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Research and Applications

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Phenotypes of engagement with mobile health technology for heart rhythm monitoring

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ABSTRACT

Objectives: Guided by the concept of digital phenotypes, the objective of this study was to identify *engagement phenotypes* among individuals with atrial fibrillation (AF) using mobile health (mHealth) technology for 6 months.
Materials and Methods: We conducted a secondary analysis of mHealth data, surveys, and clinical records collected by participants using mHealth in a clinical trial. Patterns of participants' weekly use over 6 months were analyzed to identify engagement phenotypes via latent growth mixture model (LGMM). Multinomial logistic regression models were fitted to compute the effects of predictors on LGMM classes.
Results: One hundred twenty-eight participants (mean age 61.9 years, 75.8% male) were included in the analysis. Application of LGMM identified 4 distinct engagement phenotypes: "High-High," "Moderate-Moderate," "High-Low," and "Moderate-Low." In multinomial models, older age, less frequent afternoon mHealth use, shorter intervals between mHealth use, more AF episodes measured directly with mHealth, and lower left ventricular ejection fraction were more strongly associated with the High-High phenotype compared to the Moderate-Low phenotype (reference). Older age, more palpitations, and a history of stroke or transient ischemic attack were more strongly associated with the Moderate-Moderate phenotype compared to the reference.
Discussion: Engagement phenotypes provide a nuanced characterization of how individuals engage with mHealth over time, and which individuals are more likely to be highly engaged users.
Conclusion: This study demonstrates that engagement phenotypes are valuable in understanding and possibly intervening upon engagement within a population, and also suggests that engagement is an important variable to be considered in digital phenotyping work more broadly.

Key words: mobile health, patient engagement, latent class analysis, atrial fibrillation, digital phenotyping

LAY SUMMARY

Digital phenotyping involves classifying observable characteristics of human behavior, physiology, and disease using mHealth data to improve diagnosis and treatment of disease but is hampered by low user engagement with mobile health (mHealth) technology over time. Guided by the concept of digital phenotypes, the objective of this study was to identify *engagement phenotypes*, or patterns of mHealth use over time among individuals with the cardiac arrhythmia, atrial fibrillation (AF). We analyzed patterns of weekly mHealth use over 6 months in order to identify 4 engagement phenotypes among 128 participants (mean age 61.9 years, 75.8% male) using mHealth in a clinical trial: "High-High," "Moderate-Moderate," "High-Low," and "Moderate-Low." We then compared individuals who adopted the least engaged phenotype (Moderate-Low) to the other engagement phenotypes. We found that older age, less frequent afternoon mHealth use, shorter intervals between mHealth use, more AF episodes measured directly with mHealth, lower left ventricular ejection fraction (a measure of cardiac functioning; higher is better), more palpitations, and a history of stroke or transient ischemic attack were more strongly associated with phenotypes of sustained engagement (High-High and Moderate-Moderate). We conclude engagement phenotypes help characterize engagement over time in a nuanced way, and may lay the foundation to design mHealth in ways that better engage users over time.

INTRODUCTION

Mobile health (mHealth) technologies allow individuals to collect, store, and share digital, personal health data.[1,2] As the popularity of these technologies has grown, the potential for mHealth data to enhance information exchange with healthcare providers, foster management of personal health, and personalize care has been increasingly recognized.[3–6] Within the personalized care space, a growing body of research is using mHealth data to profile an individual's patterns of physiological and psychological health. This work is known as *digital phenotyping*, defined as the "moment-by-moment quantification of the individual-level human phenotype in situ using data from personal digital devices."[7] Broadly, digital phenotyping seeks to construct phenotypes of human behavior, physiology, and disease using mHealth data.[8]

Typically, digital phenotyping focuses on characterizing health-related data collected with mHealth, but does not account for variable rates of mHealth use and high rates of abandonment. Measures of mHealth use over time show that many users discontinue use within 3–6 months of initiation.[9–11] In fact, digital phenotyping studies have reported variable levels of engagement with mHealth which hampers the feasibility of phenotyping work[12,13] and may impair accuracy.[14] Prior work has identified correlates of mHealth use over time but findings are inconsistent between studies. For example, some studies report younger age and others report older age is associated with sustained engagement.[11,15,16] This suggests that solutions to improve engagement are not "one size fits all." Therefore, a methodological approach to characterize sustained engagement in a specific patient population, as well as factors associated with it, may be useful to tailor interventions and the design of technologies themselves to a patient population's unique needs. Furthermore, many studies characterize engagement as an average of usage over time, which masks variation over time. Approaches that preserve variation in engagement over time may uncover temporally heterogeneous levels of engagement.

