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Digital recovery networks: Characterizing user participation, engagement, and outcomes of a novel recovery social network smartphone application

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ABSTRACT

Background: Recovery support services, including in vivo (i.e., face to face) peer-based supports and social networks, are associated with positive effects on substance use disorder recovery outcomes. The translation of in vivo supports to digital platforms is a recent development that is mostly unexamined. The types of users and their engagement patterns of digital recovery support services (D-RSS), and the utility of objective and self-report data in predicting future recovery outcomes require further study to move the recovery support field forward.
Methods: De-identified individual user data from Sober Grid, a recovery social network site (R-SNS) smartphone application, for the years 2015–2018 was analyzed to identify the demographics, engagement patterns, and recovery outcomes of active users. Analysis of variance (ANOVA) tests were used to examine between generational group differences on activity variables and recovery outcomes. Logistic and linear regressions were used to identify significant predictors of sobriety length and relapse among users.
Results: The most active tercile of users ($n = 1273$; mAge = 39 years; 62% male) had average sobriety lengths of 195.5 days and had experienced 4.4 relapses on average since sign-up. Users have over 33,000 unilateral and nearly 14,000 bilateral connections. Users generated over 120,000 unique posts, 507,000 comments, 1617,000 likes, 12,900 check-ins, and 593,000 chats during the period of analysis. Recovery outcomes did not vary between generations, though user activity was significantly different between Generations (Millennials, Generation X, and Baby Boomers), with baby boomers and generation X having higher levels of engagement and connection among all activity markers. Logistic regression results revealed gender (female) was associated with a lower likelihood of reporting loneliness or sexual feelings as an emotional trigger. Linear regressions revealed generation, number of unilateral connections, and number of check-ins was associated with sobriety length, while generation and number of check-ins was associated with number of relapses.
Conclusions: Active users of Sober Grid engage in several platform features that provide objective data that can supplement self-report data for analysis of recovery outcomes. Most commonly uses features are those similar to features readily available in open-ecosystem social network sites (e.g., Facebook). Prediction model results suggest that demographic factors (e.g., age, gender) and activity factors (e.g., number of check-ins) may be useful in deploying just-in-time interventions to prevent relapse or offer additional social support. Further empirical examination is needed to identify the utility of such interventions, as well as the mechanisms of support that accompany feature use or engagement with the D-RSS.

1. Introduction

In the United States, an estimated 23 million individuals aged 12 and older had a past year substance use disorder (SUD) (SAMHSA, 2018), and 22.1 million adults aged 18 and older have resolved a past substance use disorder and are living in recovery (Kelly, Bergman,

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Hoeppner, Vilsaint, & White, 2017). Recovery, defined as "an individualized, intentional, dynamic, and relational process involving sustained efforts to improve wellness" (Ashford, Bergman, Kelly, & Curtis, 2019), is best supported by comprehensive systems of care that include medical, psychosocial, and recovery supports (Ashford, Brown, Ryding, & Curtis, 2019; Dennis, Scott, & Laudet, 2014; DiClemente et al., 2016; Laudet & White, 2010; White, 2009). Each of these elements have historically been delivered in vivo (i.e., face to face settings), but recently digital delivery has become more common.

Telemedicine, or telehealth, delivery platforms are gaining in popularity among medical and clinical professionals to deliver treatment and psychosocial therapy (Ekeland, Bowes, & Flottorp, 2010; Roine, Ohinmaa, & Hailey, 2001). Other digital tools, such as smartphone applications or text-messaging regiments, are also used by SUD treatment professionals to supplement individual treatment plans (Bjerke, Kummervold, Christiansen, & Hjortdahl, 2008; Cunningham, 2011; Muench, 2014; Nesvåg & McKay, 2018). More recently, the use of digital tools to support the recovery process has been highlighted in the literature (Bergman, Kelly, Hoeppner, Vilsaint, & Kelly, 2017; Campbell, Hester, Lenberg, & Delaney, 2016; Carah, Meurk, & Hall, 2015; Dennis, Scott, Funk, & Nicholson, 2015; Dugdale, Elison, Davies, Ward, & Jones, 2016; Finn, 1996; Gonzales, Ang, Murphy, Glik, & Anglin, 2014; Gonzales, Hernandez, Murphy, & Ang, 2016; Graham, Irving, Cano, & Edwards, 2018; Lyytikäinen, 2016; Muroff et al., 2017; Schulte et al., 2016; Sinclair, Chambers, & Manson, 2016; Trudeau, Black, Kamon, & Sussman, 2017; You et al., 2017). However, many of these novel digital recovery support services (D-RSS), which are categorically different from digital SUD treatment services, have yet to be thoroughly examined and little is known about their efficacy or functional mechanisms.

