictive usefulness. To fit the random forests, we applied an automated optimization procedure to select an appropriate value of the *mtry* parameter, which specifies the number of candidate variables considered at each split. The procedure iteratively evaluated several *mtry* values and selected the one minimizing the out-of-bag (OOB) error estimate. Each random forest fitted during this tuning process consisted of 50 trees.

Results

Adherence Levels in the 4HAIE Study

The participant characteristics and flow through the study are depicted in Table 1 and Fig. 1.

The distribution was centered on early-to-mid adulthood, with fewer participants at the youngest (18–25 years) and oldest (60–65 years) ends of the eligible range. Overall, the sample included balanced representation by gender and education and substantial variability in behavioral and biopsychosocial characteristics, supporting analyses of adherence predictors.

Additionally, Table 2 presents an overview of online survey completion rates. The links to the SES and Psychological online questionnaires were sent to all participants with a scheduled lab visit date. However, some of them ultimately cancelled the appointment or did not complete the laboratory visit. One participant completed all online questionnaires at baseline but only one day of the two-day laboratory

Table 1 Overview of participant characteristics

Characteristics	Total (<i>n</i> = 1314)	Burst 1 (<i>n</i> = 1305)	Burst 2 (<i>n</i> = 1262)	Burst 3 (<i>n</i> = 1215)	Burst 4 (<i>n</i> = 1170)
Age (years; mean \pm SD)	38.1 (\pm 12.6)	38.1 (\pm 12.6)	38.4 (\pm 12.5)	38.5 (\pm 12.6)	38.8 (\pm 12.5)
Gender – Men (%)	53.7	53.6	53.2	53.8	53.7
Education – High (%)	44.8	44.7	45.2	45.3	45.3
Socioeconomic status – High (%)	17.6	17.6	17.3	17.6	17.4
Marital status – married or cohabiting (%)	56.8	56.8	57.7	57.7	58.7
BMI (kg/m ² ; mean \pm SD)	24.6 (\pm 3.9)	24.6 (\pm 3.9)	24.6 (\pm 3.9)	24.6 (\pm 4.0)	24.6 (\pm 3.9)
Percent body fat (%; mean \pm SD)	30.0 (\pm 7.3)	30.1 (\pm 7.3)	30.1 (\pm 7.3)	30.1 (\pm 7.3)	30.1 (\pm 7.3)
Fitness (VO ₂ in ml/kg/min; mean \pm SD)	41.6 (\pm 10.3)	41.6 (\pm 10.3)	41.5 (\pm 10.3)	41.5 (\pm 10.4)	41.5 (\pm 10.3)
Time-based EMA surveys	146.8 (\pm 52.4)	42.4 (\pm 11.2)	38.2 (\pm 13.3)	37.2 (\pm 14.0)	36.9 (\pm 13.9)
Valid Fitbit-days	282.4 (\pm 93.2)	13.0 (\pm 2.6)	12.1 (\pm 3.6)	11.7 (\pm 3.9)	10.9 (\pm 4.5)
Weekly EMA surveys	16.5 (\pm 8.3)	0.7 (\pm 0.8)	0.8 (\pm 0.8)	0.8 (\pm 0.8)	0.8 (\pm 0.8)

BMI = body mass index, EMA = Ecological Momentary Assessment, SD = standard deviation

Table 2 Overview of completion rates for online questionnaires

Online survey	0% completion (n)	<50% completion (n)	≥50% completion (n)	Total number (n, % out of 1,314)
SES	0	10	1,405	1,415 (100)
Psychological	0	14	1,385	1,397 (100)
PA	0	0	1,315	1,315 (100)
Biomechanical	0	0	1,315	1,315 (100)
Month 6	1	41	1,076	1,118 (85)
Month 12	0	24	1,053	1,077 (82)

PA = physical activity. *N* = number

Table 3 Overview of available Fitbit data based on valid days of monitoring

Fitbit data available	N out of 1,314	%
No Fitbit data	4	0.3
0 valid days of Fitbit PA data	5	0.4
1–29 valid days of Fitbit PA data	34	2.6
30–89 valid days of Fitbit PA data	55	4.2
90–179 valid days of Fitbit PA data	101	7.7
180–269 valid days of Fitbit PA data	196	14.9
270 or more valid days of Fitbit PA data	919	69.9

PA = physical activity. *N* = number

assessments. Out of the 1,314 participants with complete baseline assessments, 1,118 (85%) completed the online questionnaire at month 6 and 1,077 (82%) at month 12.

