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ABSTRACT
Communicating within digital health interventions involves a range of behaviors that may contribute to the management of chronic illnesses in different ways. This study examines whether communication within a smartphone-based application for addiction recovery produces distinct effects depending on 1) the "level" of communication, defined as intraindividual communication (e.g., journal entries to oneself); dyadic communication (e.g., private messaging to other individuals); or network communication (e.g., discussion forum posts to all group members), and 2) whether individuals *produce* or *are exposed to* messages. We operationalize these communication levels and behaviors based on system use logs as the number of clicks dedicated to each activity and assess how each category of system use relates to changes in group bonding and substance use after 6 months with the mobile intervention. Our findings show that (1) intraindividual exposure to one's own past posts marginally predicts decreased drug use; (2) dyadic production predicts greater perceived bonding; while dyadic exposure marginally predicts reduced drug use; (3) network production predicts decreased risky drinking. Implications for digital health interventions are discussed.

Researchers find that participants benefit from using digital health interventions, but often struggle to identify the particular, centrally beneficial uses of these interventions. This issue extends to interventions that facilitate digital communication within a support network of peers. While such interventions are often broadly conceived as allowing for ongoing access to social support, communicating with a peer support network involves a range of distinguishable behaviors. For some individuals, communication may primarily involve consuming content generated by peers, whereas others engage heavily in producing content themselves. While often intertwined, these activities may influence health behavior in distinct ways (Han et al., 2019). In addition, digital health interventions may involve distinct venues, or "levels," of communication, such as private or semi-private journals, one-to-one messages, and public discussion forums (Chuang & Yang, 2014). As these levels involve distinct audiences and patterns of interaction, they may contribute differently toward health.

Improving the design of digital health interventions requires a better understanding of how these interventions achieve their beneficial effects, particularly when peer-to-peer communication is involved. This understanding would allow for optimizing the communication formats offered within digital health interventions and directing participants toward the uses of an intervention most likely to help them attain their goals. To this end, recent work has emphasized the need to disentangle different communicative practices (Pingree, 2007; Walther & Valkenburg, 2017). Some studies focus on distinguishing between sending versus receiving messages in digital health interventions (Han et al., 2019; Namkoong, Shah, McLaughlin et al., 2017). Other studies attempt to understand the differences in communicating at various levels of publicness, such as contributing to a public discussion versus sending a private message on a social networking site (Bazarova, 2012; Burke & Kraut, 2014). Approaches have also compared the content of messages sent at these levels (Bazarova et al., 2013) and examined how communicating at each level predicts health outcomes (Chuang & Yang, 2014). However, prior work has rarely considered how the production of and exposure to messages might work differently at *each* communication level.

Improving the measurement of message production and exposure across different communication levels is a critical first step to understanding the distinct effects of these communication behaviors. System use logs, and the digital trace data they provide, offer an important potential source of insight into digital health interventions and their implications for psychosocial and health outcomes. These logs capture not only explicit production of content but also more subtle behaviors associated with exposure to existing content. Here, we examine click counts, a metric that provides insight into the intensity of activity during both production of and exposure to messages. We distinguish between production and exposure at three different communication levels within a mobile application (or "app") for those in recovery for substance use disorders (SUDs): 1) intraindividual communication (i.e., a private "my motivations" journal), 2) dyadic

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communication (i.e., one-to-one messages), and 3) network communication (i.e., a group discussion board).

We examine these issues in the context of a mobile intervention provided to patients in recovery for SUDs (Ashford et al., 2020). SUDs are among the most common mental health concerns in the US and around the world and lead to negative effects for relationships, quality of life, and health (Substance Abuse and Mental Health Services Administration [SAMHSA], 2019). Evidence has begun to accumulate on the benefits of technologies for those in treatment for SUDs, including to provide ongoing access to therapeutic content and reminder systems as well as to connect individuals to supportive others (Nesvåg & McKay, 2018).

Literature review

Health interventions increasingly rely on digital technology to facilitate behavior change, often via smartphone apps (West & Michie, 2016). Many apps and digital health interventions also offer opportunities for peer-to-peer communication (Kornfield et al., 2018; Savic et al., 2013). Given online peers' shared experiences, lack of preexisting relationships, and possibilities for anonymity, the disclosure of personal experiences on digital health platforms presents a relatively low risk to participants. These factors allow individuals to seek support around stigmatized health issues (DeAndrea, 2015). Rather than relying on overburdened health services, peers may now interact directly through ubiquitous personal technologies like smartphones to exchange support and information that can be crucial for health and wellbeing (Malloch & Taylor, 2019; Zhang et al., 2017).

Mobile-based peer-to-peer support has also been applied to help those who are in recovery for SUDs involving alcohol and other drugs (Nuamah et al., 2020; Quanbeck et al., 2018). Given that patients with SUDs already have a high ownership rate of a mobile phone (Ashford et al., 2018) and perceive mobile technology as favorable for the delivery of intervention and treatment (Carreiro et al., 2020), the application of m-Health solutions provides a promising direction for recovery interventions. One randomized trial of patients discharged from residential addiction treatment facilities found that accessing a mobile app – A-CHESS – which provided information, communication, and decision-support features, reduced risky drinking days by 57% at follow-up compared to a control group who did not receive the app (Gustafson et al., 2014).

