The Communication Dynamics of mHealth Affordances: Initiation, Intensity, Duration, and Mutual influence in Online Social Support

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Abstract

The prevalence of smartphones has fostered the adoption of mobile health (mHealth) applications for computer-mediated social support in vulnerable populations. However, few studies have investigated the temporal dynamics of how users of these systems engage in message expression and reception at different communication levels: network, dyadic, and intraindividual. We consider these communication dynamics within a technology affordance framework, analyzing digital trace data from log files of an mHealth application designed for alcohol use disorder (AUD) sufferers, and we propose four time-related metrics — initiation, intensity, duration, and mutual influence — to understand message expression and reception at these different levels of communication. Results suggest that in the context of AUD recovery, female and older people were more likely to engage with communication functions, suggesting an increased willingness to adopt these technologies or possibly a potential lack of offline social support with those subgroups. Racial minorities were less likely to use dyadic communication functions for support solicitation. We also found reception (i.e., consumption) of network communication significantly boosted subsequent engagement with other communication functions, indicating a computer-mediated phenomenon of *lurking before posting*. The paper advances work on mHealth interactivity, arguing that online social support consists of distinct temporal and structural functions to facilitate communication among vulnerable subgroups.

Keywords: mHealth ICTs, communication engagement, technology affordance, vulnerable population, social support

In recent years, mobile health (mHealth) has been increasingly adopted for health care and message delivery at relatively low cost (e.g., Harari et al., 2016). Defined as mobile computing and communication technologies, an mHealth system is designed to provide information, communication, and interactive services for healthcare benefits (e.g., Free et al., 2010; Fiordelli et al., 2013; Ling, Poorisat, & Chib, 2020). By analyzing positive and negative health outcomes after using an mHealth application, researchers can assess overall effectiveness of system use and develop real-time interventions for sub-populations (Short et al., 2018; Harari, 2016). However, previous studies on mHealth effects focused on input factors, such as accessibility and usability, or output factors, such as process efficiencies (Chuang, 2014; Chib & Lin, 2018). Few have investigated communication dynamics when users engage with specific functions for interactions during longer periods. Furthermore, mHealth studies in the communication field lack a theoretical framework to understand the reciprocity between users and system design affordances for communication.

The present study introduces a message reception-expression process at the three communication levels — network, dyadic, and intraindividual — that constitute the different ways individuals can interact in mHealth system for social support. We argue that the three communication functions provide distinct support sources that can maximize users' behavioral possibilities for self-care through message processing. To observe their actual communication engagement, log data from a mHealth application were collected for the behavioral measurement. Different from self-reports, measurement of behavioral engagement using digital trace does not need latent structure considerations, as the log left on mobile devices records users' actions. We propose four time-related metrics — initiation, intensity, duration, and mutual influence — to understand message consumption and production at different communication levels. This allows us to observed how demographic sub-groups behaved differently when engaging with communication functions for social interaction, paving the way for future real-time intervention with their communication preferences. The goal of this study is to understand communication technology functions facilitate social support at a structural level, which may go beyond an mHealth app to other information and communication technologies (ICTs) designed for social support.

mHealth affordances for social support

A focus on technology affordance reflects a media-ecology framework made up of both the material features of technologies and users' possible reactions (Gibson, 1979; Norman, 1988; Gaver, 1996; Evans et al., 2017). Technology affordances exist at the intersection of a digital system's features and a user's perceptual bandwidth. For communication, Schrock (2015) categorized four aspects of mobile media affordance: portability, availability, locability, and multimediality. The four dimensions of communicative affordance examine a gamut of possibilities for social practices enabled by and expressed through mobile technologies. An mHealth system designed for social support contains all four mobile affordances.

Social support refers to the tangible (e.g., financial support) or intangible (e.g., emotional or informational) resources that individuals can obtain from social bonding (Berkman, 1984; Bambina, 2007). mHealth, as a format of computer-mediated social support (CMSS) platform, processes all advantages for support solicitation, such as anonymity to overcome identity concerns (e.g., Ho & McLeod, 2008; Walther & Boyd, 2002), enabling asynchronous communication for intangible resources (e.g., Rains & Young, 2009; Guan et al., 2020). CMSS carried over by mHealth applications can manifest these advantages through the four mobile affordances such as portability and locability to make "long-distance" caregiving possible. In addition, there is another core affordance for an mHealth application designed for social support: interactivity. We argue that interactivity is particularly essential when soliciting intangible support through communication.