Table 3 provides an overview of available Fitbit data based on valid monitoring days. Out of the 1,314 participants who completed baseline assessments, 1,305 (99.3%) had at least one valid day of Fitbit data, with participants providing on average 282.4 days (*SD* = 93.2), corresponding to 77.4% of the total 365-day monitoring period. As shown in the table, only a very small proportion of participants (0.7%) provided fewer than 30 valid days of data, while the majority maintained consistent wearable use throughout the study. Nearly 70% of the cohort (*n* = 919) accumulated 270 or more valid monitoring days, and an additional 14.9% (*n* = 196) contributed 180–269 valid days. Fewer than 8% of participants provided between 90 and 179 days, and only 4.2% had 30–89 valid days.

Table 4 summarizes the availability of Fitbit sleep data across the 12-month monitoring period. Of the 1,314 participants who completed baseline assessments, 1,308 (99.5%) provided at least three nights of valid sleep data, averaging 273.6 nights (*SD* = 98.2), equivalent to 75% of all possible nights. Only a negligible proportion of participants (1.0%) had fewer than three valid nights recorded,

Table 4 Overview of available Fitbit sleep data

Fitbit sleep data available	N out of 1,314	%
No Fitbit sleep data	6	0.5
1–2 nights of Fitbit sleep data	6	0.5
3–29 nights of Fitbit sleep data	41	3.1
30–89 nights of Fitbit sleep data	68	5.2
90–179 nights of Fitbit sleep data	116	8.8
180–269 nights of Fitbit sleep data	216	16.4
270 or more nights of Fitbit sleep data	861	65.5

N = number

Table 5 Results of bidirectional stepwise regression with EMA time-based as the dependent variable

Term	Estimate	Std. error	p-value
(Intercept)	−0.440	0.194	0.024
Age	0.202	0.033	<0.000
Satisfaction with life	0.130	0.037	0.001
Physical self-worth	−0.112	0.041	0.006
Socioeconomic status = average	0.512	0.197	0.010
Socioeconomic status = high	0.331	0.209	0.114
Controlled regulation	−0.070	0.032	0.029
Neuroticism	0.114	0.040	0.005
Perceived stress	−0.122	0.041	0.003
Physical health status	0.048	0.032	0.129
ACLS	−0.077	0.037	0.040
Barrier self-efficacy	0.069	0.037	0.063

Model: $F = 10.45$ on 11 and 1004 DF, $p < 0.0001$, $R^2 = 0.1027$, adj. $R^2 = 0.0929$

ACLS – self-reported PA level as assessed by the Aerobics Center Longitudinal Survey

confirming high compliance with nightly device wear. The majority of the cohort demonstrated strong adherence: 65.5% (*n* = 861) contributed 270 or more valid nights of data, and a further 16.4% (*n* = 216) provided between 180 and 269 nights. Smaller proportions supplied 90–179 nights (8.8%), 30–89 nights (5.2%), or 3–29 nights (3.1%).

In terms of EMA self-initiated surveys, we obtained 82,909 PA reports from 1,095 participants (mean = 76, min = 1, max = 661) with more than 1 question answered and 3,894 injury reports from 916 participants (mean = 4, min = 1, max = 330) across the 12 months. Of the 3,894 injury reports, 640 answered more than one question, indicating that 340 participants reported difficulties that limited their PA and were related to the musculoskeletal system (muscles, tendons, bones, joints). Additionally, the HealthReact platform triggered 17,425 surveys in response to detected declines in PA for 1,275 participants (mean = 13, min = 1, max = 27), with 16,562 with more

than one question answered from 1,246 participants (in 50.4% of the cases, participants endorsed their PA to be lower than usual).