Communication features are often bundled together in such digital interventions. These may include opportunities to compose journal entries for oneself, message privately within a dyad, or communicate with a group of peers on a discussion board. Communication is also often paired with psychoeducation or other services. Despite designers' and researchers' interest in identifying the mechanisms of action behind digital health interventions (Han et al., 2011; Lawlor & Kirakowski, 2014), such bundled designs introduce challenges in attributing intervention effects to any particular type of system use (Eysenbach et al., 2004). In this context, overall effects of system use may disguise the nuanced effects of specific communication behaviors. As with earlier research on television viewing (e.g., Salomon & Cohen, 1978), media scholars continue to wrestle with multiple conceptions of media use in the digital era (Burke et al., 2011).

Researchers of digital health intervention have faced two challenges: 1) the complexity of measuring system use and 2) attributing health outcomes to these well-defined types of use. As with media use in general, retrospective self-reports based on questionnaires represent a flawed solution due to recall bias and reliance on individuals' attentiveness during media use. Digital trace data offer a potential solution to these problems, translating communication processes into discrete activities captured by system use logs. These activities may include the number of logins, time spent using an intervention, the amount of content accessed, and the type of said content (Perski et al., 2017). Digital records allow for standard, scalable measurement. However, while trace data are not subject to the recall bias of subjective measures, they introduce new challenges in data management and interpretation. In the next sections, we describe how prior work has conceptualized communication uses of digital health interventions, not only differentiating message production from message exposure but also differentiating communication across different social levels.

Reception and expression

Via the emergence and growth of digital communication and social media, individuals now routinely have the opportunity to act as content creators, and not just consumers of media. As such, individuals may inhabit new social roles in digital platforms that range from passive to active. The emergence of new digital communication ecosystems has therefore required researchers to extend their focus beyond the effects of receiving messages to account for the phenomenon of "expression effects," "sender effects," or "self-effects," referring to the effects that producing content has on the content creator (Namkoong et al., 2013; Pingree, 2007; Valkenburg, 2017). Some have even suggested that these expression effects may sometimes surpass those of message exposure (Han et al., 2011; Kellogg, 1999), as composing messages requires translating one's thoughts into language, as well as packaging an argument or narrative for an audience to make sense of, which may require deeper processing of information and greater consideration of self-presentation. Therefore, one promising way to conceptualize system use is to differentiate exposure to message content (i.e., viewing existing content) and production of one's own content (i.e., expressing one's own thoughts and feelings).

A range of empirical studies show distinct antecedents and consequences of message exposure and message production. In the context of social media, studies suggest that when audiences have opportunities to respond to content through posting responses, they may have better recall, be more persuaded, or more cognitively engaged (Gil de Zuniga et al., 2013; Nekmat, 2012). Moreover, in the context of digital support platforms, a number of studies suggest benefits that come from actively producing content. Han et al. (2012) categorized participants as posters (i.e., those actively generating content), lurkers (i.e., those who read others' content but did not post), and non-users. They found these roles associated with different demographic, disease-related, and psychological factors. Another study among cancer patients showed that those who posted on a support forum reported obtaining more benefits than those who lurked (Setoyama et al., 2011). Compared to lurkers, active posters in breast cancer, fibromyalgia, and arthritis groups reported improvement in their social wellbeing (Van Uden-kraan et al., 2008). In other studies, active posters experienced greater self-acceptance (McKenna & Bargh, 1998), stigma recovery (Lawlor & Kirakowski, 2014), and improved wellbeing among caregivers (Tanis et al., 2011). These findings highlight potential benefits of message production, supporting the value of distinguishing production from exposure in digital health interventions.

Levels of communication

Distinguishing levels of communication offers another way to investigate the effects of communicating within digital health interventions. Chaffee and Berger (1987) proposed four levels of communication study: intraindividual, interpersonal, network, and societal. Intraindividual communication refers to the internal processes that occur within an individual as a result of communication activities. Interpersonal communication is built upon the relationship of a dyad or a very small group of participants. The network or organizational level includes communication between larger sets of persons with ongoing relationships, a one-to-many dynamic. When the analysis is expanded to a societal level, communication spans a larger social or cultural system within which individuals are embedded.