D-RSS are intended to be used post-treatment and recovery initiation, and have been delivered via websites and social networking sites (i.e., recovery social networking sites, R-SNS) (Bergman et al., 2017; Graham et al., 2018; Sinclair et al., 2016), text messaging services (Gonzales et al., 2016), smartphone applications (Gustafson, McTavish, Chih, Atwood & Johnson, 2014; Dennis et al., 2015), or a combination of smartphone applications and digital sensors (You et al., 2017). Many D-RSSs appear to emulate in vivo recovery supports through replication of supportive communities similar to 12-step and other mutual aid recovery communities (e.g., SMART, Refuge Recovery, etc.), disseminating recovery-related information, or by providing near real-time connection to a peer in high risk situations (Ashford, Bergman, Kelly, & Curtis, In Review). Some D-RSSs have more functionality and services than others, offering users the ability to opt-in to geo-location tracking and social media monitoring (in an effort to predict high risk situations that may lead to a recurrence of symptoms; Dennis et al., 2015), or the use of digital sensors - such as breathalyzers - to monitor abstinence (You et al., 2017). Of the D-RSSs that have been studied, there appears to be two distinct typologies - those D-RSSs which are provided or referred to by clinical professionals post-treatment, and those that exist organically, such as R-SNSs, allowing users to self-select into.

Few studies have examined D-RSS participant recovery outcomes (e.g., recurrence of substance use, recovery capital, etc.). Preliminary evidence does suggest that D-RSSs are comparable to in vivo recovery supports (Campbell et al., 2016; Dennis et al., 2015), and have performed better than controls in some instances (Gonzales et al., 2014; Gonzales et al., 2016). However, where D-RSS participation resulted in better outcomes than care as usual is limited to adolescent populations. Additionally, one study suggests that the combination of D-RSS with in vivo supports improves participant outcomes (e.g., # of risky drinking days) compared to controls (Gustafson et al., 2014).

In an effort to expand the field's knowledge of D-RSS, and to characterize a novel R-SNS D-RSS available in a smartphone application, the current study evaluates the Sober Grid (SG) digital recovery network with two aims: 1) to characterize the users who engage in SG, and 2) identify the ways and frequency in which users engage. To our knowledge this is the first study to date examining SG and a D-RSS combining a smartphone application and R-SNS. Given the novelty of this investigation, we did not define a priori hypotheses.

2. Methods

2.1. Sober Grid overview

Sober Grid is a proprietary, R-SNS that is accessible only through smartphone application. Downloads of the application are available on the Apple app store or Google Play app store and are free to any user. Features of the R-SNS include text-based and photo-based status sharing, user check-ins, a geolocation "grid" that allows users to find others in recovery near their location, user to user connections (unilateral or bilateral), alumni group pages, and a "burning desire" feature that allows users to immediately reach out for help to others in the community. The application is similar to other social network applications in that it allows engaged individuals to share statuses, comment on shared statuses, and direct messaging (person to person and group) features.

2.2. Design

Administrative data on all Sober Grid users, covering the period of from app launch, April 20, 2015 to January 16, 2018, was used for this observational study. All measures used in the analysis were demographic variables collected during user signup or in the day-to-day activities completed while on the app. The University of Pennsylvania deemed the study exempt from review as only historical data was analyzed without interacting with app users for new data collection.