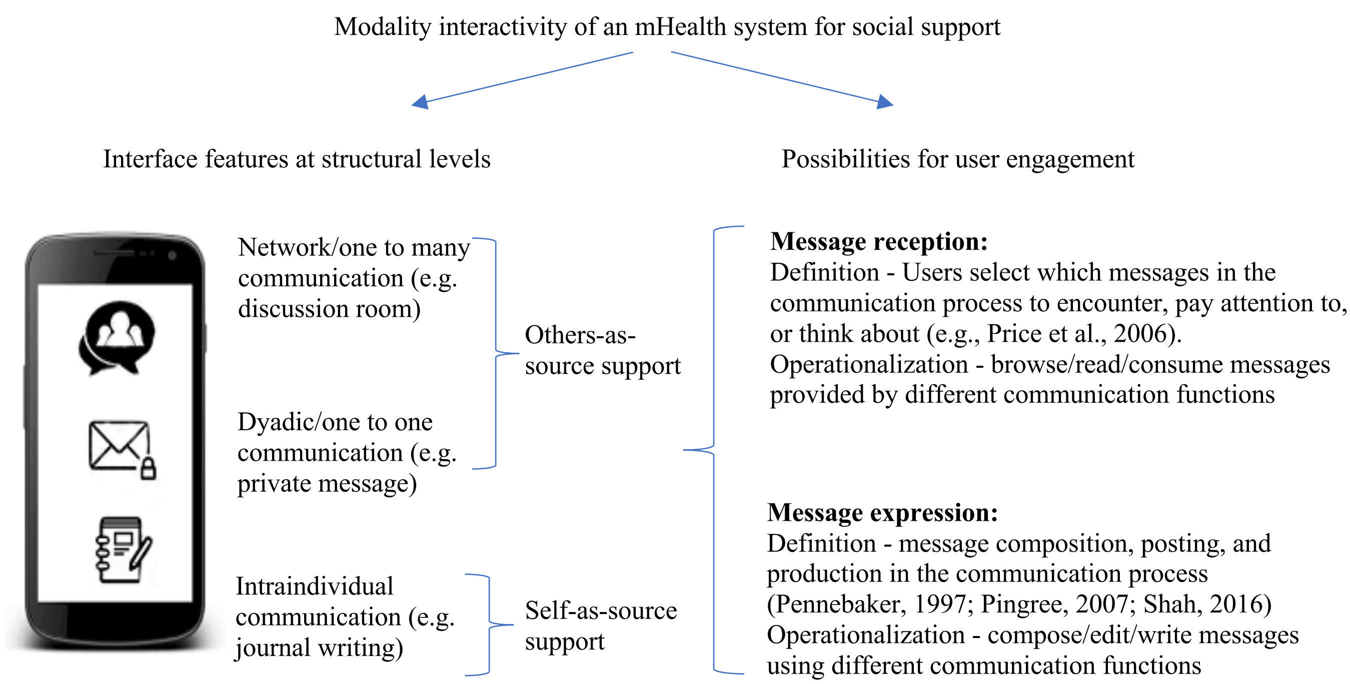
Interactivity is not a new feature to communication technology (e.g., Kreps, 2014). Information and communication technologies (ICTs) armed with interactive functions update the linear “sender to receiver” approach, improving system effectiveness and efficiency (Kreps, 2014). Interactivity is the crux of communication behaviors and interactions are inherent in face-to-face conversation (Rafaeli, 1988) and computer-mediated communication platforms (Walther, 1992; Price & Cappella, 2002). Sundar et al. (2016) concluded the interactivity is a fundamental affordance of communication technologies. Even so, few studies have demonstrated how this essential affordance empowers mHealth app users to solicit social support.

The structural functions of mHealth interactivity affordance for support communication

When referring to the kind of interactivity that best represents the relation between a technology device and user response, modality interactivity, conceptualized as “various methods of interaction offered by the interface” (p. 54, Sundar et al., 2015), is the closest one to describe the user engagement process (Steuer, 1992; Reeves & Nass, 2000). However, our research argues that modality interactivity should not only mean interactions (e.g., clicking, scrolling, hovering) with specific interface features like a 3D carousel or mouse over, but also the structural functions that facilitate user communication. The perceptual bandwidth that mHealth interactivity arouses needs to maximize users’ communication possibilities for support solicitation. It has been found that technology infrastructure embracing various communication functions could satisfy individual’s communication preferences, ultimately benefiting social bonding and information access (Mi et al., 2020).

From the functional standpoint (Rafaeli, 1988; Sundar et al., 2010), communication functions can be de facto reduced to three levels: network (i.e., one to many), dyadic (i.e., one to one), and intraindividual (i.e., self to self). The first two are widely studied in human communication behaviors, while the last has been largely neglected. Intraindividual communication is the level of communication that “occur within the person in relation to communication activities” (p. 107, Chaffee & Berger, 1987). In the psychotherapy field, self-reflections can serve as the motivational basis for positive behavioral change (e.g., Ryan, & Deci, 2008). An mHealth system involving the three communication functions can most satisfy user experiences for support communication to the most through enabling the message reception and expression process. Figure 1 maps out the generic interface structures of mHealth’s interactivity affordance designed for social support (see Figure 1)

Figure 1. An mHealth system for social support with modality interactivity affordance

