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mHealth and social mediation: Mobile support among stigmatized people living with HIV and substance use disorder

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Abstract
The social mediation role of mobile technology is typified by mHealth apps designed to connect individuals to others and support substance use disorder (SUD) recovery. In this study, we examined the use and utility of one such app designed to support people living with HIV (PLWH) and SUD. Drawing on Ling's emphasis on reciprocity and

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micro-coordination in mobile telephony as a social mediation technology, we gathered digital trace data from app logs to construct two metrics, initiation (i.e. whether a particular feature is engaged on a given day) and intensity (i.e. degree of involvement in the activity when engaged on that day), at three levels of communication—networked (one-to-many), dyadic (one-to-one), and intraindividual (self-to-self). We consider these system features alongside use of information resources, games and relaxation links, a meeting and events calendar, and support tools to address use urges. We found few differences in patterns of use by race, sex, and age, though African Americans were less likely to engage in intraindividual expression, whereas women and older users were more likely to make use of this feature. The initiation and intensity of network and dyadic reception, as well as the intensity of network expression, predicts recovery outcomes as measured on a weekly "check-in" survey, suggesting the utility of mobile log data for digital phenotyping in mHealth. By implementing this app during the COVID-19 pandemic, the study also found the disruption caused by national lockdown was negatively related to the app use.

Keywords

Digital phenotyping, expression effects, mHealth apps, mobile support, online communities, social mediation, substance use disorders

The pervasiveness and penetration of mobile phones among Americans exceeds 96% in 2021 (Pew Research Center, 2021). As such, mobile communication mediates our daily life due to its mass adoption, constant legitimation, and deep integration into our social ecology (Ling, 2012). Mobile telephony enables anytime-anyplace connectivity essential for societal integration and integral for social cohesion (Abeele et al., 2018). For these reasons, the future of mobile communication will certainly impact healthcare delivery and patient management, especially for those requiring social support and continuous monitoring (Baker et al., 2014; Ling et al., 2020). Compared with other information and communication technologies, mobile devices[1] narrow Internet access divides (Brown et al., 2011), and non-Whites and lower-income Americans rely heavily on smartphones for online access (Pew Research Center, 2015). Accordingly, researchers in public health focus on harnessing and honing mobile devices (mHealth) that provide communication, information, and other health support tools to provide benefits to vulnerable populations living with chronic conditions on a larger scale (Hochstatter et al., 2021a; Quanbeck et al., 2018).

Focusing on mobile phones as a social mediation technology, as argued by Ling (2012), with its mass of users, corresponding social ecological shifts, and mutual expectations of its integration into daily life to the point of being "taken-for-granted," we emphasize how mobile telephony can foster reciprocal communications and interplay between people allowing for sociation and interaction. Accordingly, this study examines an app designed to support recovery from substance use disorders (SUDs) through various communication functions. This app was created to support people living with HIV (PLWH) and SUDs, and implemented during the pandemic, putting this work on the forefront of mHealth. The intersecting epidemics of HIV and SUD disproportionately impact racial/ethnic minorities, individuals with chronic conditions, people with lower health literacy and higher rates of mental health problems (e.g. Blanco and Volkow, 2019; Fazeli et al., 2020). By having access to this app during the COVID-19 pandemic—the study ran from March 2019 to March 2021—when local lockdown directives constrained in-person health support, this work allowed for an empirical observation on mobile support among vulnerable groups in the midst of intersecting crises. Recent research (Hochstatter et al., 2021a) reveals that these vulnerable populations saw increases in illicit substance use and missed HIV treatment visits during the pandemic, with the death from overdoses spiking during the pandemic (Appa et al., 2021). People with HIV and SUD are also susceptible to stigma and face barriers when engaging with mHealth technologies. Studying their use patterns will provide evidence about how to effectively implement mHealth apps and gauge how specific uses are linked to recovery outcomes.

We pay particular attention to Ling's assertions concerning mobile reciprocity and micro-coordination to study the use of the mHealth app ART-CHESS (Antiretroviral Therapy-Comprehensive Health Enhancement Support System). This app was specifically designed for HIV patients coping with opioid use, and provided vulnerable patients with information resources, communication functions, and health support tools, distinguishing themselves from other apps by offering interaction in a "walled garden," free of advertising, scammers, and those who might stigmatize SUD or HIV. In particular, ART-CHESS facilitates communication among users during moments of need that support those on the system. The open communication enabled by this system is hard to achieve on other media platforms that are not designed for populations in substance use recovery (Gustafson et al., 2014).

In this implementation study, we examined ART-CHESS features that contribute to social mediation, corresponding patterns of ART-CHESS use, and the value of those usage patterns for recovery progress during the COVID-19 pandemic. By querying server data on the use of the app, we constructed measures for whether specific features were engaged on a daily basis, and the intensity of communication and information activities when engaged. We then investigate how different subsets of users with HIV and SUD use the mHealth system and relate these usage patterns to addiction recovery risk and protection factors as measured by a weekly "check-in" survey. Our research reflects a trend toward employing mobile devices to collect passive (e.g. system log) and active (e.g. surveys) data to build lapse prediction models (Kornfield et al., 2018a; Moshontz et al., 2021).

Literature review

A social mediation technology

Mobile technologies serve as channels for social interaction, as "systems governed by group-based reciprocal expectations that enable but also set conditions for the maintenance of our social sphere" (Ling, 2012: 7). In *Taken for Grantedness*, Ling (2012) advocates that mobile technology help maintain "imminent connectedness" (Wurtzel and Turner, 1977) and a sense of "connected presence" (Licoppe, 2004). Playing off Tönnies'

(1965 [1887]) notion of Gemeinschaft (i.e. community) and Gesellschaft (i.e. society), Ling (2014) argues that mobile phones cultivate digital Gemeinschaft, helping maintain intimate spheres and fostering cohesion among community members (Ling, 2014). This occurs because of the omnipresence of mobile devices, which allows people to form and maintain their online communities "on the go" (Ling, 2012).

Such connectivity fosters an expectation for reciprocal connection which is "inherently social" and "essential in order to be a member of a community" (Ling, 2012: 175). The reciprocity of mobile communication and its "anytime-anywhere individual addressability" are vital to cultivate social connections (Campbell, 2020). Ling and Lai (2016) also argue that the rise of smartphone messaging apps expands social engagement to multisided interactions, such as in task-based chat groups. Ling's (2008) earlier work emphasizes maintaining "strong ties" through mobile mediated sociation, though mobile technologies have also proven powerful for bridging "weak ties." Indeed, Chan (2015) found that people using mobiles to foster "weak ties" had higher subjective well-being.

This thesis suggests an interdependency between mobile communication and networking activities in the offline world (Campbell and Kwak, 2010; Humphreys and Liao, 2011). We argue that mHealth apps, especially their communication features permit users to form connections—fostered through mobile reciprocal—and a sense of community with others—created through social coordination. Compared with other mobile-based applications like mobile games, fitness enhancers, and calendar reminders, mHealth apps emphasizing messaging functions encourage different forms of social interactions, including one-to-one and one-to-many (Gustafson et al., 2014), among other communication functions.

In the context of HIV and SUD, such apps provide a safe space free of communication with other members of stigmatized populations. Digital spaces are especially important for HIV patients to navigate their day-to-day experiences as they are more likely to face social isolation linked to fear of disease and lifestyles perceived as "deviant," "sinful," and "evil" (Sontag, 2001). Stigma perceptions shape HIV patients' psychosocial outcomes (Turan et al., 2017) and influence treatment adherence (Turan et al., 2019). Feeling of stigma also drives HIV patients to use drugs as a way to seek comfort. Substances like opioids do not merely lead to addiction and overdose problems, but also hasten the progression of the infectious disease, affect adherence to antiretroviral therapies, and impair the overall medical treatment effects (CDC, 2021).