2.3. Measures

2.3.1. Demographics

At sign up, Sober Grid prompts users for four optional demographics: age, gender, relationship status and sexual orientation. Users are given four options for gender: female, male, other, and no response. Age is recorded as a four-digit year, two-digit month and two-digit day. Relationship status choices available to users are: dating, married, no answer, open relationship, and single. Sexual orientation choices are bisexual, gay, questioning and straight. We also calculated age as a continuous variable, identifying user age as date of birth to date of archival data retrieval; age was then recoded as a trichotomous generational variable including millennial (18–35 years), generation x (36–52 years), and baby boomer (53+ years).

2.3.2. Recovery-related characteristics

We categorized three app activities and the resulting data as user-recovery related characteristics for this study. Activities included check-ins, use of the burning desire feature, and sobriety date changes. Check-ins on the app are similar to ecological momentary assessments (Lukasiewicz et al., 2007), and allow users to provide feedback on how they are currently feeling, what they are doing for their recovery, and in the instance of a relapse (denoted by users not marking "staying sober" on the check-in prompt), provide information on emotional triggers experienced - including anger, boredom, depression/sadness, environmental, hunger, loneliness, sexual feelings, stress, or fatigue/tiredness. The burning desire feature allows users to immediately reach out for help via an app post when the user feels their recovery is at risk; burning desires can be seen by any user for up to 4 h or until the user closes out a posted burning desire, whichever comes sooner. Sobriety dates are collected at user signup and can be changed, initiated by the user, when a relapse has occurred and the sobriety date needs to be modified.

Using the Check-in feature we defined the variable *relapse (check-in)* as the number of check-ins per user that identify "staying sober" as

False (i.e., not checked by user during check-in prompt). When reporting on *relapse (check-in)* we only consider users who have used the check-in feature at least once in their activity.

From the sobriety date change activity, we defined three variables, *recovery length*, *sobriety length* and *relapse (sobriety date change)*. *Recovery length* was calculated as the number of days between a user's first sobriety date change (completed at sign-up) and the date of archival data retrieval (January 16, 2018). *Sobriety length* was calculated as the number of days between a user's most recent sobriety date change and the date of the archival data retrieval. Of note, recovery length is always longer or the same length as sobriety length, which is in line with recent definitions of recovery that suggest abstinence is an outcome, but not a definitional parameter of the recovery process (Ashford et al., 2019). As such, recovery length is the entire period someone has been engaged in a recovery process, whereas sobriety length is the most recent length of time an individual has been abstinent. *Relapse* (*Sobriety Date Change*) was calculated as the number of times a user changed their sobriety date, subtracting one change from the total as each user is denoted as having a date change when providing their sobriety date on sign-up. When reporting on *recovery length*, *sobriety length* and *relapse* (*sobriety date change*) we only consider users who had used the sobriety date change feature at least once (e.g., provided a sobriety date during signup).

2.3.3. Participation and engagement

We defined two variable types for participation and engagement: connections and activity. Connections on Sober Grid are unidirectional, following a Twitter connection framework - following another user does not imply that you are automatically followed back, a unilateral connection, but if this does occur, a bilateral connection is formed. We summed the number of unidirectional (e.g., unilateral) and bidirectional (e.g., bilateral) connections for each user. Alumni support groups are private group pages for various SUD treatment programs, aftercare programs, and affinity groups that may provide signup codes to discharging clients or engaged individuals. Users signing up with an alumni code are added to the alumni support group, and users can also apply to join an alumni support group. Alumni groups created for specific affinities (i.e., LGBTQ+) do not require a sign-up code to join, nor require approval from a group administrator. For each user, we summed the total number of connections to alumni support groups, including affinity groups, for the *alumni support groups connections* variable.

We defined several user activity variables (i.e., actions taken on platform while logged in), including: posts, comments, likes, chats, check-ins (with and without triggers), and burning desires. Posts are user-generated feed content, either text-based or image-based, and can be seen by all other users, despite unilateral or bilateral connection status, unless a specific user has been blocked. Comments are user-generated responses to posts and can be generated by any user or the original post creator. Likes are user-initiated actions on posts and comments between the original post and comment creator and any other user. Chats are private messages between connections, or through users responding to a burning desire. Check-ins and burning desires are user-generated and described above. For each of these activity variables, we summed the number of actions (e.g., number of posts, comments, likes, etc.) as individual continuous variables, with each serving as a proxy of platform activity.