Given that digital health interventions primarily promote change in individuals' health and behavior, the first three levels of communication, rather than the societal level, are the focus of this study. Intraindividual, interpersonal, and network levels of communication are often embedded into the design and affordances of many digital health interventions and, therefore, researchers have recently begun to take these different levels into consideration when analyzing communication data (Namkoong, Shah, Gustafson et al., 2017). For instance, individuals may have opportunities to address *themselves* through journal writing or note-taking venues (Ayobi et al., 2018; Gustafson et al., 2011). In addition, messages may also be exchanged within a dyad, with only one recipient targeted at a time, or exchanged at the network level for all group members to read. The literature on computer-mediated communication increasingly implicates the online audience as a key factor in how individuals think about and disclose their problems online (Bazarova & Choi, 2014; Kornfield & Toma, 2020), as well as determining the quality of help and support they receive (Chung, 2014). For instance, private messaging has been associated with "deeper" disclosure on social media platforms (Bazarova & Choi, 2014), and uses of social media for dyadic communication have been associated with greater perceived bonding (Burke et al., 2010). In contrast, participating within group forums may support access to more diverse perspectives, allowing for meeting participants' informational needs (Chuang & Yang, 2012), or may allow for developing and expressing social identities (Papacharissi, 2012). Examining message production and exposure at these different communication levels, rather than coarsely considering communication as a whole, may therefore better reflect the complex interactions afforded by the design of digital health interventions.

Operationalizing system use

While prior research offers insight into the distinct effects of message exposure and production, and communication at different levels, past studies are generally limited by operationalizing communication activities as counts of messages individuals send or receive. Such a strategy provides a relatively "brute force" translation of complex communication behaviors. For instance, in the case of a peer-to-peer discussion board within a health app, an individual may first navigate to the discussion group after opening the app. She may start reading new posts, as well as scrolling to view comments on said posts. Perhaps inspired, she may create her own message, typing and reviewing before hitting "submit." She may then re-read her post, now visible to the board, imagining how others will respond, before going back and editing the message to add an idea or fix a typo. Later on, after opening another part of the app, she may return to her post when notified of a response from another member of her network.

In the above example, while a count of messages would register several messages read and one posted, such a measure would not capture the extent of involvement in these activities. In this study, we examined click count as a measure that captures important variation in participants' communicative behaviors. Clicks capture the frequency with which a function is used or the depth of use within each function (i.e., navigation of sub-functions). Although clicks cannot precisely measure how long each action lasts, we found that idle time (i.e., time that a page remained open after active engagement) represented a substantial obstacle in our data set, with extremely skewed distributions being evident for each "time spent" variable. Therefore, this paper assessed clicks at each level, categorizing uses supporting exposure versus production, as our operationalization of system use.

Exposure and production at each communication level

We propose that it is not only theoretically rigorous but also practically important for researchers to attend to distinctions between message exposure and message production, as well as differentiating communication levels. Not only do *exposure* and *production* likely function differently in the process of health behavior change, but they likely trigger specific relational and psychological processes that occur when communicating with oneself, specific others, or a group. This study aims to examine whether message exposure and message production across communication levels will relate differently to perceived bonding and change in risky drinking and drug use among system users. These two modes of communication are deeply entwined, with exposure typically preceding production, but production necessary for exposure. Below, we review literature related to the process of production and then exposure at each level, followed by specific predictions in relation to the outcomes of our interest.

Intraindividual: Reading and writing one's own journals. At the intraindividual level, *production* occurs whenever people actively generate new, purely personal content (e.g., creating a journal entry). To understand the potential benefits of intraindividual production, we draw a connection to Pennebaker's work on "expressive writing" (Pennebaker, 1997). Hundreds of experimental studies have followed this paradigm, with the most common iteration asking participants to write about a challenging or traumatic event or experience for 15 minutes per day, over several days (Smyth & Pennebaker, 2008). Results reveal that private writing can provide a range of health benefits at follow-up, as has been explained through a "releasing effect" that writers achieve by expressing their inhibited feelings and thoughts, as well as by the cognitive processing during which writers discover new connections between ideas (Baikie & Wilhelm, 2005; Greenberg & Lepore, 2004). Thus, many accounts of the benefits of private writing focus on the act of expression itself.

However, alternative accounts suggest that *exposure* to self-generated content (e.g., reading and reflecting on one's previous journal) may also bestow benefits. The potential effect of re-reading private writing can be explained through self-regulation and self-perception accounts. In reference to self-regulation, Lepore et al. (2002) posited that expressive writing may represent a mastery experience that allows individuals to observe their expressions, monitor their thoughts, and better regulate their emotions. Similarly, King (2001) suggested that expressive writing provides benefits by prompting the clarification of personal goals and activating a writers' feedback system such that they compare future behaviors to their previously expressed goals, allowing possible adjustment to avoid "going astray." This is also consistent with Bem's (1972) self-perception theory, which posits people infer their own attitudes by observing their own behaviors. Re-reading one's own journal may facilitate such observations, revealing personal growth and circumstances that lead to positive changes. By following one's own progress over time, as occurs through reviewing prior writing, individuals may evaluate gaps between self-perception and reality, gaining new insights and motivating changes.

Some experimental studies provide evidence for the benefits of engaging with one's writing after its composition. In one early study of personal narratives, students wrote about their difficulties in adjusting to the college experience, and a subset of those students was later invited to re-read and edit their writing. This subset showed improved academic outcomes relative to those who did not re-read and edit (Wilson & Linville, 1982). Researchers also found that a majority of respondents in expressive writing studies indicated that rather than achieving insight at the point of composition, they obtained benefits as they reflected on their experience after writing, which allowed cognitive processing and the integration of the experiences into their self-concept (Pennebaker et al., 1990). Thus, prior research suggests both that writing privately and reflecting on writing could encourage reevaluation of one's behavior, supporting behavior change. Below, we present a hypothesis connecting intraindividual communication and behavioral outcomes.