In addition, the COVID-19 pandemic appears to have aggravated struggles for the people with HIV who have opioid use disorders (Hochstatter et al., 2021a). Thirteen percent of Americans started or increased substance use to cope with COVID-19-related stress, among which opioid misuse increased dramatically (NYT, 2021). The face-to-face support options like in-person recovery meetings were less available due to social distancing measures, which made it hard for PLWH and SUDs to access resources for social support, exacerbating their recovery challenges. Apps like ART-CHESS provide a means for PLWH and SUDs to have a virtual place to gather and interact free of stigmatization. Such apps can then serve as a social agent creating an online community for interpersonal reciprocity and group coordination that avoids stigmatization and meets communication and information needs for social mediation.

mHealth for communication and information

Ling and Lai (2016) argued that the emergence of smartphones and messaging apps advanced direct interpersonal ("dyadic") communication to now include multiparty coordination involving group dynamics ("network"). Although his work did not consider the distinction between these levels of communication empirically, current research distinguishes message reception and expression at multiple levels of communication (Mi et al., 2022). We contend that different communication tools embedded in the design of mHealth systems correspond to assertions about mobile reciprocity strengthening bonds and micro-coordination building networks. These different communication resources have the potential to maximize health benefits by catering to patients' preferences and needs for message reception and expression in relation to different possible audiences, small and selective or large and connected.

Most mHealth tools that enable social support permit message consumption (reception) and construction (expression) at different social levels. Message reception is understood in terms of individuals encountering content produced by others and their mental processing of these messages in relation to their existing thoughts and feelings (Bartels, 1993; Pingree, 2007; Zaller, 1992). Meanwhile, message expression refers to "mental processes underlying the composition of language, the commitment associated with articulating ideas and creating content, and the anticipation of accountability" (Shah, 2016: 13). The interplay between message reception and expression is critical for SUD recovery because basic social interactions like "lurking before posting" (i.e. reading posts for a period of time before gaining the confidence to post) support ongoing message production and bonding (Namkoong et al., 2017; Yoo et al., 2018).

Notably, expression and reception can occur outside of one-to-one and one-to-many communications within an mHealth app, where journaling features allow for intraindividual communication. Such self-directed communication can play an important role in therapeutic and educational contexts, where diary-writing and other reflective communication have proven beneficial (Hiemstra, 2001). Thus, the mHealth app in our study considers a comprehensive set of communication and information features alongside games and relaxation links, a meeting and events calendar, and support tools to address use urges, which are displayed in Figure 1.

Communication features of mHealth apps, then, enable message reception and expression behaviors at three social levels: network (i.e. one-to-many), dyadic (i.e. one-to-one), and intraindividual (i.e. self-to-self) levels. Such stratification is based on previous work in health and human communication (Barnlund, 2013; Chaffee and Berger, 1987), as well as studies about dyadic and group interactions through messaging apps. We conceptualize "app-based chat groups" (Ling and Lai, 2016) as network-level communications because they facilitate one-to-many interactions. Other formats of network communication include online peer support forums (e.g. Hwang et al., 2021; Namkoong et al., 2017), in which posting messages to all connected users is different in cognitive and social demands than one-to-one messaging. Though network reception and expression may build and sustain social connections, one-to-one dyadic interaction reflects a more intimate mediated-interaction with a higher demand for reciprocity.

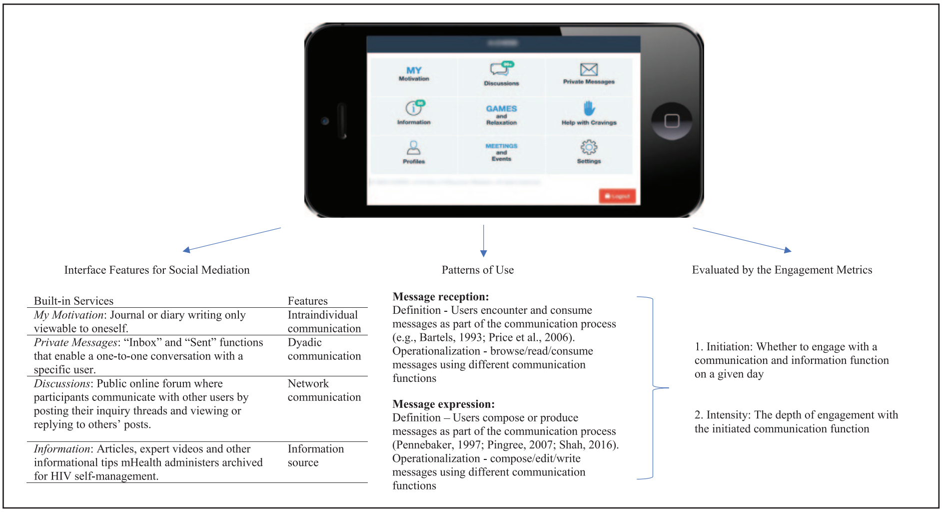

Figure 1. Communication and information features of a comprehensive mHealth app for PLWH in SUD recovery.

Compared with dyadic and network communication features of mHealth apps that trigger reciprocal communication and encourage micro-coordination, the intraindividual communication features are less well studied. The ART-CHESS app contains a journal or diary writing feature that facilitates self-reflection through expressive writing that users can revisit their past entries. Expressive writing is beneficial for health outcomes because disclosure is associated with reductions in inhibitions, stigma, and feelings associated with trauma, reducing distress and depression (Frattaroli, 2006; Pennebaker, 1997). Intraindividual communication not only allows expressive writing, but also permits self-reflection through reviewing one's own journal entries. Such self-reflection may lead to a perceptual or behavioral response. Such intra-individual communication suggests extensions to Ling's insights concerning mobile telephony.

In addition to communication features, a comprehensive mHealth system also typically contains curated information sources; for ART-CHESS, this content is stored within the *Information* tab. Unlike the unverified content found on social media, articles about antiretroviral therapy and addiction treatment are vetted by medical experts. The underlying idea is to provide informational support to improve users' knowledge about coping with HIV and SUD. The consumption of this verified content is particularly important for PLWH since they are particularly susceptible to medical misinformation (Kalichman et al., 2012). Several studies have confirmed the beneficial effects of knowledge awareness in increasing the uptake of HIV screening and treatment (e.g. Hochstatter et al., 2021b). Messages received through the *Information* tab may contribute to the knowledge gain, an antecedent for preventive behavior change (Rosenstock, 1974).

It is reasonable to assume PLWH and SUD may have different communication and information seeking preferences for many reasons, including intersectional stigmas (e.g. HIV-related stigma, SUD-related stigma, and other identities) and daily challenges of illness and recovery management. An mHealth system equipped with communication features at network, dyadic, and intraindividual levels coupled with information sources for self-management is adaptive to user preferences. Once patients are provided the tool, they may choose to initiate use of the feature (e.g. sending private messages or reading public posts) and engage with those features differently (e.g. reading selected messages or all news posts in a session). As discussed below, the ART-CHESS tool also contains other features such as games and relaxation links, a meeting and events calendar, and support tools to address use urges that we consider alongside the use of these communication and information features, though our conceptual and analytic focus remains fixed on communicative actions that encourage reciprocity and coordination, in Ling's terminology, and their relationships with recovery outcomes.

Initiation and intensity of overtime use

More specifically, this study examines how individuals use features of a system, the interactions between these feature use, and the association of feature usage patterns with the goals the system was built to address, building on frameworks for prior technology and communication adoption research (Gibson, 1979; Norman, 1988). For example, on social media, people using one-to-many (network) communication features also return to use those same features due to familiarity and routine or gravitate to using one-to-one (dyadic) communication as they begin to build relationships with other (Bazarova, 2012; Burke and Kraut, 2014). Our app allows expression (i.e. writing, posting) and reception (i.e. reading, reviewing) at the one-to-many, one-to-one, and intraindividual levels, while also allowing access to information, games, and relaxation links, a meeting and events calendar, and support tools for disease management. For each app user, the system logs whether a particular feature was accessed can be used to produce a daily time series during the study period. These time series data permit us to examine the autocorrelation (how much past use of a feature explain future use, which is typically a first step in such analysis) and lagged relationships (how much past use of one feature explains future use of other features, after accounting for the autocorrelated relationships) (Wells et al., 2019). Accordingly, we first pose a research question concerning patterns of self-driven communication and information uses to understand which ones tend to most "sticky" in prompting return use.