Therefore, we propose to leverage digital phenotyping approaches to phenotype engagement. We view *engagement phenotypes* as an extension of digital phenotypes that aim to describe profiles of engagement with mHealth over time, rather than profiles of health or disease states (as in classic digital phenotyping work). One important distinction between digital phenotypes and engagement phenotypes is that digital phenotypes, by definition, ideally use passively collected digital data as this allows for a more accurate and temporally dense reflection of an individual's natural environment.[14] Engagement phenotypes, by contrast, characterize actively collected data. While passively collected data is often considered superior to actively collected data for phenotyping research, in many cases it is not possible or logical to collect, such as in the case of subjective experiences including symptoms and mood. To our knowledge, the term *engagement phenotypes* has not previously been used in this context, although one prior study characterized phenotypes of engagement with mHealth using similar approaches,[17] and another digitally phenotyping depressive symptom severity included engagement with mHealth as a model feature.[18]

In this study, we present our approach for characterizing engagement phenotypes among adults with atrial fibrillation (AF) who self-monitored their heart rhythm using mHealth. The primary objective of this study was to identify distinct engagement phenotypes, defined as patterns of mHealth use over time, within the sample. We also explored possible predictors of engagement phenotypes. Sustained engagement with heart rhythm monitoring using mHealth is important for individuals with AF, the most common cardiac arrhythmia encountered in clinical practice.[19] AF most often occurs in sporadic episodes which may be unpredictable and uncorrelated with symptoms, making detection of AF episodes difficult without frequent electrocardiogram (ECG) monitoring.[20] Advancements in mHealth now allow individuals with AF to record highly accurate ECG data quickly, easily, and without invasive hardware.[21,22] Timely detection of AF through mHealth is needed to restore normal rhythm earlier, optimize therapies, and reduce negative sequelae of AF such as hospitalization, stroke, or death.[23–25] Thus, lack of sustained engagement is a critical problem for individuals with AF, who must regularly record and transmit ECG data to healthcare providers in order for AF to be detected and treated in a timely manner.[21]

METHODS

Study design and participants

We conducted a secondary analysis of mHealth data collected in the *iPhone® Helping Evaluate Atrial Fibrillation Rhythm through Technology* trial (iHEART, R01NR014853). The full details and primary findings of the iHEART trial have been previously reported.[26–28] Briefly, the iHEART trial was a randomized, controlled trial conducted at a single academic medical center in New York City from

2014 to 2019. iHEART participants were English or Spanish speaking adults age 18 or older who underwent a procedure (radiofrequency ablation or direct current cardioversion) to restore normal sinus rhythm in the past 30 days. Exclusion criteria were severe cognitive impairment, documented permanent or chronic AF, and clinically unstable or other arrhythmias on the day of enrollment. Participants were randomized 1:1 to either an mHealth monitoring intervention or usual cardiac care for 6 months after the baseline procedure to restore normal sinus rhythm. The primary endpoints of the trial were time to documented recurrent AF and time to treatment of the recurrent arrhythmia. In this study, we specifically examined data from iHEART participants who were randomized to the intervention arm, as the control arm did not use mHealth.

This study was approved by the Columbia University Institutional Review Board and data analysis was approved by the Weill Cornell Medicine Institutional Review Board.

mHealth intervention

Participants randomized to the iHEART intervention arm were given the AliveCor® Mobile ECG device (Figure 1) and asked to transmit ECGs using AliveCor twice daily for 6 months. The AliveCor device is FDA-approved and captures highly sensitive (98%), specific (97%), and accurate (97%) single-lead ECG recordings.[29,30] ECGs are recorded when the user places his or her fingertips on the AliveCor device. ECG recordings captured with the AliveCor device are documented in a free accompanying smartphone application, Kardia®, and are automatically uploaded via WiFi or cellular network transmission to the HIPAA-compliant, secure AliveCor cloud. An algorithm in the Kardia app uses the regularity of R-to-R intervals and presence or absence of p-waves in an ECG to identify the rhythm of each recording as either normal sinus rhythm, AF, or "unclassified," meaning the algorithm could not identify the rhythm.

