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Smartphone-based mobility metrics capture daily social motivation and behavior in schizophrenia

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ABSTRACT

Impaired social functioning contributes to reduced quality of life and is associated with poor physical and psychological well-being in schizophrenia, and thus is a key psychosocial treatment target. Low social motivation contributes to impaired social functioning, but is typically examined using self-report or clinical ratings, which are prone to recall biases and do not adequately capture the dynamic nature of social motivation in daily life. In the current study, we examined the utility of global positioning system (GPS)-based mobility data for capturing social motivation and behavior in people with schizophrenia. Thirty-one participants with schizophrenia engaged in a 60-day mobile intervention designed to increase social motivation and functioning. We examined associations between twice daily self-reports of social motivation and behavior (e.g., number of social interactions) collected via Ecological Momentary Assessment (EMA) and passively collected daily GPS mobility metrics (e.g., number of hours spent at home) in 26 of these participants. Findings suggested that greater mobility on a given day was associated with more EMA-reported social interactions on that day for four out of five examined mobility metrics: number of hours spent at home, number of locations visited, probability of being stationary, and likelihood of following one's typical routine. In addition, greater baseline social functioning was associated with less daily time spent at home and lower probability of following a daily routine during the intervention. GPS-based mobility thus corresponds with social behavior in daily life, suggesting that more social interactions may occur at times of greater mobility in people with schizophrenia, while subjective reports of social interest and motivation are less associated with mobility for this population.

1. Introduction

Social functioning is a key contributor to quality of life for people with schizophrenia (Green et al., 2018). Deficits in social functioning are largely attributed to negative symptoms, specifically low general motivation (Reddy et al., 2015) and low social-specific motivation (Blanchard et al., 2015; Fulford et al., 2018; Reddy et al., 2014). Although findings of high social anhedonia and other markers of asociality in people with schizophrenia suggest that they may experience reduced desire for social connection (Blanchard et al., 1998), they often report improved social connection as a key target for treatment (Gard et al., 2014; Lim et al., 2020), and high levels of loneliness and social isolation contribute to decreased mental and physical well-being (Lim et al., 2018; Ludwig et al., 2020). Existing evidence suggests that psychosocial interventions for social impairment can improve social skills and cognition (Bellack et al., 2013; Roberts and Penn, 2009), but the extent to which they impact social motivation is relatively unclear (Fulford et al., 2018; Velthorst et al., 2017), demonstrating a need for better understanding of the mechanisms underlying social motivation.

Improved measurement of social motivation in the context of daily life could serve to increase our understanding of this critical intervention target by capturing relevant contexts and reducing confounding factors associated with current self-report or interview-based assessments. Research on social motivation and functioning in schizophrenia has historically relied on self-report questionnaires and clinician-rated scales. Despite recent advancements in measure development (Kirkpatrick et al., 2006; Kring et al., 2013; Mucci et al., 2015), these assessments continue to rely on retrospective reporting, which is impacted by recall bias, recency/salience effects, memory impairments, and current mood state (Aleman et al., 1999; Ermel et al., 2017; Sabbag et al., 2012).

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Additional limitations include individual variation in interviewers' understanding of "normative" social behavior, the artificial nature of the laboratory or clinical environment, and the additional burden of attending in-person visits (Fulford et al., 2021b). Methods that allow for the collection of data at a higher temporal resolution, that also account for fluctuations in the environmental context of daily life, could better inform our understanding of social motivation and functional impairment in schizophrenia (Cohen et al., 2021).

Recently, mobile assessments, including both active and passive (i.e., sensors) data streams (Mote and Fulford, 2019; Wright et al., 2021), have helped fill this need. Active measures, such as those collected via ecological momentary assessment (EMA), require the participant to engage directly and regularly with a study device. As a self-report method, EMA shares some limitations of clinical interviews, but because it is completed in "real-time" and in the context of daily life, it substantially reduces many of the biases associated with retrospective reporting (Fulford et al., 2021b). Passive measures, such as those collected via sensors like accelerometer and global positioning system (GPS), allow for the collection of data without direct participation and can alleviate burden associated with active methods. Passively collected mobility data derived from geolocation from a smartphone's GPS (e.g., distance traveled, time spent at home) can also provide objective assessment of individuals' movement in time and space.