H1: Intraindividual communication, both (a) producing private journal entries and (b) exposure to one's past entries, will be related to a reduction in risky drinking and drug use.

Dyadic: Reading and writing one-to-one messages. Despite the therapeutic benefits that writers might gain from private writing and reviewing one's own writing, we regularly seek to disclose our experiences to others. Although many digital platforms afford both group-based and one-to-one messaging, not all users are equally social (Burke et al., 2010). Some prefer to communicate one-to-one, while others opt to interact with a larger number of peers.

Most interpersonal communication takes a dyadic from (Panko & Kinney, 1992). In the context of dyadic communication, *production* refers to composing a message to send to a specific, individual recipient. According to the classic social penetration theory, self-disclosure is the main driver for building and maintaining intimate relationships (Altman & Taylor, 1973). The level of self-disclosure that signals intimacy and relational bonds is highest in a dyad and decreases as group size increases, a trend found in both face-to-face interaction (Solano & Dunnam, 1985) and online settings (Bazarova & Choi, 2014). Even though researchers do not often disentangle production from exposure at the dyadic level (Burke et al., 2010; Namkoong, Shah, Gustafson et al., 2017), a meta-analysis found that people like their partner more after having disclosed personal information to them (Collins & Miller, 1994). One-on-one self-disclosure may also facilitate working through one's personal problems and is encouraged in mutual help recovery programs (Alcoholics Anonymous, 2019). Seeking help through an ongoing dyadic relationship has been associated with reduced relapse risk (Tonigan & Rice, 2010).

In contrast, *exposure* at the dyadic level refers to receiving messages from other individuals. The potential benefits of dyadic exposure are suggested by optimal matching theory, which argues that individuals are likely to experience benefits from receiving social support when it is responsive to their particular needs (Cutrona & Russell, 1990). In dyadic communication, with its high level of self-disclosure and individualized responses, there is likely to be consistency between the help solicited and the help received, allowing for support recipients to obtain benefits. Indeed, the social support found in one-to-one messages, as people work to develop and maintain relationships, plays a role in individuals' health and well-being (Valkenburg & Peter, 2011). Numerous studies have emphasized that strong ties, or close relationships, are a critical source of online social support as compared to weak ties. The perceived support derived from the dyadic exchange has been found to promote well-being (Burke & Kraut, 2013; Valkenburg & Peter, 2007), and build self-worth in recipients (Thoits, 2011). Given the evidence of benefits from both writing and reading private messages, we hypothesize that both dyadic production and exposure are catalysts for perceived bonding and reductions in risky drinking and drug use. Accordingly, we offer the following hypotheses concerning production and exposure at the dyadic level.

H2: Dyadic communication, both (a) producing one-to-one messages and (b) exposure to one-to-one messages, will be related to perceived bonding with others in the online support system.

H3: Dyadic communication, both (a) producing one-to-one messages and (b) exposure to one-to-one messages, will be related with a reduction in risky drinking and drug use.

Network: Reading and writing one-to-many posts. Audience size is not restricted to one. Often times, a larger number of peers are involved in a digital health intervention (Ancker et al., 2009). At the network level, *production* means constructing a message that can potentially be seen by the entire social network (i.e., those using the intervention), implicating many potential readers rather than one individual. As compared to dyadic private messaging, people are less likely to broadcast intimate information to a larger number of ill-defined audiences, which makes the online public space a less ideal venue to build close relationships (Bazarova & Choi, 2014).

Yet, there may nonetheless be important benefits to producing messages for larger audiences. Recent studies show that expressing oneself to a group may even outperform private disclosure in reducing both physical and psychological symptoms (MacReady et al., 2011). Public commitment is one account that connects public expression to such benefits (Nyer & Dellande, 2010). Studies on public commitment show that individuals are more likely to stick to an action plan once announcing it publicly as they feel pressure to maintain their reputations (Newman et al., 2011; Schienker et al., 1994). Moreover, individuals engaging in network communication may be influenced by group norms, adjusting their self-presentation and behavior accordingly, which might further reinforce positive changes.

Exposure at the network level involves viewing content available within a public forum. Research shows that participants in digital health interventions are likely to experience a sense of normalization regarding their condition and gain insights into the management of their own concerns through exposure to the shared experiences of others (Radin, 2006; Wright & Bell, 2003). Exposure to one's own posts is also very common within digital health interventions. Toma and Hancock (2013) found that asking Facebook users to view their personal profiles was associated with boosts in self-esteem, suggesting increases in well-being consistent with viewing previously posted public content and the responses generated. Thus, the potential benefits of network communication might stem from both production and exposure, connecting the individual to the support community and promoting health behavior change. Accordingly, we present our final set of hypotheses related to production and exposure at the network level:

H4: Network communication, both (a) producing discussion posts and (b) exposure to discussion posts, will be related to perceived bonding with others in the online support system.