In the iHEART trial, the rhythms identified by the algorithm were reviewed and confirmed by a cardiac electrophysiologist who was a co-investigator in the iHEART trial. Study coordinators in the iHEART trial who were trained in ECG interpretation reviewed ECG strips from patients daily through a secure portal.[26,27] They immediately contacted the patient's primary cardiologist or healthcare provider in the event of a clinically significant arrhythmia, who were responsible for follow-up. All study participants were patients at a single clinic. All cardiologists at the clinic were familiar with the iHEART trial, making close communication with study staff feasible.

Figure 1. AliveCor mobile ECG device.

All participants received in-person training on use of the device prior to beginning the trial using the "teach back" method, in which participants were asked to record an ECG with AliveCor to demonstrate understanding. Participants who owned a smartphone compatible with AliveCor were given the option to continue using their phone. Participants who did not own a smartphone or preferred to use a study phone were given an iPhone® and cellular service plan with unlimited data/text messaging. None of the participants in the intervention arm received any reminders or prompts to use the AliveCor device during the study, but all participants in the intervention arm received text messages 3 times per week related to AF knowledge and the American Heart Association's Life's Simple 7 (eg, diet, physical activity).[31]

Data sources

Constructing engagement phenotypes: Patterns of AliveCor use over time

iHEART participants' dated, time-stamped ECG transmissions with heart rhythm identified by the Kardia® algorithm for each transmission were extracted from the study database with support from AliveCor. ECG recordings are initiated upon the user's engagement with AliveCor. The weekly count of ECG recordings was calculated for each participant for each week they were enrolled in the trial. Weekly AliveCor use over the 6-month study period was used to construct engagement phenotypes. Of the 133 participants who used AliveCor, we ultimately analyzed data for 128 after excluding 5 participants with days of use less than a week. We clustered AliveCor use by distinct patterns over time within the sample, which we describe in further detail below. All other variables described were predictor variables in multinomial logistic regression models, also described below.

Demographics and experience with technology

Participants' baseline demographic characteristics (age, gender, race, and ethnicity) were retrieved from the iHEART trial database. At baseline, participants also self-reported experience with technology using a 10-item survey about ownership and use of various technologies (smartphones, Internet, text messaging). The complete survey is provided in the Supplementary Materials. Experience with technology is important to assess because several studies have found that the ability to use mHealth with ease contributes to higher rates of engagement.[32–35]

AliveCor use behaviors

We constructed 3 different types of variables that reflect user behaviors with AliveCor, which served as predictors in the multinomial analysis. Even though users were asked to use AliveCor for 6 months for the trial, the total duration of AliveCor use greatly differs across individuals. Therefore, the total duration of AliveCor use from first to last usage, including that after the iHEART trial, was calculated for each individual. Timing of usage was also considered to characterize AliveCor use behaviors; the proportion of morning (6 AM–12 PM), afternoon (12 PM—6 PM), evening (6 PM–12 AM), and night (12 AM–6 AM) AliveCor use was calculated over the 6-month period. Lastly, summary statistics of maximum, mean, standard deviation, median and interquartile range were calculated to represent the distribution of intervals between usage.

AF and other clinical characteristics

Participants' AF history was collected at baseline in the iHEART trial through a combination of self-report and manual review of the electronic health record. Specifically, whether participants were in AF at the time of enrollment (immediately following an intervention to attempt to restore normal sinus rhythm), healthcare utilization for AF in the past year (ER visits, hospitalizations, and specialist visits), history of prior cardioversions or radiofrequency ablations, and participants' perceived frequency and length of AF episodes were collected. Risk factors for more severe AF, including body mass index, history of stroke or transient ischemic attack (TIA), and left ventricular ejection fraction (LVEF), were also collected. Any AF recurrence during the study period and the weekly average number of AF episodes were recorded directly by participants using AliveCor.