Predictors of Adherence to EMA Monitoring

For time-based EMA adherence, the stepwise regression model identified significant predictors (Table 5). In line with H1 (capability), better psychological well-being was associated with higher adherence. Specifically, participants with greater satisfaction with life ($\beta = 0.130$, $p = 0.001$) had higher adherence, while those with higher perceived stress ($\beta = -0.122$, $p = 0.003$) and lower physical self-worth ($\beta = -0.112$, $p = 0.006$) exhibited lower adherence. Contrary to expectations, greater neuroticism ($\beta = 0.114$, $p = 0.005$) predicted higher adherence. In terms of motivation (H3), greater controlled regulation ($\beta = -0.070$, $p = 0.029$) was associated with poorer adherence. The impact of opportunity (H2) was partly supported, as average socioeconomic status (vs. low) was a positive predictor ($\beta = 0.512$, $p = 0.010$). Consistent with H4, older age ($\beta = 0.202$, $p < 0.000$) was strongly associated with better adherence. The model explained 9.3% of the variance ($F_{11, 1004} = 10.45$, $p < 0.000$, adj. $R^2 = 0.093$).

For weekly injury survey adherence, several capability-related predictors emerged, as shown in Table 6. Better optimism ($\beta = 0.065$, $p = 0.047$) predicted higher adherence (supporting H1), whereas poorer physical health status ($\beta = -0.086$, $p = 0.007$) and higher BMI ($\beta = -0.078$, $p = 0.028$) were associated with lower adherence. Older age ($\beta = 0.187$, $p < 0.000$) again predicted greater adherence, in line with H4. Having a higher percentage of body fat was unexpectedly positively related to adherence ($\beta = 0.152$, $p < 0.000$). This model accounted for 7.1% of the variance ($F_{7, 1006} = 12.12$, $p < 0.000$, adj. $R^2 = 0.071$).

Table 6 Results of bidirectional stepwise regression with EMA-weekly as the dependent variable

Term	Estimate	Std. error	p-value
(Intercept)	-0.044	0.046	0.344
Age	0.187	0.034	<0.000
Total body fat percentage	0.152	0.034	<0.000
Physical health status	-0.086	0.032	0.007
BMI	-0.078	0.036	0.028
Location = MSR	0.100	0.061	0.103
Optimism	0.065	0.033	0.047
Depressive symptoms	0.052	0.034	0.212

Model: $F = 12.12$ on 7 and 1006 DF, $p < 0.0001$, $R^2 = 0.0778$, adj. $R^2 = 0.0714$

BMI – body mass index, MSR = Moravian-Silesian Region

Table 7 Results of bidirectional stepwise regression with Fitbit-days as the dependent variable

Term	Estimate	Std. error	p-value
(Intercept)	-0.038	0.045	0.399
Age	0.383	0.036	<0.000
Barrier self-efficacy	0.137	0.036	0.000
Perceived stress	-0.084	0.032	0.009
ACLS	-0.095	0.035	0.007
VO ₂ -max	0.113	0.049	0.021
Location = MSR	0.112	0.060	0.061
Physical health status	0.051	0.031	0.105
Total body fat percentage	0.072	0.043	0.096
Controlled regulation	-0.050	0.031	0.111

Model: $F = 20.79$ on 9 and 1003 DF, $p < 0.0001$, $R^2 = 0.1572$, adj. $R^2 = 0.1497$

ACLS – self-reported PA level as assessed by the Aerobics Center Longitudinal Survey, MSR = Moravian-Silesian Region

Predictors of Adherence to Fitbit Monitoring

The model predicting wearable adherence (Fitbit-days) revealed both psychosocial and physiological influences (Table 7). Supporting H1 (capability), participants with lower perceived stress ($\beta = -0.084$, $p = 0.009$) and higher barrier self-efficacy ($\beta = 0.137$, $p = 0.000$) exhibited higher adherence. Higher VO₂-max ($\beta = 0.113$, $p = 0.021$) also contributed positively. Contrary to expectations, self-reported PA level was negatively related to adherence ($\beta = -0.095$, $p = 0.007$). In line with H4, older age ($\beta = 0.383$, $p < 0.000$) was the strongest predictor of Fitbit adherence. No significant effects were found for gender, education, or high socioeconomic status, providing only partial support for H4. The model explained 15.0% of the variance ($F_{9, 1003} = 20.79$, $p < 0.000$, adj. $R^2 = 0.150$).