H5: Network communication, including both (a) producing discussion posts and (b) exposure to discussion posts, will be related with a reduction in risky drinking and drug use.

Methods

Platform

The data analyzed in this study were collected from a mobile health app called Seva – the Sanskrit word for "selfless caring" – disseminated to primary care patients with SUDs as part of an implementation trial from 2014 to 2017 (Quanbeck et al., 2014). The study was approved by the Medical Sciences Institutional Review Board at the University of Wisconsin–Madison and was pre-registered at ClinicalTrials.gov (NCT01963234). Smartphones were paid for during the study period by the research team and came with the app installed. The app provided *addiction treatment* and *recovery support* services. The treatment component involved an interactive online curriculum called Therapeutic Education System which has proved efficacious for SUDs in a randomized trial (Bickel et al., 2008). The recovery support services provided resources to help individuals cope with emotional challenges, manage their treatment regimens, track their progress, and communicate with other study participants.

This research focuses on the communication services embedded in the recovery support component. All participants had access to communication at three levels: journal writing (i.e., the intraindividual communication level), one-to-one messaging (i.e., the dyadic level), and group discussion forums (i.e., the network level). The discussion forum participants were 97% patients with SUDs, 2% clinicians, and 1% research staff.

Participants

Participants were recruited from three Federally Qualified Healthcare Centers (FQHCs) in the United States, with the research team coordinating with clinicians at said FQHCs to identify, consent, and enroll patient participants. Participants received training on how to use the application, and all usage of the app was automatically recorded in a server log over 6 months for data analysis. Each entry included the participant's study ID, the name of the page viewed, and the date and time of each activity. Demographic characteristics and study outcomes came from two waves of survey data, collected, respectively, at baseline (in-person) and after 6 months of access to the application (by telephone).

Among 268 participants who completed the baseline survey and system use training, 147 (47%) were female. The average age was 42.33 (SD = 10.77), with the youngest being 21 and the eldest being 66 years old. These participants had completed an average of 12.65 years of education (SD = 2.24). Thirty-nine patients (15%) were of Hispanic or Latino origin. The majority indicated that they were White, N = 177 (66%), followed by African American, N = 64 (24%), Other, N = 16 (6%), and American Indian or Alaskan Native, N = 13 (5%). One reported being Asian. Of the 268 participants, 209 (78%) completed the six-month follow-up survey.

Measures

System use

Actions related to in-system communication were categorized to reflect intraindividual, dyadic, or network communication, as Table 1 shows. Each communication level included activities on several pages of the intervention, representing distinct functions. For example, intraindividual communication involved viewing a summary page of journal entries, or details of a specific journal

Table 1. Categorization of system uses by communication level and exposure vs. production.

Page Name	Description	Communication Level	Exposure or Production
Recovery Motivation			
Recovery Motivation Journal	Browse past motivation journal entries	Intraindividual	Exposure
Recovery Motivation Photos	Browse previously uploaded motivational photos	Intraindividual	Exposure
Recovery Motivation Detail	Read the full content of a motivation journal	Intraindividual	Exposure
Compose or Edit Motivation	Compose or edit a motivation journal	Intraindividual	Production
Private messages			
Inbox	Browse a preview page showing a list of messages sent from the other user	Dyadic	Exposure
Archive	Browse a preview page showing a list of messages the user archived	Dyadic	Exposure
Compose or Edit Message	Compose or edit a message	Dyadic	Production
Public Discussion			
Groups	Browse an index page showing a list of discussion groups	Network	Exposure
Discussion Group	Browse an entry page to a specific discussion group	Network	Exposure
Recent	Browse a preview page showing all discussion posts, sorted from most recent to least	Network	Exposure
Discussion Post	Read the full content of a post	Network	Exposure
My Posts	Browse a preview page showing a list of past posts generated by the user	Network	Exposure
Compose or Edit Discussion Post	Compose or edit a post	Network	Production

entry, as well as activities related to adding or editing entries. Pages were also categorized according to whether they represented message consumption (content exposure) or message composition or editing (content production). Measures of system used at each level reflected the participant's total number of interactions (or "clicks") that advanced exposure or production. These clicks were aggregated across each participant's first 6 months of access to the intervention. To compare the effects of differentiated communication behaviors to an overall measure of communication, we also created an additional variable summing click devoted to all our individual communication use measures (i.e., overall communication).

Perceived bonding

The extent to which participants felt they had bonded with others in the digital health intervention was measured using a five-item scale designed for those in SUDs recovery (Namkoong et al., 2013). Participants indicated how often they experienced positive social contact with others on a scale from 1 (Never) to 5 (Nearly Always) (e.g., "I feel stronger knowing that there are others in my situation," "I've been getting emotional support from others dealing with substance abuse," "I am building a bond with others dealing with substance abuse"). Scores were averaged from the individual items, with higher scores indicating higher perceived bonding. This measure was collected at baseline (α = .87) and at the end of 6 months (α = .87).