> *RQ1*. Does prior engagement with particular communication and information features of the mHealth app explain subsequent use of the same system features?

Next, we post a research question concerning whether past patterns of use explain subsequent use of other features to consider the cross influence among use of different system features.

> *RQ2*. Does prior engagement with particular communication and information features of the mHealth app lead to subsequent use of other communication and information features when accounting for the prior use of other recovery support system features?

In addition to understanding the relations within and between system features longitudinally, it is important to distinguish the nature of this longitudinal use—that is, whether someone opts to uses a certain system feature (i.e. initiation) and the amount of use during that occasion (i.e. intensity). This distinction between initiation and intensity has been largely ignored in communication research, despite scholars like Chaffee (1991) suggesting that media consumption behaviors should be divided into two parts: for example, whether to read a paper and the amount of reading of that paper. The underlying reasoning is that "some people never read a newspaper (many because they cannot), while others read one or more every day; still others read occasionally or often, which are intermediate categories" (Chaffee, 1991: 37).

This distinction between initiation of use and the intensity of that use intuitively maps onto many human-media interactions. The initiation stage involves individuals deciding (or habitually repeating) whether or not to use a particular medium, system or digital tool, whereas the decision about intensity of use is shaped by options and interactions within that choice set. For example, public health research centering on online smoking cessation programs examined the number of interventions completed (e.g. number of modules or activities completed) as well as the intensity of engagement with each intervention (e.g. total number of activities or time spent per log-in), finding that dose–response relationship was more closely linked with intensity of use (Donkin et al., 2013). In fact, Fiore (2000) emphasizes the strong dose–response relationship between the intensity of counseling interventions and their effectiveness, going so far as to specify the length of the session to maximize efficacy (e.g. "lasting longer than 10 minutes").

It is also notable that most users either never start using certain functions or use them sporadically. Initiation reveals users' decision to move from the default state of not doing some activity to choosing to use it, while intensity speaks to the degree of engagement with that system feature once the decision has been made to engage. Numerically, due to long periods of idling, usage cycles, and users' preferences, initiation metrics are usually zero for any given moment, with the exception of occasional moments logging use. This means there will be large volume of zero recorded on mobile logs, inducing a zero-inflation problem. One way to manage this is to disentangling user engagement into whether a feature is used with an appropriate timeframe (e.g. dichotomous daily initiation) and to what depth the engaged feature is used once activated (e.g. continuous intensity score). It is this approach that allows us to compare subsets of PLWH and SUD to examine whether their use patterns are characterized by frequent initiation of particular features and the intensity of their use. More importantly, clearly explicating these two processes in media engagement will advance research centered on social mediation.

Considering racial/ethnical disparities in HIV care (Fields et al., 2021) and SUD recovery (Hallfors et al., 2007), this study is especially interested in understanding whether racial/ethnic minorities engaged communication and information features using ART-CHESS differently. Racial and ethnic minorities are disproportionately affected by the HIV/AIDS epidemic (Schnall et al., 2015) while being more likely to use smartphones for Internet access (Pew Research Center, 2015), suggesting smartphone-based interventions are well-suited to this population.

Besides race, this research also examines age, sex, and education as factors shaping ART-CHESS engagement. Countless studies for online health support have found age, gender, race, and education levels are prominent factors in mHealth engagement (e.g. Ben-Zeev et al., 2016). It is especially worthwhile to investigate the engagement performance of vulnerable sub-groups to gain insights for evidence-based health practice for future mobile communication research. Accordingly, we examined the initiation and intensity of system use among four demographic groups that suffered compounded vulnerabilities in the wake of COVID-19: older adults, women, individuals self-identified as African-American, and the less-educated.

> *RQ3*. Do the initiation and intensity of communication, information, and recovery support features differ for older adults, women, African-American, and less-educated system users?

For mHealth apps to support PLWH and SUDs, they must enhance protection factors and reduce risk factors in patients' social environment (Chih et al., 2014). Improvement in recovery outcomes after using the app would be indicative of effective implementation of this app among its targeted populations. Identifying the relations between use patterns and health benefits can inform the development of sensing systems for digital phenotyping—moment-by-moment quantification of individuals' situational status using data from their digital devices (Moshontz et al., 2021; Torous et al., 2016). Signal detected by mobile devices can be used to predict adverse health outcomes, potentially providing the basis for alert systems that trigger support "just-in-time" (Ling and Oppegaard, 2021). We predict that frequent initiation and intense use of ART-CHESS system will be associated with recovery progress, with communication engagement suggesting available reserves for support provision or support seeking when under stress.

> *H1*. Initiation of message expression and reception at the network, dyadic and intraindividual levels, along with information consumption, will be related to *recovery progress*.
>
> *H2*. Intensity of message expression and reception at the network, dyadic and intraindividual levels, along with information consumption, will be related to *recovery progress*.

Methods

Data collection

Mobile app use data were collected from server logs of the ART-CHESS application, a system designed specifically for PLWH with SUD, with content and features designed specifically for this treatment population. Before implementing the app, we conducted focus groups with patients at an inpatient opioid treatment facility to test the feasibility of ideas. Then one-to-one usability tests were performed to ensure functional app development and adequate user experience.

Participants were enrolled from 12 March 2019 to 12 March 2020 for a study period of 12 months, with data collection ending March 2021. The project was an implementation study (no control group), so participants were not randomized. The app was developed from an existing CHESS system shown to support SUD recovery (Gustafson et al., 2014) but modified to support longitudinal engagement in clinical HIV care. The modifications included elements that are important to HIV care such as consistent adherence to prescribed medication and regular evaluations with medical providers. To minimize stigma, all communication were among PLWH and SUD who were under supervision from expert medical providers. The curated information stored in *Information* tab catered directly to HIV and SUD recovery self-management and was vetted by clinical experts. And the weekly survey collected information about users' recovery progress, protection factors and risk factors in their social environment.

Participants were eligible for the study if they were adults older than 18, receiving medical care for HIV infection, and had a lifetime history of a SUD with either (1) active use of alcohol or other drugs in the past 12 months or (2) current participation in an SUD treatment program. They were recruited in three ways: (1) posting recruitment flyers at two health clinics spanning three counties across the state in which the study was conducted; (2) having project managers contacted social workers/case managers at the clinical sites and asking them to refer patients to the study; and (3) asking physicians at the clinical sites to review the medical records of upcoming appointments and recommend ART-CHESS to eligible patients. This study was approved by the Institutional Review Board (IRB) at the university where the study was conducted and funded by the National Institutes of Health.

A total of 208 subjects were recruited. They were asked to download the ART-CHESS using their own smartphones, which was available on both Apple and Android OS. Users entered the app by creating a deidentified username that masked their offline identities. Figure 1 displays the home screen of system features subjects encountered when logged in using their username and password. The "My Motivation" tab leads users to write and upload journal entries or other self-produced content viewable only to themselves. The "Discussion" tab provides access to a discussion forum for participants. The "Private Messages" tab allows users to select from a list of usernames and to send personal messages and review new and existing messages. The "Information" tab contains short articles and quick tips about managing opioid addiction and HIV. The "Games and Relaxation" tab links users to game apps, such as Angry Birds and Candy Crush outside the system but installed on their phones, or mindfulness meditation recordings. The "Help with Cravings" tab links to pre-stored phone contacts, support events and relaxation tips that users can access when they face an urge to use. The "Meeting and Events" tab opens a calendar function that displays sober meetings and events in the local community. The "Profiles" and "Settings" functions allow users to customize system features, including the image linked with the username. All secondary interfaces are detailed in Appendix 1.

Whenever patients used communication, information, or other recovery support features, the back-end server recorded their activity.[2] All actions were stored with timestamps, unique user ID, and the count of "clicks" for each page representing users' navigation behaviors. Demographic data collected at baseline and weekly surveys

Table 1. Measurement of communication and information engagement with ART-CHESS.