Additionally, participants completed several surveys at baseline. Symptom burden was assessed using the University of Toronto AF Severity Scale (AFSS), which assesses the severity of 7 symptoms: palpitations, shortness of breath at rest, shortness of breath during physical activity, exercise intolerance, fatigue at rest, lightheadedness/dizziness, and chest pain/pressure.[36] Participants report the degree each symptom has bothered them in the past 4 weeks on a scale from 0 (have not had this symptom) to 5 (extremely bothersome). Total scores range from 0 to 35 with higher scores indicating more severe AF symptoms. AF-related quality of life was assessed using the AF Effect on Quality of Life (AFEQT) scale. AFEQT assesses quality of life across 4 domains: symptom burden, daily activities, treatment concerns, and treatment satisfaction. The total AFEQT score and subscale scores range from zero (complete disability) to 100 (highest quality of life).[37] AF knowledge was measured using the AF Knowledge Scale (AFKS), which measures knowledge about AF in general, symptom recognition, and treatment on a scale of 0–11 with higher scores indicating higher AF knowledge.[38] The Control-Attitudes Scale-Revised measures perceived control, a construct relevant to effective self-management of disease.[39] The Self-efficacy for Appropriate Medication Use Scale (SEAMS) measures medication self-efficacy in chronic disease management.[40]

Statistical analysis

We constructed engagement phenotypes using one variable: patterns of AliveCor use over time (measured by weekly count of ECG recordings) from baseline to 6 months, representing engagement with mHealth technology. We used latent growth mixture models (LGMMs)[41,42] to detect subgroups with specific patterns of weekly change in ECG recordings from baseline to 6 months. LGMM is a multilevel model with repeated observations nested within individuals, which uncovers within-subgroup latent changes in patterns over time. Each latent class is characterized by a distinct trajectory in longitudinal measures and represents a distinct engagement phenotype. We fitted LGMMs with 2, 3, 4, 5, and 6 classes with linear, quadratic, and cubic effects of time (week) and compared them using the Akaike Information Criterion (AIC). The AIC is an information criterion with a penalty for model complexity, dealing with both the goodness of fit and the parsimony of the model.[43] Models with imbalanced class sizes (defined as less than 5 individuals or more than 70% of the sample in at least one class) were excluded for comparison.

The association of engagement phenotypes was explored with demographics, experience of technology, and clinical characteristics. Variables that reflect the pattern of AliveCor use were included as potential predictors of engagement phenotypes as well. Analysis of variance (ANOVA) and chi-square tests were conducted to test the association of engagement phenotypes with numeric and categorical predictors, respectively. The omega-squared (ω^2)[44] and Cramér's V[45] were reported as effect size measures for ANOVA and chi-square tests, respectively. Univariate multinomial logistic regression models were fitted to compute the effects of the same predictors on engagement phenotypes. The odds ratio (OR) as well as its 95% confidence interval (CI) were reported for each multinomial logistic regression model. We did not correct for multiple comparisons for variables in the same family as these were exploratory analyses.

All the analyses were conducted using R statistical software version 3.6.1 (R Core Team, Vienna, Austria). The R package "lcmm" was used for fitting LGMMs.[46]

RESULTS

Description of the sample

Supplementary Table S1 describes the characteristics for 128 iHEART participants who had completed the intervention arm of the trial and were ultimately included in our analysis. Study participants were 61.9 years old on average (SD 11.6 years) and predominantly male (75.8%), White/Caucasian (95.1%), and non-Hispanic (84.1%). Nearly all participants reported that they owned a cell phone (98.9%), smartphone (89.8%), and many were comfortable using the Internet on a smartphone (82.8%). The average total duration of use was 434 (SD 331.7) days. Participants used AliveCor most often in the morning (42%) and the average interval between uses was 1 day. More than half of participants (61%) experienced AF recurrence and participants had an average of 1.4 (SD 3.3) AF episodes per week during the study period. In addition, 10% had a prior stroke or TIA at baseline and the mean LVEF was 54% (SD 11.6), indicating moderate to high levels of cardiac functioning on average. The mean AFEQT score was 65.0 (SD 21.0), indicating a moderate AF-related quality of life. The mean AFSS score was 10.1 (SD 9.0), indicating a low burden of AF symptoms; the most burdensome symptoms were shortness of breath on exertion, palpitations, and fatigue on exertion.