Variable Importance

Random forest analyses confirmed the regression findings (Fig. 2). Age consistently emerged as the strongest predictor across EMA and Fitbit adherence, supporting H4. Indicators of psychological capability (satisfaction with life, optimism, stress), motivational style (barrier self-efficacy, controlled regulation), and physical health (body fat, BMI, VO₂-max) were also ranked among the most influential factors, providing partial support for H1–H3.

Discussion

This study investigated participant-level predictors of adherence to a 12-month monitoring protocol that combined EMA with continuous wearable activity tracking in a large,

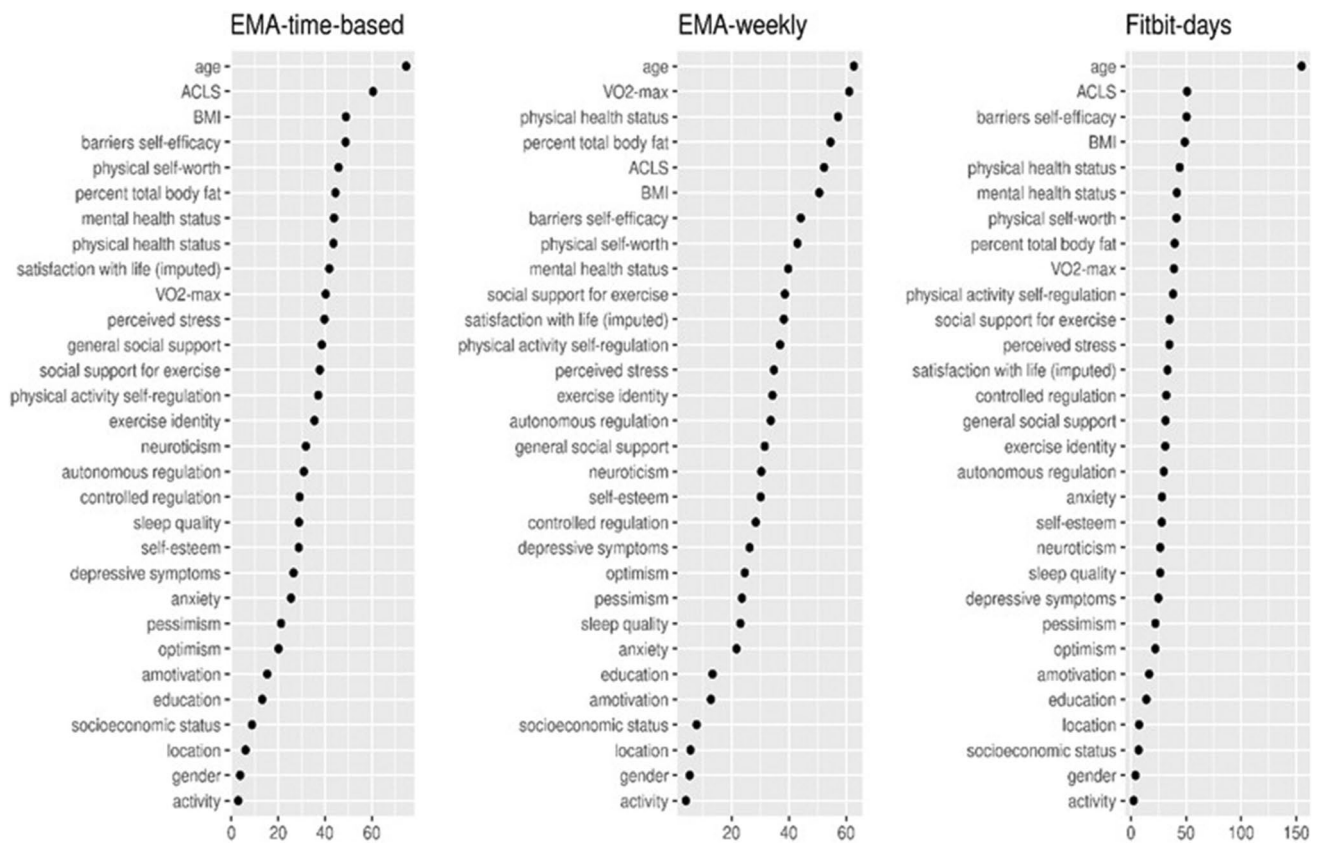


Fig. 2 Variable importance characterized by the “Increase in Node Purity” of Random Forest models predicting EMA-time-based, EMA-weekly, and Fitbit-days

community-based cohort of Czech adults. Although long-term wearable adherence is often challenging, recent large-scale digital health cohorts have demonstrated that sustained adherence over many months is feasible when supported by participant contact, feedback, and ongoing adherence monitoring [29, 44–46]. Our study integrated these recommended practices, resulting in high retention and data completeness despite the extended duration. By integrating multiple bursts of EMA with sustained Fitbit monitoring, the study provided a rigorous test of the feasibility of long-term ambulatory assessment and the individual factors shaping adherence. Overall, findings indicate that while adherence rates were high across both modalities, participant-level differences in psychological capability, motivational style, and health status influenced adherence over time.

Adherence in the 4HAIE study was remarkably robust given the length and intensity of the monitoring protocol. Participants achieved, on average, 77% valid Fitbit-days and 75% valid sleep nights, with sustained EMA participation across four measurement bursts. These levels compare favorably to prior EMA and wearable studies, the majority of which included shorter study durations or less demanding study procedures [10, 23], Wrzus & Neubauer, 2023b).

While our findings suggest that high adherence can be achieved in such community-based cohorts with systematic monitoring and support, caution is needed when extrapolating these results to populations with lower baseline motivation or digital literacy.

Predictors of Adherence and the COM-B Model