Engagement variables		Operationalization
Comm. levels	Message mode	Counts of clicks per user per day for relevant pages
Network	Message reception	Site page displaying: view a message and its comments in the discussion group, a list of discussion groups, list of messages in a discussion group
	Message expression	Site page allowing producing, saving and editing of a post or comments
Dyadic	Message reception	Site page displaying: view an individual private message thread, view list of private message threads that a user has
	Message expression	Site page of adding and editing a message to a private messaging
Intraindividual	Message reception	Site page displaying self-written journal entries.
	Message expression	Site page to compose or edit entries for the self-written journals.
Information	Message reception	Site page displaying the list and the contents of videos, news articles, local resource information and quick tips in the library sections.

delivered and collected via the app measuring recovery progress were merged with log data via the unique user ID.

Measurement

Raw data of clicks indicating use of a particular system feature were aggregated daily. The count of clicks between weekly survey intervals was used to make the initiation and intensity metrics. Descriptions about the measurement of engagement with communication and information features are in Table 1.

Initiation metric. Users were coded as “0” if there was no engagement with each of the seven features and “1” for any day on which a server record of action existed.

Intensity metric. Among users who entered the system and used particular functions each day, the intensity measure was calculated as the number of clicks for each specific feature. Intensity was coded as missing for the seven engagement types if “0” for the initiation measure. This operationalization only assesses intensity if an activity was initiated for that specific feature.

Risk and protective factors for SUD recovery. Weekly self-administered surveys using the brief addiction monitor (BAM), a valid SUD monitoring and recovery progression evaluation metric, measured recovery risk and protective factors (Cacciola et al., 2013). Four BAM items assessed risk factors and the other four assessed protective factors. For the risk factors, users were asked to rate on a 0–7-point scale from “0—not at all” to “7—a lot" for their risky situations, difficulty sleeping, drinking or drug urges, relationship troubles with family or friends in the past week (Cronbach's $\alpha = .75$). Protective factors also used a 0–7-point scale to rate patients' confidence to stay clean and sober, involvement with spiritual activities, involvement with work, school, or volunteering, and recovery support meeting attendance (Cronbach's $\alpha = .63$). BAM scores are calculated as the difference of risk and protective factors (range: −28 to + 28). As such, BAM scores systematically monitor patient progress during substance abuse treatment.

Demographics. Self-reported race and ethnicity, gender, age, and education levels were collected via a baseline survey. Age was measured through asking the users how old they were at the time the survey was given. Given that 65.9% of the recruited pool of participants were African American, Race/ethnicity was recoded as "African Americans versus Others." Education was measured on an ordinal scale and transformed into the actual years of attainment for analysis.[3] To control differences in substance use status, a question asking "In the past 30 days, did you use any illegal/street drugs (including marijuana) or abuse any prescription medications? (0 No, 1 Yes)" was collected at baseline.

COVID-19 lockdown variable: A dummy variable was created to account for the 12 March 2020 national lockdown in the United States in response to community spread of COVID-19.

Analytical approach

To assess RQ1, we used autocorrelation function (ACF) to examine how patterns of initiation of the seven communication and information features were associated with use of the feature on prior days. Specifically, the ACF calculates the correlation between observations of a time series that are separated by k time units (y_t and y_{t-k}) between the first day and the lagged days. There were seven features examined for self-driven processes: network reception, network expression, dyadic reception, dyadic expression, intraindividual reception, intraindividual expression, and information consumption.

To assess RQ2, we applied vector autoregression models (VARs) to disentangle mutual influences across time-series variables (Wells et al., 2019). VARs trace latent relations among time-variant variables without imposing rigid assumptions on the relationship directions. In the present study, we assess the types of communication and information use that are associated with subsequent engagement with other types of communication and information use, without any assumption for their precursor orders and while accounting for the prior use of other recovery support system features. After VAR models were estimated, Granger causality tests were used to verify which variables can be considered temporally prior, accounting for endogenous variables.

To assess RQ3, we employed hurdle models using a binomial distribution with a logit link function for the dichotomous part and a truncated Poisson distribution for the count stage. We report clustered robust standard errors (clustered by user) to account for within-user correlation and potential overdispersion in the count stage model. Hurdle models are advantageous as they provide separate estimates for the initiation and intensity metrics. Notably, a daily dichotomous observation of initiation was first modeled, separately for each communication and information feature. Next, the continuous metric for intensity, which was only assessed among users who already initiated the behavior, was modeled. The hurdle model estimates associations between user characteristics and (1) initiating communication and information features (zero vs non-zero clicks) and (2) depth of engagement (intensity). We also assessed initiation of the "games and relaxation," "meetings and events," and "help with cravings" tabs, though server-side logs did not retain intensity metrics for these uses because a number of these functions pushed users out of the system to other phone apps and systems.

To assess H1–H2, we used linear models with clustered robust standard errors to estimate the impact of initiation and intensity on the risk and protection factors, including initiation of the other recovery resources like games and relaxation. We also include a dummy variable representing the 12 March 2020 lockdown to account for shifts associated with disruptions caused by the COVID-19 pandemic. We cluster our standard errors on individuals to account for the overtime correlation between responses from the user. The scripts using R and STATA for the above analysis are available at (website anonymous for review).

Results

We included 173 PLWH and SUD who used at least one communication feature, information resources, or other three functions (games and relaxation, meetings, and events, and help with cravings) during the study period. The resulting sample ($N=173$) had a mean age of 46 ($SD=11.2$), 77.46% male, and 67.05% non-White. There were 64.16% ($N=111$) retained users identified themselves as African-American. Overall, 42.2% had at least some college-level education, and 60.12% reported illegal/street drugs (including marijuana) or prescription medication abuse in the 30 days before joining this study. On average, patients used this mHealth app for 32.44 ($SD=35.06$) days over the 6-month period. Table 2 displays the descriptive statistics of the initiation and intensity metrics.

RQ1: autocorrelation of feature initiation

Figure 2(a) to (g) present the ACF graphs for the seven types of usage patterns. The *x*-axis refers to the number of days after the first day, and the *y*-axis indicates the correlation estimate (ϕ) between the first day and the lagged days. All the time-series had significant autocorrelations with different values in ϕ, indicating notable amounts of self-driven behavioral patterns for each one of the initiation metrics. Post hoc analysis suggests that network (i.e. one-to-many) reception had the highest correlation ($\phi_1=0.62$) between the first and the second day. By the 14th day, the autocorrelation became insignificant ($\phi_{14}=0.13$). The least sustained use pattern was the intraindividual (i.e. self-to-self) reception (reading one's own journal posts) and information reception. The intraindividual reception only extended for 5 days until a nonsignificant correlation ($\phi_5=0.13$) while information reception sustained for 3 days ($\phi_3=0.15$). Overall, all seven types of communication and information engagement had strong self-driven patterns.[4]

Table 2. Description of initiation and intensity for each system feature for users during the study period ($N = 173$).

	Initiation (whether to engage)		Intensity (degree of engagement—click count)	
	Count	Proportion (%)	*Mean*	*SD*
Network				
Reception	149	86.13	69.78	212.58
Expression	51	29.48	13.16	27.91
Dyadic				
Reception	139	80.34	17.29	19.41
Expression	57	32.95	5.46	6.58
Intraindividual				
Reception	99	57.23	9.88	18.58
Expression	155	89.60	23.49	32.42
Information				
Reception	102	59	16.11	28.29
Help with cravings	89	51	NA	NA
Games & relaxation	103	60	NA	NA
Meet & events	109	63	NA	NA

SD: standard deviation; NA: not applicable.