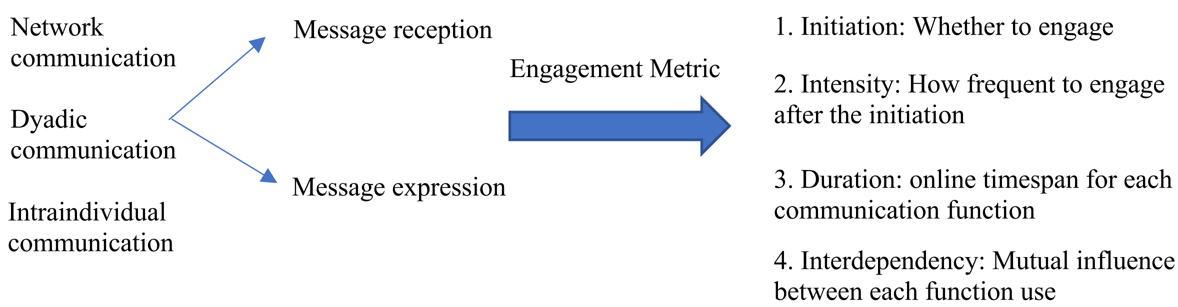


Three main communication functions are outlined. The network communication function encourages users to interact with other users, so as to build relational bonding to cope with difficulties (Yoo et al., 2014; Han et al., 2012), enhance individuals' wellbeing (Shaw et al., 2006), and promote health behaviors (Nyer & Dellande, 2010). The second communication function allows one-to-one conversation, or dyadic messaging, which is particularly beneficial for individuals with low family cohesion offline (Namkoong et al., 2017a). Both network and dyadic communication functions are on the "others-as-source" ground for support solicitation. The last structural feature is the intraindividual communication function, offering "self-as-source" engagement (i.e., writing/ reading journals only by users themselves). We highlight the "self-as-source" for social support because intraindividual communication may strengthen the autonomy-supportive satisfaction for positive change (Ryan, & Deci, 2008), but has been largely ignored by media effect research. Previous research also suggests that reading and writing in a diary can help patients recover from psychological trauma (Tausczik & Pennebaker, 2010; Pennebaker, 1997). Therefore, an mHealth system containing the three communication features can maximize the social support functions linked to the three levels of communication.

Based on the threshold criteria for conceptualizing an affordance (Evan et al., 2017), the structural features should relate to the processes of users' perceptual responses to those functions. We argue that it is the message reception-expression process that links communication features with user engagement for support communication. Different communication behaviors enable the process of message reception and expression, leading to outcomes/effects. Message reception refers to the process by which users encounter or think about the content to which they are exposed (e.g., Pingree, 2007), meanwhile message expression involves "mental processes underlying the composition of language, the commitment associated with articulating ideas and creating content, and the anticipation of accountability" (Shah, 2016, p. 13). The reception-expression process contains the expectation of expression, message composition, and subsequent interaction by other senders (Pingree, 2007; Shah, 2016). This study claims message reception and expression are the two fundamental roles in understanding media effects. For example, when participants talked to each other (i.e., message expression) after seeing anti-smoking advertisements (i.e., message reception), they were more motivated to quit (Jeong et al., 2015). When an mHealth system is equipped with intra- and inter- communication modes, it provides users the maximum possibility to be both a receiver and sender simultaneously. Thus, the mHealth interactivity affordance connects communication features like technology materiality with users' perceptual bandwidth for message reception and expression, constructing a "process of involving users in health content in ways that motivate and lead to health behavior change" (p. 667, Craig Lefebvre et al., 2010).

To examine user actualization of mHealth interactivity, we adopted a four-dimension metrics to measure the extent to which users are engaged: initiation, intensity, duration, and interdependence (see Figure 2). The initiation means the first interaction with one particular function of the system. It is reasonable to believe users do not prefer to use every communication function equally and may start with what appeals to them first. Initial engagement with an mHealth application can reveal the pre-existing communication preferences as one user's predisposition. The second engagement dimension is intensity, referring to the number of actions taken after initiation. Intensity differs from initiation in the varying degree of time involved. While engagement initiation is a type of one-time interaction in the beginning, engagement intensity asks for long-term commitment, showing lasting interactions with the system, easily leading to users' adherence.

Figure 2. Engagement metrics to assess communication reception and expression at three levels



The third dimension of engagement touches upon the duration of use. Duration of use is a sequential characteristic for general mobile use, the most intuitive aspect in mobile research (Peng & Zhu, 2020). Duration of use often refers to time spent on an appliance, indicating which mobile function people engaged with most in the time-budget approach (Peng & Zhu, 2020). One conceptualization tracks offline time intervals between logins, which implicate glancing or adherence behaviors (Gouveia, Karapanos, & Hassenzahl, 2015). For others, duration of use is defined as counts of logging in (Harries et al., 2013) or time spent on specific functions, such as posting to community boards (Butryn et al., 2016; McCallum, Rooksby & Gray, 2018). Our study treats duration of use as the time span between prior and next use for each communication function. In the context of social support solicitation, the time interval between the last use of one communication function to the next use of the same function reveals the temporal need for online support-seeking from users.

Other than the frequency and duration, the final engagement behavior addresses the interdependent influences between use of communication functions. The affordance approach discussed in the previous section purports the existence of a complementary interaction between organisms within a technological system (Gibson, 1979; Norman, 1988). Previous research also found that one-to-many (network) communication on social media induced one-to-one (dyadic) communication (Burke & Kraut, 2014; Lange, 2007; Bazarova, 2012), suggesting a mutual influence between function use. Given that mHealth interactivity for social support contains self- and other-as-source communication functions, it is possible that increased use of one interface feature could lead to the engagement with other features. But we do not know which communication engagement is the primitive force that triggers other types of engagement. Figure 2 displays the four dimensions of engagement metrics we propose to examine user engagement with communication functions within the mHealth interactivity affordance framework.