Our hypotheses were guided by the Capability, Opportunity, Motivation – Behavior (COM-B) model [34], which posits that adherence in health-related behaviors depends on individuals’ capability, social opportunity, and motivation. Consistent with H1, several indicators of psychological and physical capability predicted adherence. Lower perceived stress and greater life satisfaction were associated with higher adherence to both EMA and wearable monitoring. These findings align with prior evidence that stress and poor mental health reduce adherence (possibly also engagement) with digital health interventions [9, 47]. Higher optimism also predicted adherence to weekly EMA surveys, consistent with research linking positive affective dispositions to sustained health behaviors [48]. Conversely, poorer health

status and higher BMI were associated with lower EMA adherence, suggesting that physical limitations or health challenges may undermine sustained participation.

Unexpectedly, higher neuroticism was positively associated with adherence to time-based EMA surveys. While counterintuitive, this may reflect greater vigilance and responsiveness to health-related prompts among individuals high in neuroticism, consistent with findings that such individuals often exhibit heightened attention to health threats [49], suggesting that psychological traits may play complex roles in shaping adherence.

Support for H2 was limited. Socioeconomic status emerged as a predictor of EMA adherence, with participants reporting average SES adhering more strongly than those with low SES, but social support did not significantly predict adherence. This diverges from some prior studies that identified social support as a facilitator of adherence in both mHealth interventions and EMA studies [9, 35]. One possibility is that in a highly structured research protocol with regular monitoring and contact, study infrastructure may substitute for social support as a source of accountability.

In line with H3, motivational style influenced adherence. Higher barrier self-efficacy was associated with stronger Fitbit adherence, aligning with prior findings that confidence in overcoming obstacles predicts both PA behavior and adherence to monitoring protocols [50, 51]. Conversely, higher controlled regulation predicted poorer EMA adherence, supporting the view that extrinsic, pressuring motives undermine sustained adherence compared to autonomous, self-endorsed motives [52]. This reinforces the importance of fostering autonomous motivation to maintain adherence in long-term studies.