RQ2: mutual influence

The VAR results in Table 3 summarize the Granger test among the seven types of time series for message reception and expression across communication and information levels while controlling for use of other recovery support features (e.g. games & relaxation). We found that engagement with network and dyadic levels for message reception and expression often led to subsequent engagement with other features. For example, network reception (i.e. reading posts) led to subsequent network expression (i.e. writing posts; $\chi^2 = 8.70$, $p = .013$) and dyadic reception (i.e. reading private messages; $\chi^2 = 8.00$, $p = .018$). Network expression (i.e. creating posts) also led to dyadic expression (i.e. writing private messages; $\chi^2 = 20.24$, $p = .00$) and information reception ($\chi^2 = 6.15$, $p = .046$). Likewise, dyadic reception activates intraindividual expression (i.e. journal writing; $\chi^2 = 32.81$, $p = .00$) and intraindividual reception (i.e. reading journal entries; $\chi^2 = 7.40$, $p = .025$), while dyadic expression (i.e. writing private messages) activates dyadic reception (i.e. reading private message; $\chi^2 = 14.68$, $p = .001$) and intraindividual reception (i.e. reading journal entries; $\chi^2 = 13.96$, $p = .001$). Intraindividual reception can also lead to intraindividual expression ($\chi^2 = 7.66$, $p = .022$). In all, we observed "lurking before posting," with prior message reception encouraging subsequent engagement with other functions on the mobile app. We also found expression at network (posting in the discussion room) and dyadic (sending private messages) facilitated communication at other levels, such as reading private messages and self-written journals. All of this was observed while controlling for initiation of other recovery support system features.

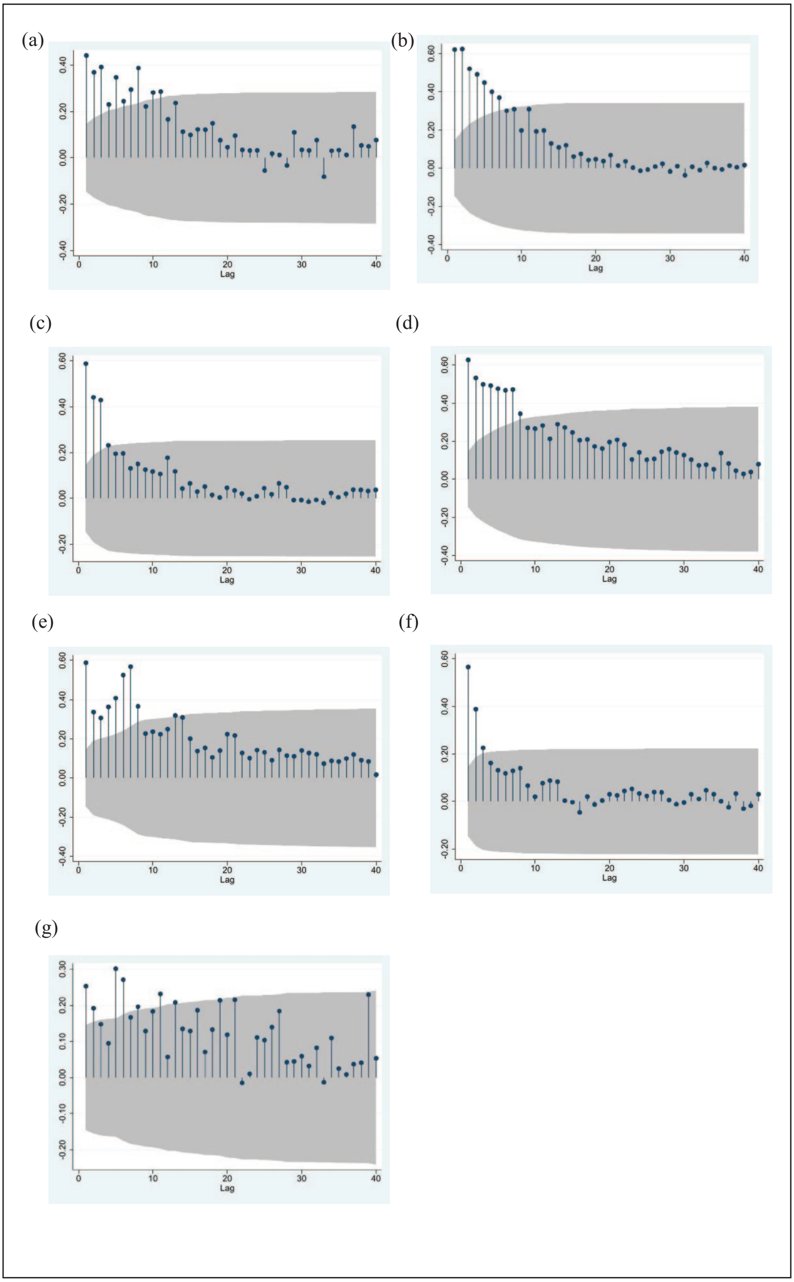

Figure 2. Auto-correlation function for the communication and information time series on a daily basis (N = 180 days). (a) Network expression. (b) Network reception. (c) Dyadic expression. (d) Dyadic reception. (e) Intraindividual expression. (g) Information reception. (f) Intraindividual reception.

The graphs show the auto-correlation between the lagged 40 days and the first day. The afterwards 140 days were not plotted as they did not have significant auto-correlation and would remain within the same gray areas.

Table 3. Granger causality tests for the six communication engagement types.

	χ^2	p
1. Network reception → Network expression	8.70	.013
2. Network reception → Dyadic reception	8.00	.018
3. Network expression → Dyadic expression	20.24	.000
4. Network expression → Information reception	6.15	.046
5. Dyadic reception → Intraindividual reception	7.40	.025
6. Dyadic reception → Intraindividual expression	32.81	.000
6. Dyadic expression → Dyadic reception	14.68	.001
7. Dyadic expression → Intraindividual reception	13.96	.001
8. Intraindividual reception → Intraindividual expression	7.66	.022

Only significant tests are presented due to word space.

RQ3: initiation and intensity by user characteristics

Table 4 displays the results of hurdle models treating initiation and intensity as components for each communication/information feature. We found that African-American users had less initiation in intraindividual message expression (i.e. journal writing; $\beta = -0.42$, $p < .01$) and more intensity in network message reception (i.e. reading messages in the discussion forum; $\beta = 0.51$, $p < .01$), with no significant differences in terms of use intensity compared with other racial groups. Results also revealed that gender, age, and education were significantly associated with initiation and intensity metrics. Female users were more likely to initiate intraindividual reception (i.e. reading journal entries) ($\beta = 0.60$, $p < .01$). Female's intensity of intraindividual expression ($\beta = 0.60$, $p < .01$) and information reception ($\beta = 0.48$, $p < .05$) was also greater than males. Older users were also more likely to initiate intraindividual expression (i.e. journal writing; $\beta = 0.02$, $p < .05$) and were more likely to use this feature intensively ($\beta = 0.02$, $p < .001$). They were less likely to engage in network reception intensively ($\beta = -0.02$, $p < .001$). Participants with higher education degree had less frequent expression of dyadic communication ($\beta = -0.21$, $p < .05$). Drug use at baseline was negatively associated with the intensity of network expression ($\beta = -0.51$, $p < .05$). With respect to the event impact from the national lockdown of COVID-19, we found that user decreased initiating dyadic expression ($\beta = -0.72$, $p < .05$), use of the help with cravings features ($\beta = -1.13$, $p < .001$) and meetings/events ($\beta = -0.89$, $p < .01$). The event also reduced the intensity of network expression ($\beta = -0.62$, $p < .05$), intraindividual reception ($\beta = -0.95$, $p < .001$), intraindividual expression ($\beta = -1.14$, $p < .001$), as well as information consumption ($\beta = -0.33$, $p < .05$).

H1 and H2: linear models predicting recovery outcomes

Table 5 displays the results examining initiation and intensity as predictors for SUD recovery progress. After controlling for initiation of other recovery support features use such as game and relaxation and the 12 March 2020 lockdown, we found that initiating

Table 4. Hurdle model estimates for demographic subgroups engaging with the mHealth system ("ART-CHESS").