Vulnerable groups in the mHealth engagement for support communication

Demographic differences are major conditions that may influence the actualization of mHealth interactivity engagement. Countless studies for online social support have found age, gender, race, and education levels are the four prominent factors varying in mHealth engagement (e.g., Ben-Zeev et al., 2016), adoption intention of mHealth (e.g., Hoque, 2016; Zhang et al., 2014), and giving and receiving support (e.g., Yoo et al., 2018). Poor health literacy may also prevent certain population groups from utilizing and adhering to technology services, particularly those who suffer from health disparities (e.g., ethnic minorities, people with less education, etc.). It is worthwhile to investigate the engagement trajectories of vulnerable sub-groups in the four-dimension metrics for evidence-based health practice. As the actualization of affordances (i.e., engagement) depends on a variety of goals and conditions for which the technology platform is designed (Rice et al., 2017; Strong et al., 2014), we purport that for an mHealth app disseminated among alcohol use disorder (AUD) suffers[1], the elderly, at risk women, racial minorities, and less-educated users will have distinct performances on the engagement metric.

[1] The app we collected data from was designed for users with AUD problems so the contextual goal of this mHealth is to provide social support for AUD suffers.

The Elderly

Elderly people are related to social vulnerability due to their changing social circumstances, like a decrease in economic resources (e.g., Gerst-Emerson & Jayawardhana, 2015), cognitive decline (e.g., Blazer, 1982), loss of contemporaries (e.g., Oxman et al., 1992), and chronical illness (e.g., Jennifer Yeh & Lo, 2004). Social support is important to buffer loneliness and enhance quality of life. However, elderly groups were less familiar with technology or have less interest using ICTs (e.g., Bujnowska-Fedak, & Pirogowicz, 2014), which makes their engagement with mHealth for support engagement different from others.

RQ1: Do elderly AUD sufferers behave differently on the engagement metric when using the (a) network, (b) dyadic, and (c) intraindividual communication functions for social support?

At Risk Women

For AUD suffers, gender is a determining factor for support solicitation. Recent research found adult women have a more rapid progression to AUD than men (Guinle & Sinha, 2020). One reason is the key roles of depression and anxiety that may trigger AUD; females are more often found in settings that make them vulnerable for depression due to uneven division of labor at home (Wright, 2000), reproductive events (Soares & Zitek, 2008), emotional costs of caring (Kessler & McLeod, 1984), and media stigma (Nadeem, et al., 2007). In addition, men and women differ in expression behaviors online and offline (e.g. Shapiro & Swensen, 1977, Parker & Parrott, 1995, Tufekci, 2008, Zhang & Fu, 2020). Female AUD suffers may seek online peer support differently. Exploring gender differences in mHealth engagement can help understand gender-based navigation styles. For example, if male users are not likely to initiate mHealth functions for social support, we may design messages promotion to stimulate their participation.

Such intervention can alleviate the common “cold-start problems” caused by lack of user engagement with mHealth systems.

RQ2: Are female AUD sufferers more likely to initiate, intensify, and have long-term (re-)engagement with the (a) network, (b) dyadic, and (c) intraindividual communication functions on an mHealth app for social support?

Racial Minorities

Users from racial and ethnic minority groups are at increased risk of mental illness (CDC, 2019), more reluctant to seek healthcare (e.g., Gary, 2005), and have more stigma perceptions about behavioral health treatments (e.g., Alegría et al., 2016). Racial minorities like African Americans and First Nations populations disproportionately suffer from infectious diseases like COVID-19, regardless of education, occupation, and commuting patterns (McLaren, 2020). The race-based health disparity may expand to communication engagement for social support solicitation. Though no evidence suggests that there exists racial disparities for giving and receiving social support, perceived support satisfaction can improve quality of life and self-management practices for racial minorities such as African Americans with type 2 diabetes (Tang et al., 2008). The current study aims to disentangle whether race plays a role in their engagement with mHealth interactivity for support communication.

RQ3: Do AUD sufferers from African/ Asian/ Latino/indigenous American backgrounds, have different engagement metrics when using the (a) network, (b) dyadic, and (c) intraindividual communication functions on an mHealth app for social support?

Less Educated Users

Education background impacts health literacy because it can enable users to access, understand, and apply resources for positive outcomes (e.g., Kreps, & Neuhauser, 2010). Less educated users have insufficient competence for support seeking and the "digital divide" is thus exacerbated with more educated counterparts (Kreps & Neuhauser, 2010). However, we do not know if less educated users have different communication preferences, such as self-as-source support, when they are given access to mHealth for support seeking. It is highly likely that engagement metrics of less educated users are distinct from their counterparts.

RQ4: Are less educated AUD sufferers less likely to initiate, intensify, and have long-term (re-)engagement with the (a) network, (b) dyadic, and (c) intraindividual communication functions on an mHealth app for social support?

In regard to interdependent influences between use of communication functions, we propose to observe general patterns regardless of demographics first. Little research has observed how message reception and expression engagement impact each other longitudinally, much less the major precursor, or dominant power, in their reciprocal dynamics.

RQ5: Will message reception and expression engagement with certain communication functions lead to the subsequent use of other communication functions?