Risky drinking

Participants reported the number of days in the past 30-day period that they reached or exceeded the threshold for binge drinking, defined as four standard drinks in a 2-hour period for men or three standard drinks in a 2-hour period for women and the elderly (Center for Behavioral Health Statistics and Quality, 2018). This measure was collected at baseline and repeated at the end of 6 months.

Drug use

Participants reported the number of days in the past 30-day period that they used any illegal drugs or abused any prescription medications. This measure was collected at baseline and repeated at the end of 6 months.

Control variables

Age, gender, education, ethnic group, race, and depression were collected at baseline.[1] The extent to which participants experienced depressive symptoms was also measured at baseline using the Patient Health Questionnaire (PHQ-8, Kroenke et al., 2009). Participants indicated how often during the past 2 weeks they were bothered by symptoms of depression on a scale from 0 (Not at all) to 3 (Nearly Every day). Scores were totaled from the sum of eight items, with higher scores indicating greater depression (α = .84).

Analytic approach

We conducted simple linear regression analyses predicting the effects of system usage on our outcomes of interest: perceived bonding, risky drinking, and drug use. For each outcome, since we were interested in change over time, we computed change from the start of the study by subtracting the baseline score from the six-month score (Allison, 1990). We controlled for demographic variables, followed by baseline depression score and number of active login days to account for general mental health and overall system use, respectively. We then regressed message exposure and production across communication levels on change in the dependent variables to test our hypotheses. The predictor variables were entered simultaneously. Descriptive statistics including the means, standard deviations, and correlation matrix for these predictors[2] are provided in Table 2. Analysis was conducted based on a complete case analysis for each outcome.

In a separate model, we also considered that overall communication (regardless of level or production versus exposure) might predict the outcomes of interest. Testing this additional model allows us to understand whether differentiating message production and exposure across different levels allows us to identify new relationships to our outcomes, as compared to communication as a whole. Those results are reported in the Appendix and summarized below.

Table 2. Descriptive statistics and correlations for system use predictors.

Predictors	Mean (SD)	1	2	3	4	5
1. Clicks on Intraindividual exposure	6.84 (13.89)	_				
2. Clicks on intraindividual production	22.03 (35.78)	0.75***	_			
3. Clicks on dyadic exposure	491.71 (929.27)	0.48***	0.26***	_		
4. Clicks on dyadic production	0.62 (1.37)	0.21***	0.18**	0.64***	_	
5. Clicks on network exposure	3.35 (5.57)	0.38***	0.24***	0.54***	0.31***	_
6. Clicks on network production	12.83 (23.72)	0.30***	0.28***	0.49***	0.49***	0.61***
Overall communication	537.38 (971.80)					

** $p < .01$. *** $p < .001$

Results

Our dependent variables – perceived bonding, risky drinking days, and drug use days – all saw improvements in aggregate over the 6-month period. Table 3 shows the mean and standard deviation for each dependent variable at baseline and at 6 months.

For change in perceived bonding, older participants reported less perceived bonding (see Table 4 for details). When message production and exposure across the three communication levels were entered as predictors, dyadic production was found to significantly predict perceived bonding, $\beta = .205$, $p = .033$, indicating that participants who engaged more in the production of one-to-one messages perceived increased bonding with others over the 6-month period. Overall communication, however, (see Appendix Table A1 for the full model) was not associated with perceived bonding change, $\beta = -.001$, $p = .988$.

For change in risky drinking days, message production at the network level proved to be a significant predictor, $\beta = -.219$, $p = .033$, suggesting that individuals who engaged more in the production of messages for the group discussion board had reduced risky drinking days over the 6-month period. In contrast, overall communication was not associated with change in risky drinking days, $\beta = -.044$, $p = .571$.

For changes in drug use days, older participants and those who were less depressed reported a reduction in drug use days. Our data also revealed that when exposure and production were examined at each level, both intraindividual exposure, $\beta = -.223$, $p = .070$, and dyadic exposure, $\beta = -.202$, $p = .068$, trended toward significance in predicting decreased drug use days. This trend suggests that individuals who viewed, rather than produced, more personal motivation journals and one-to-one messages are also more likely to reduce drug use over the 6-month period. Overall communication was also marginally associated with reduction in drug use days, $\beta = -0.135$, $p = .074$. Table 5 summarizes our findings in relation to our hypotheses.

Table 3. Descriptive statistics of health measures at baseline and 6-month.

	Baseline		6-month	
	Mean	SD	Mean	SD
Bonding	3.52	1.02	3.86	1.06
Drinking	1.25	3.77	0.69	2.56
Drug use	3.22	7.57	2.14	6.55

Only those who stayed through 6-month period are reported here for baseline statistics.

Discussion

Scholars have long considered ways to design digital health interventions to foster health behavior change (Cassell et al., 1998); however, little work has considered the distinct roles that may be played by message exposure and production as they occur at different communication levels: intraindividual, dyadic, and network. To address this gap, we assessed communication behaviors and their distinct effects in the context of a mobile support application for SUDs recovery, testing whether message exposure and production have different

Table 4. Regression models predicting change over the 6-month period in perceived bonding, risky drinking, and drug use.