Stage 1: Initiation metric										
Subgroups	Network		Dyadic		Intraindividual		Information	Help with Cravings	Games & Relaxation	Meetings & Events
	Reception	Expression	Reception	Expression	Reception	Expression	Reception	Reception	Reception	Reception
African-Americans (= 1) vs Others	0.39 (0.25)	0.65 (0.48)	−0.19 (0.15)	0.18 (0.31)	0.14 (0.20)	−0.42** (0.16)	−0.13 (0.17)	0.08 (0.25)	−0.30 (0.22)	−0.07 (0.22)
Female (= 1) vs Male	−0.15 (0.30)	0.08 (0.48)	0.21 (0.20)	0.20 (0.33)	0.60** (0.22)	0.14 (0.22)	0.33 (0.20)	0.07 (0.35)	0.49 (0.26)	−0.26 (0.26)
Age	−0.02 (0.01)	−0.03 (0.02)	−0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.02* (0.01)	−0.00 (0.01)	0.01 (0.01)	0.00 (0.01)	−0.00 (0.01)
Education	−0.02 (0.04)	0.05 (0.06)	−0.02 (0.04)	−0.21** (0.07)	−0.02 (0.05)	0.01 (0.04)	0.02 (0.04)	−0.04 (0.08)	−0.04 (0.08)	−0.02 (0.04)
Use drug before the study (Yes = 1)	−0.29 (0.25)	−0.81 (0.42)	−0.22 (0.16)	−0.22 (0.29)	−0.04 (0.21)	0.23 (0.16)	−0.12 (0.17)	0.40 (0.28)	−0.02 (0.25)	0.27 (0.21)
COVID lockdown control	−0.22 (0.37)	−0.57 (0.38)	−0.03 (0.26)	−0.72* (0.35)	−0.48 (0.34)	−0.09 (0.20)	0.13 (0.19)	−1.13*** (0.30)	−0.77 (0.45)	−0.89** (0.30)

(Continued)

Table 4. (Continued)

Stage 2: Intensity metric

Subgroups	Network		Dyadic		Intraindividual		Information
	Reception	Expression	Reception	Expression	Reception	Expression	Reception
African-Americans (= 1) vs Others	0.51* (0.24)	0.36 (0.27)	0.10 (0.13)	−0.11 (0.29)	−0.09 (0.17)	−0.05 (0.16)	−0.10 (0.16)
Female vs Male	−0.04 (0.25)	−0.05 (0.24)	−0.02 (0.13)	0.39 (0.31)	0.31 (0.20)	0.60** (0.18)	0.48* (0.22)
Age	−0.02*** (0.01)	−0.02 (0.01)	−0.01 (0.01)	0.01 (0.02)	0.01 (0.01)	0.02*** (0.01)	−0.00 (0.01)
Education	0.01 (0.04)	0.05 (0.04)	−0.02 (0.10)	0.04 (0.09)	−0.10 (0.05)	−0.06 (0.04)	0.02 (0.07)
Whether to use drug before the study (Yes = 1)	−0.21 (0.22)	−0.51* (0.25)	−0.18 (0.11)	0.24 (0.33)	0.10 (0.23)	0.20 (0.17)	−0.07 (0.20)
COVID lockdown control	0.19 (0.20)	−0.62* (0.32)	−0.13 (0.13)	−0.37 (0.39)	−0.95*** (0.17)	−1.14*** (0.30)	−0.33* (0.15)
Log Likelihood	−9953.09	−1262.10	3118.37	−672.86	−1716.71	−4824.28	−2680.06

Standard deviation is in the parentheses. *$p < .05$; **$p < .01$; ***$p < .001$.

Table 5. Predicting SUD outcomes using engagement types (N = 173 users, average engagement days = 32.44).

Predictors	Effect estimates for the outcome		
	Protection	*Risk*	*Recovery progress*
Network reception initiation	0.50***	−0.34	0.84*
	(0.18)	(0.18)	(0.24)
Network reception intensity	−0.07*	−0.00	−0.07*
	(0.03)	(0.02)	(0.03)
Network expression initiation	−0.36	0.42	−0.78
	(0.36)	(0.29)	(0.41)
Network expression intensity	0.29***	0.01	0.28**
	(0.07)	(0.07)	(0.09)
Dyadic reception initiation	−0.37	0.47*	−0.84**
	(0.22)	(0.23)	(0.32)
Dyadic reception intensity	0.17*	−0.19**	0.36**
	(0.08)	(0.07)	(0.09)
Dyadic expression initiation	−0.43	0.32	−0.76
	(0.43)	(0.34)	(0.56)
Dyadic expression intensity	−0.03	−0.02	−0.01
	(0.27)	(0.17)	(0.32)
Intraindividual reception initiation	−0.19	−0.13	−0.05
	(0.28)	(0.26)	(0.44)
Intraindividual reception intensity	0.15	−0.03	0.18
	(0.10)	(0.12)	(0.18)
Intraindividual expression initiation	0.40*	−0.18	0.58
	(0.19)	(0.23)	(0.31)
Intraindividual expression intensity	−0.12	0.05	−0.17
	(0.08)	(0.08)	(0.14)
Information reception initiation	−0.42	−0.18	−0.24
	(0.26)	(0.25)	(0.29)
Information reception intensity	−0.02	0.20	−0.22
	(0.17)	(0.12)	(0.12)
Help with cravings initiation	0.20	−0.30	0.50
	(0.32)	(0.26)	(0.45)
Games & relaxation initiation	−0.52*	0.14	−0.66
	(0.24)	(0.19)	(0.34)
Meet & events initiation	0.02	0.28	−0.26
	(0.29)	(0.20)	(0.39)
COVID lockdown control	−0.73	−0.50*	−0.23
	(0.38)	(0.23)	(0.51)
Constant	3.91***	2.89***	1.02***
	(0.20)	(0.20)	(0.30)

Standard error is in the parentheses. *$p < .05$; **$p < .01$; ***$p < .001$.

network reception positively related to protective factors ($\beta = 0.50$, $\rho < .001$) and the overall recovery progress ($\beta = 0.84$, $\rho < .05$). Most initiation metrics were not significantly related to SUD outcomes except for the initiation of intraindividual expression, which had a positive relation with protection factors ($\beta = 0.40$, $\rho < .05$). As regards to the intensity metrics, we found the intensive use of network expression (e.g. posting multiple public posts) was positively related to protective factors ($\beta = 0.29$, $\rho < .001$) and the overall recovery progress ($\beta = 0.28$, $\rho < .01$). Intensity of dyadic reception was also positively associated with protective factors ($\beta = 0.17$, $\rho < .05$) and overall recovery progress ($\beta = 0.36$, $\rho < .01$), and negatively related to relapse risks ($\beta = -0.19$, $\rho < .01$). However, intensity of network reception was negatively associated with protection factors ($\beta = -0.07$, $\rho < .05$) and overall recovery ($\beta = -0.07$, $\rho < .05$), implying discrepant effects for initiation of network reception (positive) versus intensity of network reception (negative). Compared with the initiation metric, intensity played a larger role in predicting recovery progress. Thus, H1 received little support and H2 received partial support.

Conclusion and future directions

This study extended work on social mediation to study an mHealth app for PLWH and SUD. Specifically, it used app log data to consider Ling's conception of reciprocity and micro-coordination of mobile telephony through assessment of communication at differential social levels. Extending this framework, we examine user engagement using two time-related metrics, initiation and intensity, for seven communication and information features. In particular, we undertook a detailed temporal examination of network (one-to-many), dyadic (one-to-one), and intraindividual (self-to-self) communication expression and reception and their relation to sociodemographic characteristics. Perhaps most important, we linked these usages patterns to weekly recovery risk and protective behaviors that are targets of the app.

Results reveal self-driven processes in engagement with system features, especially for network communication, as well as evidence of "lurking before posting." There were a few differences in patterns of use by race, sex, and age. African Americans were less likely to initiate writing journals (i.e. intraindividual expression) and may prefer "lurking" in the discussion forums (i.e. network reception). Females and older PLWH and SUD were more likely to engage with journaling features that are more self-reflective. Those with drug use at baseline and those with higher education degrees were less expressive in their use of communication features. It appears engagement metrics with network and dyadic communication features are associated with recovery indicators, which may be key to future digital phenotyping research. Also notable, the disruption caused by national lockdown was negatively related to the use of ART-CHESS.