Our findings only partly supported H4. Age consistently emerged as the strongest predictor of adherence across EMA and Fitbit monitoring, with older participants exhibiting higher adherence. This pattern is consistent with several large-scale digital health studies that have reported higher retention and adherence among older adults [44–46]. It also aligns with emerging evidence that age-related differences in digital adherence are often nonlinear, with the lowest adherence frequently observed in younger and middle-aged groups balancing competing work and family demands, rather than at the oldest ages [53]. In our cohort, older (upper middle-aged) participants may have benefited from the structured nature of the EMA and wearable protocol, placed greater value on personalized study feedback, or had more stable daily routines that facilitated consistent participation. While younger adults often show higher enthusiasm for adopting new technologies, this does not necessarily translate to adherence with structured research tasks [54]. While participants at the lower and upper ends of the age spectrum were less represented, the wide overall age range and large sample size ensured adequate variability and statistical power for

detecting age-related differences in adherence. Nevertheless, generalization of age effects should be made with caution for very young and older adults, who remain underrepresented in many EMA and wearable monitoring studies.

By contrast, gender, education, and high SES did not predict adherence. These null findings diverge from reviews showing higher adherence among women and more educated participants [9, 13]. One explanation may be the cultural context. In the Czech Republic, smartphone penetration and digital literacy vary across demographic subgroups [32], and factors such as regional infrastructure or lifestyle differences may play stronger roles than gender or education per se.

Although adherence levels were generally high, EMA participation declined across bursts, a phenomenon consistent with “EMA fatigue” [7, 11, 12]. Even highly engaged participants may experience declining motivation over repeated prompts, particularly in long-term protocols. While the HealthReact platform employed reminders and adaptive survey triggering, these strategies did not fully offset declining adherence. This suggests the need for more dynamic engagement approaches, such as just-in-time adaptive interventions (JITAIs), which can tailor prompting intensity or offer motivational feedback based on real-time adherence or other engagement patterns [55].

Although the overall variance explained by our models was modest, this is consistent with other large-scale EMA and digital health studies (e.g., [9, 13, 45, 46]), which typically report low-to-moderate R^2 values when predicting adherence from baseline characteristics. These findings underscore that adherence is shaped by a complex interplay of individual, contextual, and time-varying factors, many of which lie beyond what can be captured by static predictors measured at study entry.

Strengths and Limitations

A key strength of the study was the integration of EMA and Fitbit monitoring in a large cohort. This hybrid design allowed for both subjective self-reports and objective sensor-based assessments of PA and health. The triggering of EMA surveys based on declines in Fitbit-measured PA illustrates the potential of sensor-informed EMA to contextualize behavioral change. Such integration enhances ecological validity and may also support adherence by providing participants with meaningful, responsive interactions [2, 10].

This study is one of the largest EMA cohorts to date, with over 1,300 participants followed for 12 months, enabling robust examination of adherence predictors. The design integrated both EMA and wearable monitoring, providing complementary insights. The study was also conducted in Central Europe, contributing culturally diverse evidence to a

literature dominated by North American and Western European samples.

Although our findings do not prescribe specific adherence enhancing strategies, they identify individual characteristics that may inform their development. For example, higher perceived stress and lower self-efficacy were associated with poorer adherence, suggesting that adherence approaches addressing stress management, coping resources, and confidence building could be beneficial. Similarly, lower autonomous motivation predicted poorer EMA participation, implying that strategies fostering intrinsic or self-endorsed motives (e.g., meaningful feedback, autonomy-supportive communication) may enhance adherence. Thus, identifying participant characteristics is a critical intermediate step for tailoring adherence approaches, since it helps to determine which subgroups may require additional support and which psychological mechanisms to target. Future qualitative work could explore these subgroups' experiences in depth to design concrete, contextually relevant adherence-enhancement strategies.