Methods

Data collection

Log data were collected over one year using an mHealth application providing online social support for AUD users from 2014 to 2017. The users were recruited from three Federally Qualified Healthcare Centers (FQHCs) for recovery support services in the United States, two in the Midwest and another in the Northeast (reference for blind review). Participants were at least 18 years old and had no history of suicidality or significant developmental, cognitive, or vision impairments limiting their capacity to use mobile applications (N = 275). They all received a smartphone pre-installed with an mHealth application containing a variety of informational and communication resources. Each user had one-year access to the mHealth application. The Institutional Review Board at the (University name) approved the study.

The mHealth system provided three levels of communication opportunities via group discussion forums (i.e., network), private messaging (i.e., dyadic), and self-writing and reading motivational journals (i.e., intraindividual). The discussion room allowed participants to communicate with other users by clicking either the top right corner to start a new post or any title in the "Mypost" list to respond to others' posts. The private messaging feature contains "Inbox" and "Sent" buttons that enable a one-to-one conversation with a targeted user. The motivational journal is a diary-like function where users can write, read, and upload photos only visible to themselves. Any actions in the system were stored in time-stamped server log files. The dataset used in this study includes the unique user ID, the day they log in, and the count of their clicks for each page that will be labeled with particular communication on that particular day, and their demographic features.

Measures

Log data related to the use of three communication functions for message reception and expression were collected from the mHealth system for social support. We summed daily user clicks for relevant page categorized by the communication levels and behaviors. The six types of engagement are depicted in Table 1.

(Table 1 inserts here)

Demographics. Self-reported age, gender, education, ethnic group, and race were collected. Education was measured at an eight-point scale from 1 ("8th grade or less") to 7 ("more than 4-year college degree"), and ethnicity was dummy coded as "White" versus "Minorities."

Analytical approach

For modeling initiation and intensity, hurdle model[2] captures estimates from binomial distribution and negative binomial distribution is applied to answer 1) if demographic subgroups are different in terms of whether to use the system (zero versus non-zero clicks) and 2) if their use intensity is different after the initiation engagement (Mullahy, 1986; Cameron & Trivedi, 2005; Zeileis, Kleiber & Jackman, 2008). The advantages of using hurdle model are derived from its capability to simultaneously accommodate two parts of engagement behaviors with computational simplicity (Bu, Li, Tan, & Zucker, 2012).

For estimating the duration of engagement, the Cox proportional hazard function[3] from survival analysis was used. The Cox hazard regression estimate is widely applied in lifetime data to address if one or more explanatory covariates can impact the duration of time before some event occurs (Fisher & Lin, 1999). In our case, demographic variables are the explanatory covariates at the baseline level, to influencing the length of users' next engagement with mHealth communication functions. The time interval between the previous to next use per communication function is taken as the dependent variables in this model.

For mutual influence, panel vector autoregression models (VARs)[4] were applied to capture the trend of interdependency in a time-series manner (Wells, et al., 2019; Box-

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[2] We used 'pscl' package in R to estimate the two parts of the hurdle model function:

$$p(y|\theta,\lambda) = \begin{cases} \theta & if\ y = 0, \\ (1-\theta)\dfrac{binomial(y|\lambda)}{1 - binomalCDF(0|\lambda)} & if\ y > 0 \end{cases}$$

(θ is the parameter for engagement initiation and λ is the parameter for engagement intensity)

[3] We used 'survival' package in R to realize Cox proportional hazard estimate:

$$h(t|x) = h_0(t)e^{\beta_1 x_1 + \beta_2 x_2(t)}$$

(t is the outcome variable representing each user's time duration from the first day they interacted with one function to the last day they stopped use permanently)

[4] The panel VAR is:

Steffensmeier et al., 2015). VARs differ themselves from other regression models in taking latent relations between time-variant variables into account for structural equations, without impositions of rigid assumptions on hypothetical directions of modeling variables. In our research, we do not know which type of communication function could be the provoker for other functional use. Panel VARs advance the standard VARs by controlling cross-sectional differences. The data is organized as per user per day for the three estimates modeling.

Results

Only those who accessed all three communication functions during the one-year study period were included in this study. The resulting sample (N = 275) had a mean age of 42 (SD = 10.74), and were 53% male, and 68% Caucasian. The education scale shows that about 49% of users are below college, 31% with some college degree, and 20% graduated from college. More than half (56%) reported a history of abusing drugs beyond alcohol (e.g., alcohol, cocaine, opiate) in the survey before using the mHealth. Table 2 displays the descriptive statistics for the sociodemographic characteristics in terms of the six types of engagement.

(Table 2 inserts here)

RQ1 – The Elderly

Table 3 shows the two-part results from the hurdle model estimation. It is interesting to notice there is a discrepant pattern between initiation and intensity for older AUD users. Older users were more likely to start engaging with message reception in discussion room (β = .01, ρ < .01) and self-writing journals (β = .03, ρ < .01). Though their engagement initiation did not differ on network and intraindividual expression, their engagement intensity for posting on

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$$y_{it} = A_{0i}(t) + A_i(\delta)Y_{t-1} + \mu_{it} \quad i = 1, \dots, N \quad t = 1, \dots, T$$

(A is the matrix of user constants with time; δ is the coefficient estimates for interdependence of each function; μ_{it} is the vector of random disturbance) public boards and composing self-read journals was significantly, 2% and 6%, higher than younger users after using those functions. In summary, the elderly AUD users tended to start with reception engagement at network and intraindividual levels and once they expressed themselves at these two levels, they kept the communication engagement. would stick to those behaviors.