Engagement phenotypes

Our final LGMM identified 4 distinct engagement phenotypes based on distinct patterns of use over time (AIC 17132.7). Models with quadratic and cubic effects of time consistently and comparably outperformed those with linear effects; thus, the final LGMM was fitted with quadratic time effects. Each line in Figure 2 represents the weekly average number of ECG recordings among individuals in each phenotype. Participants in the "High-Low" phenotype ($n = 6$) started the iHEART trial with the highest weekly AliveCor use (over 15 ECG recordings per week) but declined rapidly over 6 months. Participants in the "High-High" phenotype ($n = 26$) also started the trial with high weekly AliveCor use and sustained high use for 6 months. Participants in the "Moderate-Moderate" phenotype ($n = 44$) maintained the same level of use for 6 months, but with lower weekly use than participants in the High-High phenotype (approximately 10 ECG recordings per week, versus 15 in the High-High phenotype). Participants in the Moderate-Low phenotype ($n = 52$) started with the lowest use, declined rapidly in the first 3 months, and maintained low use (approximately one to 2 ECG recordings per week) during the subsequent 3 months.

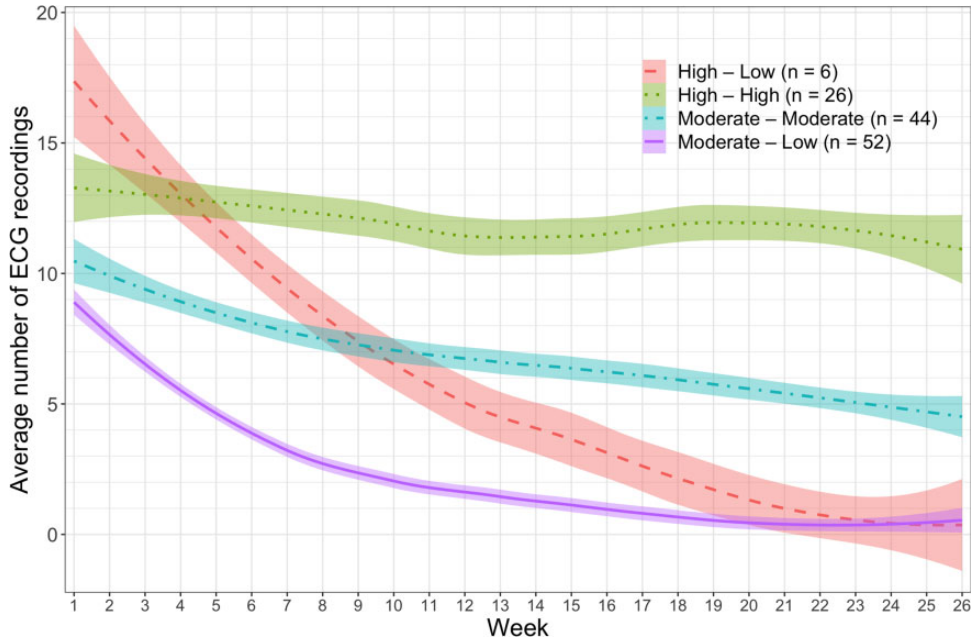

Figure 2. Weekly average number of ECG recordings among individuals in each phenotype. Lines represent the phenotype-specific average calculated using locally estimated scatterplot smoothing (LOESS) and the shaded area represents the 95% confidence interval for the fitted LOESS curve.