2.4. Data analysis

Our original data source consisted of 102,292 distinct users and their logged activity. We used three criteria to restrict our sample to control for unique users that had signed up, but not actively engaged with the app. Criteria included a requirement that users self-reported age between 18 and 80 years (criterion #1), gender (criterion #2), and had at least 30 days between last login and account creation (criterion #3). In order to further control for actual users of the platform, we created an “login index”, which we defined as the number of total logins divided by the number of days between account creation and last login. This index was necessary as the complete historical data of individual user logins was unavailable – only date of first login, last login, and total logins was provided. From this “login index”, we restricted the final analysis to the upper tercile, or the most active users. Upper tercile users had a range of logins from 1 to 1572, with an average total login count of 12.47 and an average age of account of 396 days. The middle tercile had a range of logins from 1 to 7, with an average total login count of 1.84 and an average age of account of 646 days. The lower tercile had a range of logins from 1 to 2, with an average login count of 1.03 and average age of account of 803 days.

2.4.1. Statistical analysis

Descriptive statistics were used for user demographics and activity variables. To examine the relationship between user demographics (e.g., age and gender) and check-ins with a specific trigger (e.g., anger, boredom, etc.) we used binomial logistic regressions, modeling instance of a specific trigger (0 = not present, 1 = present) predicted by generation (proxy for age) and gender (0 = male, 1 = female). Additionally, we used multivariate linear regression models to examine the relationship between relapse (*relapse (sobriety date change)*) and *sobriety length*, and user activity and connections, while controlling for user demographics. For the linear regression models, we entered demographic controls only in model 1, and demographic controls with user connection and activity continuous variables in model 2.

3. Results

3.1. Participants

Of the original sample (n = 102,242 unique users), 3819 met inclusion criteria based on our a priori parameters (i.e., reporting gender, age, and at least 30 days between account creation and last login). The final analyzed sample (n = 1273) was the upper tercile of these 3819 unique users. Users did not statistically significantly vary based on demographics between terciles (p = .066). Users in the final sample (n = 1273) were mostly male (62.29%) and had a mean age of 38.97 years (SD = 9.7). Male users were, on average, older than female users (mean difference = 5.73 years, p = .02). Users were comprised of 40.06% millennials, 48.78% generation X, and 11.16% baby boomers. Full user demographics are available in Table 1.

3.2. Recovery-related outcomes

Users had average lengths of recovery of 265.9 days (SD = 113.62) and an average 195.58 days (SD = 130.15) of sobriety length. Users self-reported 236 relapses via check-in (M = 0.32, SD = 1.57), while relapses inferred from sobriety date changes were 3307 (M = 4.44, SD = 7.81). Of those reporting a relapse and an accompanying emotional trigger (n = 584), stress (19.52%), depression/sadness (17.29%), environmental (15.07%), and loneliness (12.0%) were reported most often. ANOVA omnibus test results found no statistically significant differences among recovery-related outcomes between user generations.

Logistic regression models for predicting reporting of emotional triggers found that gender, but not generation, significantly predicted loneliness (r^2 = 0.08, OR = 0.25, 95% CI = 0.09–0.69) and sexual feelings (r^2 = 0.13, OR = 0.15, 95% CI = 0.04–0.54) reports. Female users were 6.66 times less likely than males to report sexual feelings, and 4 times less likely to report loneliness, than male users.

The multivariate linear regression models for predicting *sobriety length* ($F(7, 744) = 5.85$, $p < .001$, $r^2 = 0.06$) found that generation, number of unilateral connections, and number of check-ins were statistically significant predictors when controlling for user demographics;

Table 1
Sober grid user demographics.