(Table 3 inserts here)

With the duration dimension in the engagement metrics, older people were more likely to re-engage with message reception provided by network, dyadic, and intraindividual communication functions. The elderly also had a shorter timespan for consecutive use in terms of dyadic expression, indicating their communication preferences at the private messaging level. Detailed ratio estimates are referred in Table 4.

(Table 4 inserts here)

RQ2 – Vulnerable AUD Women

The results in table 3 suggest that females, compared to males, were more likely to engage with mHealth communication functions. Regarding the initiation dimension, female AUD users were more likely to interact with all communication functions for message reception and expression engagement except for intraindividual message reception. For the intensity dimension, female users were significantly different on network and intraindividual message reception engagement. In other words, once participants start engaging with network communication functions per log-in, female users' clicks for message reception were 46% higher, suggesting a more intensive use of such functions. They also had 79% more clicks when engaging with messages they have written for themselves.

For Cox hazard estimates, female users engaged with most communication functions for a relatively shorter time-span, except for message reception engagement with network communication functions. The strong coefficient estimates are network expression (β = .33, ρ < .01) and intraindividual expression engagement (β = .41, ρ < .01), suggesting that female AUD users had 39% shorter time intervals from between uses of network posting function, and 50% shorter timespans between each use for intraindividual writing functions[5]. In other words, female users indicated more need to engage with these two functions. The significant differences on consecutive engagement between men and women may reveal an offline support status between men and women.

RQ3 – Racial Minorities

For the initiation and intensity dimensions, marginal significant results in Table 3 suggest that compared with racial minorities, Caucasians were more likely to engage with message reception at an intraindividual level (β = .48, ρ < .01), though their intensity was not high as minority groups (β = -.91*, ρ < .05). The results implied that once racial minorities started engaging with intraindividual communication for self-support, they were likely to keep frequent use, which may inform health practices to trigger their self-support communication. However, racial minorities were less likely to engage with dyadic expression for support solicitation (β = 1.3**, ρ < .05) and their re-engagement time span was longer than their counterparts.

RQ4 – Less Educated Users

For education level influence, hurdle model suggests that users with higher education were less likely to view self-written journals (β = -.18, < .001), but once they were used, their click-

[5] The likelihood/possibilities is deduced from the formula: 1 - e^{β}, in which β is the estimated ratio in the Table 2.

frequency was much higher than lower educational groups ($\beta = .18$, $\rho < .001$). Users with higher education also had more clicks once they began self-as-source communication (refer to Table 3).

RQ5 – Mutual Influence

Results estimated by panel VARs[6] supported that communication reception engagement incurs subsequent expression. Namely, antecedent reception engagement using network communication functions (one/two day-lag) significantly improved all five other types of engagement. Increasing message reception activities in the discussion room one/two days beforehand will promote user activities like posting content, private message communication, as well as self-read and written recovery journal exposure. Tables 5 and 6 display the estimation results from the panel VAR and Granger causality Wald tests, both of which cross-validated the precursor role of network message reception behaviors .

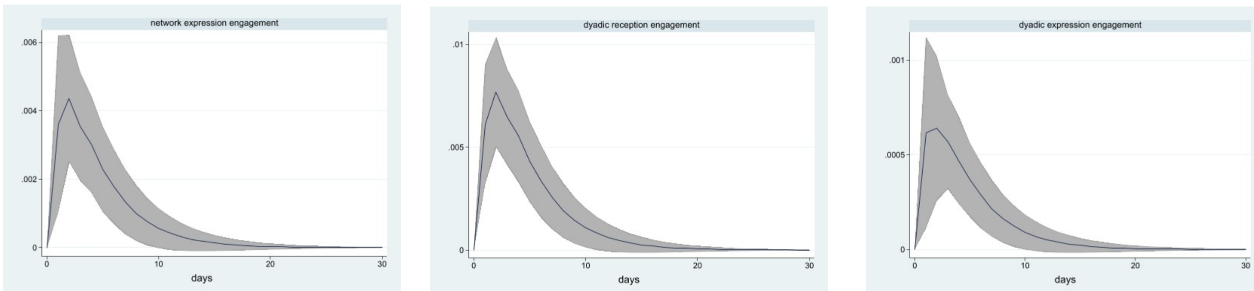
(Table 5 and 6 insert here)

Simulating impulse response functions (IRF) were applied for predictions based on the VAR estimation. The IRF can simulate any instant and delayed impacts on the variables under consideration. As we found that message reception engagement with network communication functions was a significant impactor for other types of engagement, we took network reception engagement as the impulse to observe how prior one day standard deviation shock caused directional change in other variables and the duration of those effects. Figure 3 displays the results that one prior day engagement lurking on the network will have as an immediate effect on the network expression, dyadic reception, and expression, and intrapersonal reception

[6] Two prerequisites before applying panel VARs were conducted: Dickey-Fuller test for stationary series and information criteria estimation for lag selection. More detailed operation can be referred to Love, I., & Zicchino, L. (2006). *Financial development and dynamic investment behavior*: *Evidence from panel VAR*. STATA codes are available from the authors upon request.

engagement for the following 1-2 days. The 5% confidence bands were generated by Monte Carlo simulation methods based on 200 draws.