Predictors of engagement phenotypes

We set the Moderate-Low phenotype (ie, the phenotype with the lowest weekly engagement) as a reference and fitted univariate multinomial logistic regression models. Supplementary Table S2 presents the ORs and the 95% CIs of each of the first 3 phenotypes compared to the reference phenotype. Consistent with tests of association in Supplementary Table S1, the OR estimates from multinomial logistic regression models identified a statistically significant difference in predictors between engagement phenotypes. Compared to the Moderate-Low phenotype, the High-High and Moderate-Moderate phenotypes are most distinctively different. Older participants were more likely to be in the High-High (OR: 1.06; 95% CI [1.01, 1.11]) and Moderate-Moderate phenotypes (OR 1.05; 95% CI [1.01, 1.09]). Participants who used AliveCor in the afternoon were less likely to be in the High-High phenotype (OR 0.91; 95% CI [0.87, 0.96]), and participants with the higher standard deviations of the mean intervals between AliveCor use were less likely to be in the High-High phenotype (OR 0.50; 95% CI [0.28, 0.89]). Participants with more AF episodes during the study were more likely to be in the High-High phenotype (OR 1.42; 95% CI [1.07, 1.89]). Participants with more palpitations were less likely to be in the Moderate-Moderate phenotype (OR 0.70; 95% CI [0.51, 0.95]). Additionally, participants with a history of a stroke or TIA were more likely to be in the Moderate-Moderate phenotype, and participants with a higher LVEF were less likely to be in the High-High phenotype.

DISCUSSION

This study was among the first to consider digital phenotyping of engagement behaviors.[17] We identified 4 distinct engagement phenotypes representing distinct patterns of engagement over time. Declines in engagement differed; rapid declines characterized the High-Low phenotype while more gradual declines characterized the Moderate-Low phenotype. More stable, but differing, levels of engagement characterized the High-High (approximately 15 uses per week) and Moderate-Moderate phenotypes (approximately 10 uses per week). These findings provide more nuance to prior reports of general declines in engagement with mHealth over time. This study also illustrates a methodological approach for constructing engagement phenotypes, which represents an important step toward understanding how certain individuals engage with mHealth. Future work, particularly qualitative studies, can build upon the identified engagement phenotypes to explore why certain individuals adopt a specific engagement phenotype. Such work may lay the foundation for improved design of mHealth technologies that engage individuals in collecting personal health data for a sustained period of time.

We also explored predictors of engagement phenotypes and found that clinical factors (AF episodes, symptoms, and cardiovascular history), AliveCor use behaviors, and age were among the most distinguishing variables. Participants who sustained engagement (ie, High-High and Moderate-Moderate phenotypes) appeared to have a more significant cardiovascular history, including prior stroke or TIA and lower LVEF, during the study period. Participants in the High-High and Moderate-Moderate phenotypes also had more AF episodes, although this variable was measured directly with AliveCor and therefore may be directly related to the outcome of engagement. Nonetheless, supported by our qualitative work,[47] this suggests that these participants may have viewed AliveCor as a tool for better documenting AF rhythm at home and better managing their cardiovascular health, thus motivating their engagement. It is also possible that heavy symptom burden may have been a barrier to frequent engagement, as participants with moderate engagement throughout the study (Moderate-Moderate) were less likely to experience burdensome palpitations than those with low engagement (Moderate-Low). However, this is difficult to assess because of the complex relationship between AF episodes and symptoms; patients may report AF symptoms while not actually having an AF episode, while others may be totally asymptomatic during AF episodes.[19]

Our qualitative work showed this complexity led to an inability to interpret symptoms of AF that was frustrating to patients and increased levels of anxiety about AF. Ultimately, it was a major reason they decided to decrease or discontinue use of mHealth.[47] Incorporating features that facilitate understanding of AF symptoms may be an opportunity to improve engagement with mHealth through design for patients with AF.

Participants who maintained the highest levels of engagement (High-High phenotypes) also used AliveCor in the afternoon less and had less variance in the intervals between AliveCor use, indicating that they used AliveCor more regularly. This aligns with our qualitative work in which engaged users reported incorporating AliveCor use into their daily routines; many reported using it when they took their morning and evening medications (explaining the less frequent afternoon use).[47]

The general lack of many significant predictors in this study may reflect inadequate statistical power due to a small sample size, or may suggest that there are not strong associations of demographic, technological, and clinical characteristics with sustained engagement. Many variables that others have hypothesized are related to engagement, including comfort with technology, knowledge, and gender,[48,49] were not statistically significantly predictors, or were not clinically significant as in the case of the age variable. Older age was associated with higher engagement in this study; participants in both the High-High and Moderate-Moderate phenotypes were older than those in the Moderate-Low phenotype. However, there was only a difference of 6 to 7 years in the mean age of participants between phenotypes. This is consistent with prior studies reporting that age predicts usage, but the difference in age between more and less engaged users is less than 10 years.[11,15,16,34] This is important in light of prior questions surrounding the ability of older adults to consistently use mHealth to collect personal health data.[50,51] Taken together, the lack of significant predictors may suggest the way users engage with mHealth over time may largely be independent of their clinical symptoms or demographic characteristics.