Variable		All (N = 1273)	Millennial (*N* = 510)	Generation X (*N* = 621)	Baby boomer (*N* = 142)
		M (SD)	M (SD)	M (SD)	M (SD)
Age		38.97 (9.70)	29.62 (3.94)	42.65 (4.52)	56.42 (4.52)
Sobriety length (Days)		195.58 (130.15)	191.05 (130.45)	193.37 (129.83)	227.90 (125.68)
		%	%	%	%
Generation	Millennial	40.06	–	–	–
	Generation X	48.78	–	–	–
	Baby boomer	11.15	–	–	–
Gender	Female	37.71	46.47	33.33	25.35
	Male	62.29	53.53	66.67	74.65
Sexual orientation	Bi-sexual	1.41	1.76	1.45	0
	Heterosexual	36.84	33.92	38.33	40.85
	Homosexual	5.73	4.9	4.83	12.68
	Questioning	0.08	0	0.16	0
	Not reported	55.93	59.41	55.23	46.48
Relationship status	Committed relationship	1.81	1.76	1.45	3.52
	Dating	0.63	0.2	0.97	0.7
	Married	3.22	0.39	4.03	9.86
	Open relationship	0.08	0.2	0	0
	Single	6.28	4.12	7.57	8.45
	Not reported	87.98	93.33	85.99	77.46

Baby boomers were more likely to have longer sobriety lengths compared to millennials (0.369 days longer, $p = .005$, 95% CI: 0.11, 0.63), users with more unilateral connections were more likely to have longer sobriety lengths (+0.19 days for each additional unilateral connection; $p = .011$, 95% CI: 0.04*, 0.33), and users that used the check-in feature more were more likely to have shorter sobriety lengths (−0.22 days for each additional check-in; $p < .001$, 95% CI: −0.29, −0.15).*

The multivariate linear regression models for predicting *relapse (sobriety date change)* ($F(7, 744) = 2.51$, $p = .008$, $r^2 = 0.02$) found that generation and number of check-ins were statistically significant predictors when controlling for user demographics; Baby boomers were more likely to have a lower number of relapses compared to millennials (−0.276 relapses, $p = .039$, 95% CI: −0.54, −0.01), and users that used the check-in feature more were more likely to have a great number of relapses (0.12 more relapses for each additional check-in; $p < .001$*, 95%* CI: 0.05, 0.19*).*

3.3. Participation and engagement

Among all users, there were 33,441 unilateral (M = 26.27, SD = 76.26), 13,837 bilateral (M = 10.87, SD = 29.26), and 458 alumni support group (M = 0.36, SD = 1.17) connections. Users generated 120,435 unique posts (M = 94.61, SD = 289.66), 507,631 comments (M = 398.77, SD = 1617.78), 1617,124 likes (M = 1270.33, SD = 4905.26), 12,964 check-ins (M = 10.18, SD = 24.50) - 208 of which were with triggers, 593,082 chats (M = 465.89, SD = 2190.20), and 95 burning desires (M = 0.07, SD = 0.49). Full user activity by generation is available in Table 2.

ANOVA omnibus test results (Table 3) found statistically significant differences between generations for unilateral connections, bilateral connections, posts, comments, check-ins, and likes (*ps* < 0.001). Significant post hoc tests revealed that millennials had the least number of unilateral connections on average compared to both generation X and baby boomers, as well as lower number of bilateral connections on average compared to generation X. For activity, millennials also had the least number of posts, comments, check-ins, and likes compared to both generation X and baby boomers. No statistically significant differences between generation X and baby boomers were found.

Table 2
Sober Grid User Connections and Activity.

Variable		Millennial (N = 510)	Generation X (N = 621)	Baby boomer (N = 142)
		M (SD)	M (SD)	M (SD)
Connections	Unilateral** (*n* = 33,441)	16.16 (36.77)	33.90 (99.79)	29.18 (55.67)
	Bilateral** (*n* = 13,837)	7.11 (18.00)	13.85 (35.20)	11.36 (31.66)
	Alumni Groups (*n* = 458)	0.33 (1.32)	0.34 (0.82)	0.56 (1.74)
Platform activity	Posts** (*n* = 120,435)	47.10 (142.82)	121.74 (334.04)	146.57 (420.61)
	Comments** (*n* = 507,631)	135.07 (561.57)	503.59 (1707.89)	887.44 (3006.20)
	Check-Ins** (*n* = 12,964)	5.41 (14.05)	12.73 (27.32)	16.16 (35.55)
	Check-In Triggers (*n* = 208)	0.16 (0.85)	0.13 (0.62)	0.33 (2.33)
	Chats (*n* = 593,082)	431.49 (1836.14)	523.84 (2611.06)	336.04 (1022.02)
	Burning Desire (*n* = 95)	0.11 (0.67)	0.05 (0.27)	0.08 (0.39)
	Likes** (*n* = 1617,124)	476.28 (1922.96)	1711.52 (5839.90)	2192.70 (7022.33)