Overall, these results support the utility of mobile telephony for social mediation (Ling, 2012) and reinforce its value of understanding the use of communication and information features on a mHealth app for micro-coordination (network), reciprocal communication (dyadic), and journaling (intraindividual), along with the association of using those features to health outcomes. These results suggest mHealth apps intended to support PLWH and SUD should include communication features at network (i.e.

one-to-many), dyadic (i.e. one-to-one), and intraindividual (i.e. self-to-self) levels to cater to patients' communication preferences. mHealth apps reflects the potential of combining communication and information features in mobile technologies with other support systems. Designing technology with social mediation considerations in mind (e.g. cultivating social capital through micro-coordination, increasing personal bonding and norms of reciprocity, reinforcing self-reflection) can enhance the performance of health apps, especially for populations who face intersectional stigmas, and may need to carefully curate their social practices to assist recovery progress. The global COVID-19 pandemic further highlights the necessity of digital health support due to the limited access to in-person health services, especially one found to support recovery among PLWH during a pandemic and despite the lockdown. Mobile apps can provide a comfortable channel to support health through message reception and expression in the middle of such public crisis.

Methodologically, the app use data that gleans patients' digital traces allow communication researchers to identify users' engagement patterns with mobile devices in an unobtrusive manner yet with direct observation. We constructed two time-related metrics—initiation and intensity—to investigate different patterns of use over time and related this to recovery outcomes. These two metrics build on prior work in health promotion and public health, as well as mass communication and econometrics, that distinguish between the initiation or frequency of an activity (e.g. number of sessions attended, modules completed, or readership days), and the dose–response relationship between intensity of engagement and outcomes of concern. While research has been more attentive to the latter, recent work suggest intensity, not regularity or frequency of initiation, that drives many observed effects. By applying a mixed-method approach, combining digital trace data with survey responses, opportunities to test these relationships become viable for communication researchers.

As for social implications, understanding patterns of system use among PLWH and SUD may help optimize mHealth usability and benefits through behavior-tailored interventions. A key finding was that the initiation of network reception, the intensity of network expression and the intensity of dyadic reception were associated with recovery benefits, suggesting the need for further research to understand the causal relationship underlying this association. All three of these results point toward the import of reciprocal communication and micro-coordination via mobile telephony for SUD recovery. Nonetheless, these results beg the question, do individuals who are experiencing challenges to recovery use features of the app intensely during periods of need, or does using selected features of the app intensively actually support recovery? The significant role of network communication is also suggestive of the potential of mobile technologies to construct digital communities for SUD recovery.

Future research could investigate other types of digital trace data such as language features to predict and deploy real-time interventions for relapse prevention (Kornfield et al., 2018a, 2018b). This study suggests future mobile communication research should focus on digital phenotyping—that is, "moment-by-moment quantification of the individual-level human phenotype in situ using data from personal digital devices" (Moshontz et al., 2021; Torous et al., 2016). Mobile devices can collect a wide range of actual behaviors due to their omnipresence in everyday life, their powerful sensors capable of collecting granular data (e.g. GPS positions), and access to phone logs and texted content (Harari et al., 2016). Mobile-based apps may be the most effective and popular medium to collect digital phenotyping data, for as Onnela and Rauch (2016) write, "the accelerometer can generate hundreds of thousands of observations per day, GPS can be sampled thousands of times a day, and smartphone microphones can record high-quality audio data at the rate of a compact disc" (p. 1693). Digital phenotyping is the future of "just-in-time" digital health support and adaptive mHealth systems.

One potential application of granular data collection through mHealth is to apply the analytic framework used in this study to short message services (SMS) through mobile texting. It is accepted that SMS can change perceptions and behaviors across health (Kannisto et al., 2014) and political contexts (Hermanns, 2008). Combing pattern recognition from data extracted at communication and information levels from mobile phones could then inform which individuals need support. The content of the support could also be tailored and tested, with some benefiting from group messaging and others from information provision. It will also allow researchers to scale up message delivery based on group patterns identified through longitudinal observations.

There are three main concerns about collecting data from targeted populations through mobiles. The first one is privacy when collecting sensitive, sometimes stigmatizing, and occasionally illegal activities through mobile devices, especially if done passively. However, researchers can overcome this problem through rigorous IRB review, guarantees to protect data from legal authorities, and fully informed consent from the participants. Procedures like deidentification for sensitive and personal information can protect user privacy and study ethics. The process should be mindful of the ethical restrictions in the use of digital trace data, especially in ways that might be identifying. Once these issues are addressed, the main ethical concerns become (1) an objective estimation of net benefits to initiate use of the system (i.e. the benefits of curbing the HIV and opioid epidemic at the community level while providing social and instrumental support to PLWH and SUD) and (2) actionable ethics during the program process, namely ongoing privacy, security, trust, and accountability (Mello and Wang, 2020; Nebeker et al., 2019). Appendix 2 details how ART-CHESS incorporated these ethical values.

The second problem is the financial and time cost for mobile log data collection. There are commercial companies like *beiwe* who help collect mobile sensing data for researchers, but the price for such data collection is high compared with surveys and experiments. One way to resolve this issue is to utilize apps that can retrieve personal log from the user's end, though development costs are also quite high. Some physical exercise and journal apps authorize user access to their own data, so that researchers can download personal log data from each participant once getting the IRB approval which may present a work around to researchers who cannot develop customized systems. The advantage of using mobile devices for data collection is the potential for continuous longitudinal observation. If researchers want to understand temporal dynamics, proximal triggers, and accumulated influence of system use, adopting mobile devices like smartphones for health behavior observation would be optimal.

The last concern is digital divides and health disparities that often leave minority populations behind when technological innovations are used for health support. Notably, the access to mobile devices among racial and ethnic minorities and the ease of installing apps across mobile operating systems help overcome some of these barriers for PLWH and SUD. Indeed, given the patterns of use observed, the usage among different subgroups of participants, and the association with recovery outcomes, the results of this study indicate that if these systems were made widely available, they would have utility for at-risk populations.

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Notes

1. Despite distinct definitions between mobiles, smartphones, and apps installed on smartphones, this article uses "mobile" to refer all interface functions operated on mobile-based Internet devices, including apps compatible with mobiles, smartphones, and other mobile computing tools (e.g. tablet PC).
2. Keystrokes that did not change the screen interfaces were not recorded.
3. Eighth grade or less = 7 years, some high school but did not graduate = 11 years, high school graduate or GED = 12 years, some college/2-year associate degree = 13.5 years, 4-year college graduate = 16 years, more than 4-year college degree = 20 years.
4. Partial autocorrelations (PACF), which provide the association of a stationary time series with its own lagged values, while also regressing on the values of the time series with shorter lags. Unlike the ACF, which does not account for the shorter lags, PACF is a stricter test. All PACF were also plotted and are presented in Appendix Figure 3; they showed no signs of seasonal patterns.