Many studies have examined engagement as an average over time. By extending the concept of digital phenotyping into the domain of engagement, we were able to characterize individuals based on variation in mHealth usage over time. These findings are not only important in improving understanding around the phenomenon of sustained engagement but may also carry importance for a broader scope of digital phenotyping research. Others attempting to use mHealth data to construct digital phenotypes of disease should carefully consider engagement with mHealth, as digital phenotypes may be driven by the abundance or sparsity of the data itself. For example, in our study individuals with the lowest engagement (Moderate-Low phenotype) had fewer AF episodes than the other groups, which may suggest a disease phenotype characterized by less AF burden. However, the relative sparsity of mHealth data from this group was intrinsically linked to the documentation of AF episodes using mHealth.

This study had several limitations. Participants in our moderate sample size were relatively homogeneous in terms of their gender, race, and ethnicity. Study participants were recruited from one electrophysiology clinic, causing the risk of potential bias in generalizing the findings related to engagement phenotypes to all patients with AF. Additionally, this was a secondary analysis of a randomized, controlled trial; participants may have been more engaged than in a non-trial setting, thus biasing the resulting engagement phenotypes. While participants received educational text messages during the study which may have prompted use, participants did not receive any explicit prompts or reminders to use the device during the trial. Moreover, the sizes of the 4 phenotypes varied widely from 6 participants in the High-Low phenotype to 52 participants in the Moderate-Low phenotype. The imbalanced samples likely explain the lack of differences we observed between these 2 phenotypes in multinomial models. Finally, additional variables that may relate to engagement were not measured, or not measured at multiple time points, as this was a secondary analysis of data from a clinical trial whose primary endpoints were not related to technology use or acceptance. Moreover, 6-month follow-up data were not used as there was significant missingness, possibly because it required an in-person visit. As such, most predictors were measured only at baseline and failed to capture fluctuations in these constructs throughout the 6-month study. This also made it challenging to generate hypotheses about potential reasons for differences in engagement between participants. In future work, capturing relevant predictor variables with greater frequency using the same mHealth technology may represent an opportunity to improve data completeness and more accurately capture fluctuations in variables over time. Qualitative investigations may also be useful in elucidating reasons individuals adopt different engagement phenotypes.

CONCLUSION

Lack of sustained engagement with mHealth limits important potential uses of mHealth data but continues to be a poorly understood phenomenon. By extending the concept of digital phenotyping to characterize engagement, we constructed 4 engagement phenotypes describing patterns of mHealth use among adults with AF over a 6-month period. Moreover, we identified meaningful differences between individuals who adopted different patterns of use over time, including many clinical variables. This study demonstrates that engagement phenotypes are valuable not only in understanding and possibly intervening upon engagement within a population, but also by suggesting that engagement is an important variable to be considered in digital phenotyping work more broadly.

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AUTHOR CONTRIBUTIONS

JL and MRT designed this study, analyzed and interpreted the data, and drafted and revised the manuscript. KH and SB secured funding for the parent study and enabled the acquisition of data for this study. SB provided crucial contributions to the study design and interpretation of data. SB, RMC, and AB revised the manuscript for important intellectual content.

SUPPLEMENTARY MATERIAL

Supplementary material is available at *Journal of the American Medical Informatics Association* online.

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CONFLICT OF INTEREST STATEMENT

MRT is affiliated with Iris OB Health Inc., New York, a startup company focused on postpartum depression, and has equity ownership. The remaining authors have no conflicts of interest to declare.

DATA AVAILABILITY STATEMENT

The data underlying this article cannot be shared publicly for the privacy of individuals that participated in the study. The data will be shared on reasonable request to the corresponding author.

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