	Perceived bonding	Risky drinking days	Drug use days
n	201	202	199
Age	−0.226** (0.07)	0.086 (0.08)	0.165* (0.07)
Gender[a]	−0.105 (0.07)	0.038 (0.07)	−0.005 (0.07)
Education[b]	−0.138[†] (0.07)	−0.087 (0.07)	0.039 (0.07)
Hispanic[c]	0.101 (0.07)	0.073 (0.08)	0.014 (0.07)
Race: White[d]	−0.099 (0.07)	−0.023 (0.08)	0.064 (0.08)
Depression	0.119[†] (0.07)	−0.080 (0.07)	−0.189** (0.07)
Login days	−0.008 (0.07)	−0.010 (0.08)	0.089 (0.07)
Intraindividual exposure	−0.092 (0.12)	0.059 (0.13)	−0.223[†] (0.12)
Intraindividual production	0.070 (0.11)	−0.086 (0.11)	0.087 (0.11)
Dyadic exposure	0.022 (0.11)	0.035 (0.12)	−0.202[†] (0.11)
Dyadic production	0.205* (0.10)	0.127 (0.10)	0.085 (0.10)
Network exposure	−0.004 (0.10)	0.024 (0.10)	−0.056 (0.10)
Network production	−0.087 (0.10)	−0.219* (0.10)	0.116 (0.10)
Total R^2 (F)	0.161** (2.75)	0.060 (0.92)	0.158** (2.67)

Standardized Regression Coefficients (standard errors in parentheses) are reported.
[a]1 = male, 2 = female. [b]Years of education. [c]0 = no, 1 = yes. [d]0 = nonwhite, 1 = white.
[†]*p < .10 *p < .05. **p < .01. ***p < .001.*

Table 5. Hypotheses testing results.

	Hypothesized association	Results
H1(a)	Intraindividual production predicts behavior change	Not supported
H1(b)	Intraindividual exposure predicts behavior change	Partially supported
H2(a)	Dyadic production predicts perceived bonding	Supported
H2(b)	Dyadic exposure predicts perceived bonding	Not supported
H3(a)	Dyadic production predicts behavior change	Not supported
H3(b)	Dyadic exposure predicts behavior change	Partially supported
H4(a)	Network production predicts perceived bonding	Not supported
H4(b)	Network exposure predicts perceived bonding	Not supported
H5(a)	Network production predicts behavior change	Partially supported
H5(b)	Network exposure predicts behavior change	Not supported

health effects depending on whether individuals are communicating with themselves, within dyads, or with a group. Our results suggested that exposure and production function differently at each communication level. We found that (1) intraindividual *exposure* marginally predicted decreased drug use; (2) dyadic *production* enhanced perceived bonding, while dyadic *exposure* marginally predicted reduced drug use; and (3) network *production* predicted decreased risky drinking. We will discuss the implications of these findings for measuring and theorizing expression effects in digital media, as well as for refining the design of digital support forums.

Our results suggest, first, that measures of overall communication might not be adequate in revealing some nuanced effects of exposure and production. Specifically, when examining communication as a whole (i.e., total clicks devoted to communication activities), it was only marginally associated with one of our outcomes of interest: reduced drug use days. Yet additional relationships of communication emerged through disentangling exposure and production occurring at each communication level, with actions related to message production significantly predicting both relationship building and behavior change. Thus, examining communication overall may disguise nuanced effects that can be disentangled through the categorization of system use logs.

As far as theoretical implications, our findings broadly provide support for the importance of message production and not just exposure, supporting the "expression effects" paradigm. Expansion of digital communication has played a disruptive role in media effects research, as anyone with access to the Internet access and digital tools (e.g., laptops, smartphones) can now reach audiences on a potentially large scale, and to act as a message sender, receiver, or both (Ball-Rokeach & Reardon, 1988). These expression effects have been hypothesized to exceed those of message exposure, which is consistent with our general pattern of findings here. The potential effects of producing one's own content have been explained through a number of accounts related to self-persuasion, self-concept change, and productive processing of one's experience and viewpoints (Valkenburg, 2017). Yet, given the early stage of this research paradigm, it has been largely unclear which mechanism might be implicated when communicating in differing online venues.

Our findings add nuance to the expression effects literature by suggesting that message production may have different outcomes, and different mechanisms, depending on the level of communication. Prior work has suggested that exchanging one-to-one messages may be important, within a dyad, to the extent that they signal relational intimacy, build a sense of connection, and promote health-related outcomes (Burke et al., 2010; Collins & Miller, 1994; Valkenburg & Peter, 2011). However, levels of engagement in production and exposure-related behaviors have not generally been distinguished. Our findings suggest that the act of messages production, rather than exposure, at dyadic level may be particularly associated with perceiving oneself as close to others, perhaps because of participants' acute awareness of the vulnerability involved in self-disclosure. We also found a marginal effect of exposure to dyadic messages on substance use, which could be consistent with the benefits of social support in recovery (Han et al., 2019), including informational and emotional support that can guide and motivate recipients' recovery process. Yet, this marginal effect requires verification.