**Analysis of variance omnibus test results significant at the < 0.001 level.

Table 3
ANOVA Between Group (Generations) Differences of Activity and Engagement.

Variable	df	F	p	N_p^2
Unilateral connections	2	7.77	0.01	0.01
Bilateral connections	2	7.52	0.01	0.01
Posts	2	12.07	< 0.001	0.02
Comments	2	14.87	< 0.001	0.02
Check-ins	2	17.69	< 0.001	0.03
Likes	2	11.90	< 0.001	0.02

df = Degree of freedom, N_p^2 = partial eta squared.

4. Discussion

The results from the current study provide the first examination of characteristics of Sober Grid app users and these users recovery outcomes, such as sobriety length and number of relapses. Additionally, results are the first to combine self-report and platform generated data (i.e., objective data) that we are aware of. Findings suggest that a diverse set of individuals engage with Sober Grid, making use of several distinct features such as commenting, posting, liking, check-ins, and connecting/chatting with others.

Overall, users of the Sober Grid platform vary along demographics, though the app did not allow for robust demographic data collection, limited to age, sexual orientation, and gender. Baby Boomers and Generation Xers made more use of the platform and its features compared to Millennials, evidenced by more connections and activity among these cohorts. While the reason for increased use among these specific individuals is unknown, it may be explained by increased access to resources (e.g., the means to engage digitally with high speed internet access and digital devices), pertinent for both Generation X and Baby Boomers, and time, at least for Baby Boomers who may be out of the workforce and have additional free time, both of which would be required to engage. However, recent evidence suggests that socio-economic and socio-demographic status is becoming increasingly less predictive of technology usage and adoption (Carroll et al., 2017). It is perhaps a more plausible explanation that the underlying mechanics of the Sober Grid app (e.g., text-based status sharing, still image uploads) appeal more to an older demographic, as Millennials engaging in SUD treatment have previous been found to use apps featuring more anonymous sharing and live/recorded video, such as Snapchat, more frequently (Ashford, Lynch, & Curtis, 2018).

On average, users had less than a year of sobriety, suggesting the Sober Grid platform may be most engaging for those in early remission/recovery. It is also plausible, given the social network aspects of the D-RSS, that individuals with less sobriety time were suggesting their friends with shared characteristics (i.e., similar lengths of sobriety) download and use the app. Future examination of self-reported reasons for joining Sober Grid, as well as the reasons for staying, would be helpful in answering this empirical question. Among all users, certain features were more utilized than others, specifically posts, comments, likes, check-ins, and chats, while triggers and burning desires feature were used less often. The features used more often are consistent with features available on other social network sites, such as Facebook, and users may have felt more comfortable using them given their familiarity.

Participant outcomes included check-in and sobriety date change reported relapses (i.e., calculated from the number of sobriety date changes), the selection of emotional triggers when checking-in, and current sobriety length. Check-in relapses were lower than relapses derived from sobriety date changes, suggesting that users' willingness to report relapse may be limited for various reasons (e.g. shame, stigma, etc.). Emotional triggers most often reported by users were stress, depression/sadness, environmental, and loneliness, which is consistent with previous research describing risk factors for relapse and is an expected finding (Marlatt & Gordon, 1985).