Some additional limitations must be acknowledged. First, selection bias is likely to have occurred. Individuals willing to participate in a year-long monitoring study may already be more motivated, health-conscious, and digitally literate than the general population [9]. While our sample cannot be considered fully representative of the general adult population, it contributes valuable diversity to the existing EMA literature. Prior EMA studies on PA and health behavior have predominantly targeted younger, low-active adults or student samples [9, 13], with few including habitually active populations. By incorporating both active runners and inactive adults across two geographically and environmentally distinct regions differing in air pollution levels, our study extends the evidence base to more behaviorally and contextually diverse participants. This design choice (reflecting the primary research objectives of the 4HAIE study) inevitably entails some selection bias but also offers insight into adherence patterns among a group that is, on average, both digitally literate and behaviorally engaged, i.e., a segment often targeted in digital health interventions. Therefore, while findings should not be generalized to all populations, they enhance the ecological and contextual breadth of adherence research and highlight the need for future studies to test these mechanisms across broader and more diverse cohorts.

The inclusion of an initial laboratory assessment likely introduced additional self-selection, as individuals with higher intrinsic motivation, health consciousness, or available time may have been more willing to participate. While such procedures are common in cohort studies integrating physiological and behavioral measures, they can reduce representativeness by deterring individuals with lower motivation or limited time resources. However, the laboratory visit was a necessary component to ensure data quality,

standardized device setup, and participant training for the subsequent EMA and wearable monitoring. To partly offset this potential bias, we employed a stratified quota sampling approach that balanced participants by age, gender, and PA level across two environmentally distinct regions, thereby preserving diversity within the cohort.

To deal with this limitation, future studies could consider hybrid onboarding approaches (e.g., remote baseline assessments, mobile testing units) to further reduce barriers to participation and enhance inclusivity.

Second, adherence was operationalized using thresholds (e.g., ≥ 10 h daily wear time), which may not capture qualitative engagement (e.g., syncing frequency, attentiveness to survey content). Third, while multiple predictors were examined, causality cannot be inferred due to the observational design. Finally, although adherence predictors were identified, the models explained modest proportions of variance (7–15%), suggesting that additional unmeasured contextual or behavioral factors contribute to adherence. Within the COM-B framework, such influences may include dynamic capability factors (e.g., daily variations in fatigue, cognitive load, or acute stress that fluctuate beyond baseline measures), opportunity-related factors (e.g., day-to-day time pressure, competing responsibilities, or changes in social and environmental contexts), and motivational factors (e.g., short-term shifts in autonomous motivation, perceived relevance of the study tasks, or satisfaction with feedback). These time-varying and contextual influences are well documented in EMA and digital health research [9, 47] and likely account for a portion of the residual variance. Future studies combining real-time contextual sensing with adaptive designs (e.g., JITAIs) may help capture and model these dynamic mechanisms more effectively. Despite these limitations, the study helped identify psychological capability, motivational style, and health indicators as additional salient adherence predictors than demographic factors alone, which could contribute to refining theoretical models of adherence as well as serve as a basis for practical recommendations for studies with a similar hybrid design (see Table 8). It also extends cultural and contextual variability by providing evidence from a Central European sample, an underrepresented population in the EMA literature.

Future Directions

Future research should build on these findings in several directions. First, interventions to enhance adherence could target stress reduction and foster autonomous motivation, which is in line with COM-B principles. Embedding JITAIs within EMA protocols could help adapt prompting schedules and feedback based on real-time adherence signals [55]. Second, future studies should examine adherence among vulnerable or digitally excluded