Figure 3. IRF forecast network reception engagement as impulse



Discussion

This study advanced previous conceptualizations of modality interactivity into mHealth application for social support, arguing that mHealth interactivity provides the possibilities of message reception and expression through “self- and others- as-source” communication functions. Specifically, network (one-to-many), dyadic (one-to-one), and intraindividual communication features are core components of mHealth interactivity affordance. This structural design reflects the emergence of mass-personal communication channels brought about by digital media tools (O’Sullivan & Carr, 2018). The study also highlighted the existence of intraindividual communication for self-support. Observations found network message reception engagement was the precursor for other types of communication engagement. The phenomena may be attributed to low effort of non-public participation compared to visible interaction, such as message expression engagement, which implies that an mHealth infrastructure armed with network communication functions can empower more users seeking social support.

The adoption of the four-dimension engagement metrics shows that we need to take time perspectives into consideration when examining communication behaviors, as they differentiate short-term versus longitudinal involvement. Incorporating a time element may enable researchers to untangle the universal communication phenomena manifest in mHealth applications and to go beyond platform constraints (Flanagin, 2020). Without taking time dynamics into consideration, we would not have been able to reveal the distinct trajectories of vulnerable groups such as the elderly and racial minorities engaged with mHealth communication functions.

One limitation of our study is the lack of incorporating message interactivity. Sundar (2015) stated that mobile catering websites should examine the combination of modality interactivity and message interactivity, as they all can reinforce message effects. Message interactivity may be different at the three communication levels as it was found that users engaging with Facebook conducted activities differently for broadcast (one-to-many) and private, directed communication purposes (Burke & Kraut, 2014). Another limitation is the absence of other types of engagement measurements alongside the system use observation. Qualitative data can be combined with device-generated logs to answer why people engaged questions (Crane et al., 2017; Alkhaldi et al., 2017). The answers can help us sort out whether shorter time spans of consecutive usage connects to vulnerable status (e.g., female groups) or hesitance for support communication (e.g., racial minorities).

We also admit the limited generalization power of this study because of our focus on one specific mHealth app for AUD social support. Since technology affordances vary across media platforms (Ellison & Vitak, 2015) and depend on the context, user, and purpose (Rice et al., 2017), we encourage future studies to connect accessible data from the mHealth industry with established theories in academia to fully understand the intricacy of communication engagement behaviors. In the foreseeable future, activity-centric analysis extracted from mobiles or other digital platforms is possible by strengthening the close cooperation between academia and the ICT industry.

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Table 1. Measurement of communication engagement with the mHealth interactivity affordance

Engagement variables		Operationalization
Communication levels	Message reception and expression	Counts of clicks per user per day for relevant pages
Network	Message reception	Pages relating to browsing an index page showing a list of discussion groups, browsing an entry page to a specific discussion group, browsing a preview page displaying all discussion threads, browsing a list of past post generated by the user, and reading one particular post.
	Message expression	Pages allowing composing or editing a post.
Dyadic	Message reception	Pages relevant to browsing a preview page showing a list of messages sent from the other user, browsing a preview page with a list of messages the user archived and reading private messages sent or received by the user.
	Message expression	Pages that could compose a message to a targeted user.
Intraindividual	Message reception	Pages relating to browsing or reading previous self-written journals and browsing past journal entries.
	Message expression	Pages relating to composing or writing a motivation journal only viewable to oneself.

Table 2. Daily count of mean clicks for the six types of engagement in terms of demographics (N = 279)

		Network		Dyadic		Intraindividual	
		Reception	Expression	Reception	Expression	Reception	Expression
Gender							
	Male	2.538 (5.194)	.052 (108)	.164 (.268)	.028 (.099)	.038 (.077)	.002 (.005)

Female	3.458 (4.349)	.010 (.156)	.202 (.334)	.036 (.068)	.063 (.109)	.005 (.013)
Age						
20-30	2.22 (3.49)	.064 (.129)	.096 (.118)	.021 (.061)	.050 (.112)	.004 (.012)
31-40	2.656 (3.10)	.0755 (.115)	.207 (.406)	.032 (.059)	.063 (.108)	.006 (.013)
41-50	2.573 (4.48)	.0741 (.161)	.169 (.280)	.038 (.129)	.031 (.056)	.003 (.007)
51-60	4.173 (7.08)	.0825 (.134)	.218 (.271)	.026 (.046)	.059 (.103)	.003 (.007)
Over 60	3.879 (4.32)	.0782 (.112)	.266 (.410)	.066 (.120)	.072 (.189)	.003 (.007)
Race						
Caucasian	3.085 (5.195)	.064 (.109)	.186 (.331)	.032 (.095)	.052 (.100)	.004 (.010)
Others	2.708 (3.959)	.097 (.176)	.172 (.223)	.030 (.061)	.045 (.080)	.004 (.008)
Education						
Middle school	2.821 (4.367)	.109 (0.187)	.190 (.237)	.042 (.082)	.045 (.079)	.004 (.012)
High school/some college	3.039 (5.194)	.065 (0.117)	.179 (.327)	.029 (.089)	.050 (.097)	.003 (.008)
University/Postgraduate	2.833 (3.366)	.053 (0.071)	.181 (.264)	.026 (.071)	.056 (.110)	.006 (.015)