As a preliminary study, identification of variables that may serve as useful predictors of D-RSS engagement and activity, or recovery-related outcomes (e.g., relapse, recovery length, etc.) in future research is an important task. From the results, we find that the number of unilateral connections were associated with sobriety length as a significant predictor, which suggests that connections may promote resilience against relapse, though we note a temporal, or causal, relationship cannot be identified with the current methods. However, promoting recovery-positive connections (e.g., connections with others engaging in the recovery process) for users may be an important method for bolstering supportive networks and reducing the risk of future relapse for Sober Grid and other similar D-RSSs – similar to the supportive mechanism these types of relationships serve in real-world communities (Litt, Kadden, Kabela-Cormier, & Petry, 2007; Kaskutas, Bond, & Humphreys, 2002; Bond, Kaskutas, Weisner, 2003; Best, Irving, Collinson, Andersson, & Edwards, 2017). Number of check-ins was also a significant predictor for sobriety length, but was associated with decreases. A possible explanation for this is that users using the check-in feature may be those who are in need of more support and more likely to relapse - whereas those with longer sobriety lengths may not use the feature as frequently because they require less support as they are doing well. Number of check-ins was also a significant predictor of derived relapses (i.e., not using self-report data), with more check-ins being associated with a greater number of relapses. This lends support to the explanation that users who need less support, or are at lower risk of relapse, use the feature less often, but additional insight and data is needed to make appropriate claims.

The data available from emotional triggers reported on the platform can provide insight into what users are struggling with over their time on the platform. Female users were less likely than males to select a loneliness or sexual feelings emotional trigger, which is partially line with previous research that suggests males struggle with sexual feelings during the recovery process more than females, especially in learning how to model and frame appropriate romantic relationships (Downs, Houghtaling, Wampler, & Shumway, 2009). However, previous studies also suggest that females can experience isolation in social networks when initiating recovery (Kandall, 2010; McCrady, 2004), which would seem counterintuitive to their decreased likelihood of reporting loneliness as an emotional trigger. Perhaps, for female users in this study, Sober Grid fosters social inclusion and connection, and serves to reduce the experience of loneliness that we might expect. Further examination of why female users was less likely to experience loneliness emotional triggers is needed, however.

4.1. Limitations

Findings from this study should be viewed in light of several limitations. First, results cannot be generalized outside of the most active users of Sober Grid, including to other D-RSSs. Additionally, several variables were researcher derived, which may inadequately capture user intent or actual activity/events, though these derived variables were from objective system data which may minimize this risk. Finally, the rate of variance explained in regression models was low overall, suggesting that other factors not currently tracked or available are more important in accurately modeling user behavior and outcomes.

4.2. Future directions

As the study of D-RSS continues, experimental designs comparing users assigned to use Sober Grid versus other similar D-RSS and in vivo supports are needed to study the benefits and effects of engagement. Dose-response designs and just-in-time interventions would also be beneficial to understand how levels of engagement and activity affect user outcomes, and the ability for intervention at the point of greatest risk to occur successfully using application data. D-RSS developers should also consider embedding recovery outcome variables, such as recovery capital and quality of life, directly into the platform for future efficacy research. These should include outcomes that are more than relapse, percent days abstinent, etc. so as to cover a range of outcomes related to behavior change, recovery progression, and intrapersonal outcomes.

5. Conclusion

Sober Grid is one of many novel D-RSS that have an active user base of individuals in early recovery from SUDs. While attrition (i.e., users downloading but not regularly returning to use the application) appears to be high, rates are similar to other health intervention smartphone applications (Payne, Lister, West, & Bernhardt, 2015) and are not necessarily an indicator of poor adoption or a lack of user interest in Sober Grid. Users who have a greater number of connections tend to have longer lengths of sobriety, suggesting that D-RSS, such as Sober Grid, that foster peer-to-peer connection may promote recovery resiliency for engaged users. Feature usage, such as check-ins, is associated with shorter lengths of sobriety and increased number of relapses which may provide an opportunity for future just-in-time interventions among Sober Grid and other D-RSSs that have such a feature. Other means of tracking user outcomes related to relapse, such as objective platform data, may be helpful for other D-RSS as user-reported tracking may be less sensitive and accurate.

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Declaration of competing interest

Authors BM, CP, and LS are employed by Sober Grid as full-time staff. All other authors report no conflicts of interest.

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