Table 8 Practical recommendations for designing EMA and wearable studies

Challenge	Recommendation for researchers
EMA fatigue and declining adherence	Use adaptive prompting (e.g., JITAIs), shorter bursts, or varied scheduling. Taper prompts gradually rather than maintaining high frequency for long durations
Higher perceived stress or poorer health associated with lower adherence	Screen for stress and health status at baseline and provide optional support modules (e.g., stress management tips, recovery feedback). Consider shorter EMA bursts or reduced prompt frequency for participants reporting high stress or poorer health
Lower autonomous (higher controlled) motivation undermines adherence	Use autonomy-supportive communication (emphasize choice, personal relevance, and self-initiated reasons for participation). Provide individualized feedback or progress summaries highlighting participants' contribution to science and personal insight
Higher BMI linked to lower adherence	Offer additional onboarding support and encouragement; ensure comfort with wearable fit; provide feedback focused on effort and consistency rather than performance
Younger participants showing lower adherence	Use more dynamic or gamified engagement strategies (e.g., digital badges, micro-goals) and reminders via preferred digital channels; emphasize convenience and brief participation
High participant burden	Keep surveys brief (< 1–2 min); prioritize core items; integrate sensor-informed EMA (e.g., Fitbit-triggered surveys) to reduce unnecessary prompts
Unnoticed non-adherence	Implement real-time adherence dashboards; use personalized reminders (notifications, text, or calls) to re-engage participants promptly
Assumptions about demographic predictors	Do not assume younger or more educated participants are always more adherent; consider cultural context, daily routines, and digital literacy
Selection bias and representativeness	Simplify onboarding (pre-installed apps, device setup assistance); provide ongoing technical support; report dropout rates and reasons transparently
Limitations of self-report or wearables alone	Use hybrid designs: pair EMA with wearable data to validate behaviors, provide context, and deliver “smart” triggers for more relevant and less burdensome surveys

populations, who may face greater barriers to sustained adherence but are often underrepresented in digital health research. Third, predictive models could be enriched by incorporating digital engagement “biomarkers”, such as prompt response latency, syncing regularity, or interaction patterns with devices, to provide early warning signs of disengagement.

Conclusion

In summary, this study provides new evidence on the determinants of adherence to long-term EMA and wearable monitoring in a large community-based cohort of adults that included both active runners and inactive individuals. Findings highlight the importance of psychological capability, motivational style, and health status in shaping adherence, whereas demographic predictors such as gender and education played a lesser role than anticipated. While the results primarily reflect adherence patterns among relatively motivated and health-conscious participants, they offer valuable insight into mechanisms that may underlie adherence in broader digital health contexts. These findings underscore the importance of developing theoretically informed and tailored strategies to support adherence in intensive digital monitoring, which remains essential for ensuring data quality in observational

research and for optimizing the real-world implementation of digital health interventions.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s12529-025-10433-3>.

Acknowledgements We would like to thank the project “Healthy Aging in Industrial Environment HAIE CZ.02.1.01/0.0/0.0/16_019/0000798” which is co-financed by the European Union for the use of the data and to all research assistants involved in the data collection and adherence monitoring.

We would like to thank the CzechMates Study Abroad Program (<https://www.czechmates.org/>) for facilitating an internship opportunity for A. Lashinsky at the Behavioral Laboratory at the Department of Human Movement Studies, University of Ostrava.

Author Contributions AL: data curation, writing – original draft; LK: data curation, investigation, methodology, project administration, supervision, writing – original draft; MB: methodology, formal analysis, visualization, writing – original draft; BK, MS, DB: investigation, methodology, writing – review and editing; RF, VU: investigation, writing – review and editing; MR: methodology, writing – review and editing; SE: conceptualization, data curation, investigation, methodology, project administration, funding acquisition, supervision, writing – original draft.

Funding Open access publishing supported by the institutions participating in the CzechELib Transformative Agreement. This study is from the project “Research of Excellence on Digital Technologies and Wellbeing CZ.02.01.01/00/22_008/0004583” which is co-financed by the European Union.

The manuscript has been prepared also with the support of the European Union under the LERCO project

(CZ.10.03.01/00/22_003/0000003) via the Operational Programme Just Transition.

Data Availability Transparency Statements. 1. Study registration. This study was not formally registered. 2. Analytic plan pre-registration. The analysis plan was not formally pre-registered. 3. Data availability: De-identified data from this study are available in a public archive: <https://zenodo.org/records/18220125>. 4. Analytic code availability. Analytic code used to conduct the analyses presented in this study are available in a public archive: <https://zenodo.org/records/18220125> (or at DOI <https://doi.org/10.5281/zenodo.18220124>). 5. Materials availability. Materials from the study are available on the study website <https://haie-lerco.cz/data/>.

Declarations

Competing interests The authors declare no competing interests.

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