For the network level of communication, the production of public posts was linked with changes in health behavior, specifically decreased risky drinking. This may indicate, consistent with the public commitment literature (Nyer & Dellande, 2010), that individuals who expressed themselves publicly may have felt greater motivation to live up to their expressed intentions to reduce their alcohol abuse. Further research is needed to test the specific mechanisms through which producing messages at the network level may have predicted substance abuse.

In contrast, at the intraindividual level, the production of new content was not associated with behavioral outcomes. Furthermore, we found that exposure to one's past writing was marginally associated with reduced drug use. While additional studies in larger samples should be undertaken to confirm the revealed exposure effect, this finding suggests the potential importance of reflecting on one's own private writing, rather than the act of writing it, as would be potentially consistent with self-regulation (Lepore et al., 2002) and self-perception (Bem, 1972) accounts of private writing. These accounts suggest that private writing benefits individuals because it produces a record of their commitments and personal qualities, against which writers can measure their present performance. In the recovery context, viewing one's recovery journal might translate into behavioral change by reminding people why they are in recovery and why it is important to stick with it.

Our findings suggest several implications for the design of digital health interventions. First, given our findings related to the potential benefits of intraindividual message exposure, intervention design might consider ways to prompt review of self-created content. For instance, the system might use notifications to prompt users to review their own past journals, perhaps targeting those moments where recovery motivation is waning. Such a reflection process might help individuals in recovery recognize their progress or remind them of their "better selves." Second, the findings regarding the benefits of message production at the dyadic and network level suggest that those designing health interventions might encourage these interactions.

We should also acknowledge that this study has several limitations. The nature of our analysis is correlational, with changes between baseline and 6 months related to communication behaviors taking place during the same timeframe. Therefore, it is impossible to determine a causal relationship between these variables, although we have tried to control for variables that could introduce confounding. Accordingly, the results need to be interpreted with caution. Future research might systematically manipulate the communication features available at different communication levels (e.g., lock the journal writing function for participants in one condition and lock the private message section for the other, etc.). Such a design would allow us to identify the causal effects of each type of system use.

Additionally, the current study relied solely on system use logs as an objective and efficient measure of communication behaviors, yet these findings could be extended through an examination that considers the content of messages. A range of past studies have examined how health outcomes may be predicted by the particular ways that individuals communicate in support forums. This work highlights potential benefits of giving and receiving supportive messages (Han et al., 2011, 2019; Yoo et al., 2014), and also points to potential benefits of processing one's own experience more deeply within support forums (Kornfield et al., 2018). A promising future research direction would be to combine message content coding with system logs, an approach which may stand to shed some light on why these levels of communication had their distinct relationships with the focal outcomes. For instance, interacting at different levels may call forth different types of communication, with public commitments perhaps being disproportionately elicited within the public forum, or empathy expressions within dyadic messages. Thus, future work might examine whether levels of communication have distinct effects on health-related outcomes via the ways they shape the content of communication exchanged.

Last, due to multicollinearity issues, we were not able to enter the interaction terms between these independent variables in addition to their main effects. As participants tend to engage in multiple communication functions within digital health interventions, future work may wish to examine interactions between communication behaviors occurring at different levels. We also encourage future research to adopt other modeling techniques (e.g., time series modeling) to reveal how one type of system use motivates other sub-function utilization (Chung, 2014). Combining more dynamic analytic techniques with content coded message posts, all while distinguishing between production and consumption of these messages at different communication levels, would open up new research avenues and insights.

Notes

1. Survey and coding details are available from the corresponding author.
2. We computed variance inflation factor (VIF) score for all predictors entered simultaneously in our regression model. With all VIF scores below 4.0, we determined that our models did not suffer from multicollinearity issues.

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Appendix

Table A1. Alternative regression models using overall communication to predict change over the 6-month period in perceived bonding, risky drinking, and drug use.

	Perceived bonding	Risky drinking days	Drug use days
n	201	202	199
Age	−0.203** (0.07)	0.084 (0.08)	0.181* (0.07)
Gender[a]	−0.098 (0.07)	0.027 (0.07)	−0.002 (0.07)
Education[b]	−0.143* (0.07)	−0.083 (0.07)	0.007 (0.07)
Hispanic[c]	0.104 (0.07)	0.052 (0.08)	0.028 (0.07)
Race: White[d]	−0.081 (0.07)	−0.014 (0.08)	0.092 (0.07)
Depression	0.135† (0.07)	−0.077 (0.07)	−0.192** (0.07)
Login days	0.003 (0.07)	−0.015 (0.08)	0.086 (0.07)
Overall communication	−0.001 (0.07)	−0.044 (0.08)	−0.135† (0.08)
Total R^2 (*F*)	0.124** (3.40)	0.024 (0.60)	0.091* (2.37)

Standardized Regression Coefficients (standard errors in parentheses) are reported.
[a]1 = male, 2 = female. [b]Years of education. [c]0 = no, 1 = yes. [d]0 = nonwhite, 1 = white.
†*p* < .10 **p* < .05. ***p* < .01. ****p* < .001.