Note. Standard deviation is in the parentheses

Table 3. Hurdle model estimates for demographic subgroups engaging with the mHealth system

Stage 1: Engagement initiation						
	θ estimate for the outcome					
	Network		Dyadic		Intraindividual	
Demographic Subgroups	Reception	Expression	Reception	Expression	Reception	Expression
Female vs. Male	.31**	.74*	.31*	.59*	.11	.70**
	(.13)	(.22)	(.15)	(.23)	(.23)	(.23)
Age	.01*	.00	.03**	.01	.03*	-.02
	(.01)	(.01)	(.01)	(.02)	(.23)	(.23)
Education	-.00	$-.16^{+}$	-.00	-.13	-.18**	-.02
	(.05)	(.09)	(.06)	(.10)	(.23)	(.23)
White vs. Others	.27	-.34	.05	-.20	$.48^{+}$	-.06
	(.14)	(.24)	(.16)	(.29)	(.23)	(.23)
Log-Likelihood	-676.8485 (df=21)					

Stage 2: Engagement intensity						
	λ estimate for the outcome					
	Network		Dyadic		Intraindividual	
Demographic Subgroups	Reception	Expression	Reception	Expression	Reception	Expression
Female vs. Male	.46*	.04	-.24	-.75	.79**	.38
	(.23)	(.26)	(.23)	(.53)	(.27)	(.46)
Age	.03**	.02*	$-.01^{+}$	.02	-.05**	.06*
	(.01)	(.01)	(.01)	(.02)	(.01)	(.02)
Education	.03	.09	.03	-.13	.18*	.39*
	(.07)	(.09)	(.07)	(.12)	(.08)	(.18)
White vs. Others	.05	-.08	.10	1.3**	-.91*	-.30
	(.21)	(.28)	(.21)	(.48)	(.41)	(.47)
Log-Likelihood	-676.8485 (df=61)					

Note. Number of users = 255, total N = 337, 956.
Standard deviation is in the parentheses. $^{+}$ $p < .01$ *p <. 05 **p <. 01 ***p <. 01

Table 4. Cox proportional hazard exponential estimates for re-engagement timespan (duration)

	Ratio estimate for the outcome					
	Network		Dyadic		Intraindividual	
Vulnerable Groups	Reception	Expression	Reception	Expression	Reception	Expression
Female vs. Male	.13	.33**	.18**	.36***	.28*	.41^{+}
	(.10)	(.12)	(.08)	(.12)	(.12)	(.22)
Age	.10*	.08	.20*	.16**	.17***	.05
	(.04)	(.06)	(.04)	(.06)	(.06)	(.11)
Education	-.002	-.02	-.01	-.03	.0006	.14
	(.05)	(.06)	(.04)	(.06)	(.06)	(.11)
White vs. Others	.25*	-.06	.10	.06	.04	-.04
	(.10)	(.13)	(.09)	(.13)	(.13)	(.24)
Frailty (Users)	.60	.72	.46	.53	.51	.73
	(.36)	(.52)	(.21)	(28)	(.36)	(.53)
Log-Likelihood	4637.28	597.65	437.89	80.22	71.67	
df			5			

Note. Number of users = 255, total N = 337, 956.
Standard deviation is in the parentheses. $^{+}p < .01$ *p <. 05 **p <. 01 ***p <. 01

Table 5. Panel VAR estimates per communication function (lag = 1-2 days, Ave no. of days = 164)

	Effect estimate for the outcome					
	Network		Dyadic		Intraindividual	
Predictors	Reception	Expression	Reception	Expression	Reception	Expression
Network reception	.39***	.003***	.006***	.001**	.002*	.0002*
(-1)	(.04)	(.00)	(.00)	(.00)	(.00)	(.00)
Network reception	.29***	.002*		.01*		
(-2)	(.04)	(.00)		(.00)		
Network expression		.14*	.01*			
(-1)		(.03)	(.00)			
Network expression	.94*	.09*				
(-2)	(.03)	(.03)				
Dyadic reception		.01*	.22**	.01*		
(-1)		(.01)	(.04)	(.00)		
Dyadic reception			.10*			-.002***
(-2)			(.03)			(.00)
Dyadic expression				.04*		
(-1)				(.02)		
Dyadic expression				.03*		
(-2)				(.01)		
Intraindividual reception					.05*	
(-1)					(.02)	
Intraindividual expression	2.26*	.13*				
(-1)	(1.14)	(.06)				

Note. The format *Row heading (-number)* in the first column represents previous communication function use with number-day lag. Only significant results are presented.

Table 6. Granger causality tests for the six communication engagement types

	χ^2	*p*
Network lurking → Network posting	26.72	.00
Network lurking → Dyadic lurking	32.71	.00
Network lurking → Dyadic posting	14.20	.00
Network lurking → Intrapersonal lurking	9.88	.01
Network posting → Dyadic posting	6.44	.04
Dyadic lurking → Dyadic posting	7.54	.02
Dyadic lurking → Intrapersonal posting	10.71	.01
Intrapersonal posting → Network posting	5.80	.05

Note. Only significant tests are presented