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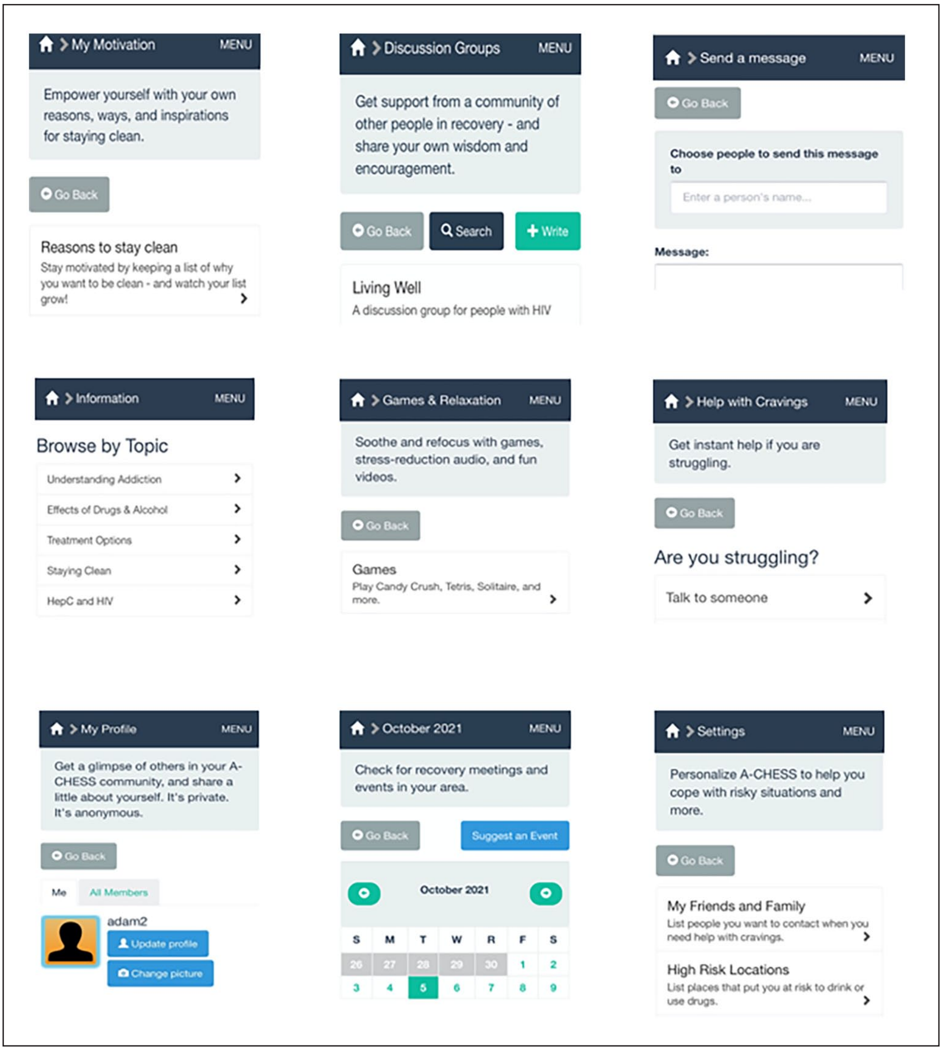
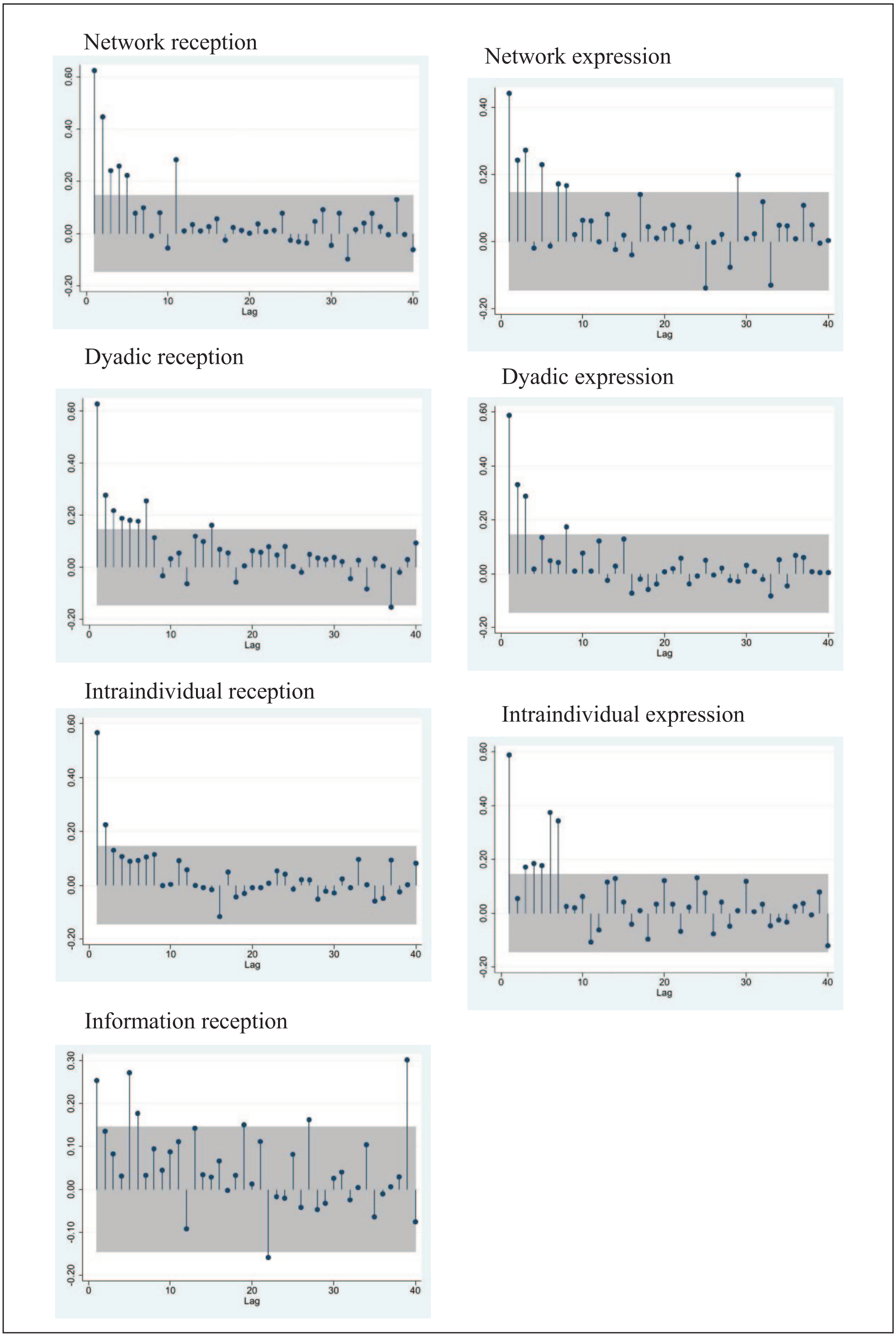
Ryan Westergaard is an infectious disease physician, epidemiologist, and the chief medical officer for the Wisconsin Department of Health Services. His research aims to improve the quality and continuity of care for vulnerable populations living with HIV and viral hepatitis – with special emphasis on current or formerly incarcerated individuals, people who use drugs, and people with psychiatric illnesses.



Appendix 1. The secondary interfaces under nine system features.

Privacy	Security	Trust	Accountability
- Before the study begins, every subject was assigned a unique code number, and the profile was kept in a locked file in the CHESS office. - Data collection from the clinic records and ART-CHESS removed the patients' real name and attached the code number by the study coordinator. - Any dataset accessed by project staff was de-identified unless the project managers match the blind code number with their names stored in the locked files. - All students, faculty and staff who accessed the data must provide training certificates of completion of the (University Name) Human Subjects online training and the online HIPAA Privacy Rule training. Furthermore, they are required to complete training on Center security procedures and sign a "Center Data Security Policy Certification" upon completion of this training.	- Any computer-based and patient-identifiable data was stored on the secure servers of the center Intranet only and not be stored on individual workstations (e.g., users' personal smartphones, laptops, or computers). - All paper-based files for survey collection will be stored in locked rooms inside locked file cabinets with limited access. - The app will automatically log out when the workstation is unattended for ten minutes. Cookies last only for the duration of the session and encryption software is used to block cyber-attack when the ART-CHESS app is in service.	- Informed consent was required for every subject and users need to sign agreement before using the ART-CHESS. - Data collection including personal information such as medical records must be fully disclosed to the study subject. - Participants do not have to answer any questions that make them uncomfortable. They also can change their minds and choose not to participate at any time to reduce potential psychological stress regarding sensitive issues.	- There are minimal risks of ART-CHESS implementation among HIV patients with SUD relapse and the benefits of this intervention surpass the potential risks. - ART-CHESS staff also provide training to providers about appropriate use (e.g., need password protection and to not share information outside of the App or the EMR) to protect patient privacy that arises when providers are given access to ART-CHESS data generated by one or more of their patients. - Study participants were taught how to use these features in the training session.

Appendix 2. Ethical guidelines substantiated by the ART-CHESS.
HIPAA: Health insurance portability and accountability act of 1996; SUD: substance use disorder; EMR: Electronic medical record.



Appendix 3. Partial auto-correlation function (PACF) for communication and information time series ($N = 180$ days).