Studies of mobility in schizophrenia have commonly focused on participants' movement trajectories between locations as potential markers of negative symptoms (Fraccaro et al., 2019; Wright et al., 2021). Analyses of GPS data in these studies have involved the computation of "flights" (i.e., timepoints spent in transit), "pauses" (i.e., timepoints spent in a single location), and mobility metrics derived from patterns of flights and pauses (e.g., similarity of a person's pattern of movement on a given day compared to their typical pattern). Two recent studies found that participants with schizophrenia demonstrated lower overall mobility compared to both participants with bipolar disorder and controls (Depp et al., 2019; Raugh et al., 2020).

Additional studies have found greater mobility to be associated with less severe negative symptoms and better functional outcomes. For example, more time spent outside the home and in transit was associated with lower symptom severity and higher functioning (Raugh et al., 2020; Wang et al., 2016, 2017), while more time spent at home and higher likelihood of pausing were associated with higher symptom severity and lower functioning (Depp et al., 2019; Fulford et al., 2021b; Parrish et al., 2020). Additionally, higher likelihood of following one's typical daily routine of flights and pauses was associated with lower psychiatric symptoms, though the mechanism driving this association is unclear (Fulford et al., 2021b; Henson et al., 2020). Anomalies in behavioral patterns of mobility (e.g., a significant reduction in observed mobility compared to expected mobility) have also successfully predicted relapse rates (Barnett et al., 2018; Ben-Zeev et al., 2017; Henson et al., 2021). This literature suggests that mobility patterns, as assessed via smartphone-based geolocation, may provide clinically relevant information regarding symptom severity and global functioning among people with schizophrenia.

The relationship between mobility and social functioning specifically has yet to be examined in people with schizophrenia. The current study was conducted in the context of a 60-day smartphone intervention designed to improve social motivation and functioning in people with schizophrenia. This intervention provided an opportunity to examine social behavior and mobility over a longer duration than typically done in EMA studies, and to incorporate clinician-rated and self-report measures collected in the laboratory with daily assessments. We expected that greater mobility (e.g., less time at home, more locations visited), as an objective measure of behavior representing movement within the community, would also be associated with greater social activity. In addition, we expected that increased behavioral activities, as measured via self-reported social behavior and GPS mobility metrics, would be associated with greater social motivation. Specific to our analyses, we predicted that greater mobility would be associated with 1) more EMA-reported social interactions, 2) greater EMA-reported social motivation during the intervention, and 3) lower baseline levels of negative symptoms and social impairment. Measuring these components in both daily life and a lab setting may help to understand how passively collected mobility data may be of use to future studies and clinical trials targeting social functioning, as the literature shows a promising correspondence between mobility and clinical outcomes.

2. Methods

Data were collected in an open pilot smartphone intervention study conducted in the Boston and San Francisco Bay areas over the course of 60 days (registered clinical trial NCT03404219). The study was conducted from 2018 through early 2020. All data were collected prior to the COVID-19 pandemic. Preliminary outcomes and additional details of this clinical trial have been previously reported (Fulford et al., 2021a).

2.1. Participants

Thirty-one participants completed the mobile clinical trial. Inclusion criteria were a diagnosis of schizophrenia or schizoaffective disorder, receiving current treatment (pharmacological, psychotherapy, or both), between ages 18–65 years, and fluency in English. Exclusion criteria were presence of a substance use disorder within the past six months (participants were not excluded based on tobacco use), current suicidal ideation, or diagnosis of a neurological disorder (all self-reported during screening and structured diagnostic interviews).

2.2. Measures

Measures included clinical assessments collected during study visits in the lab, surveys administered twice daily via EMA, and GPS collected passively throughout the smartphone intervention.

2.2.1. Clinical assessments

2.2.1.1. Diagnosis and symptoms. Diagnoses were confirmed via the Structured Interview for DSM-5 — Research Version (SCID-5; First et al., 2015). Negative symptoms were assessed using the Clinical Assessment Interview for Negative Symptoms (CAINS; Kring et al., 2013). In this study we examined experiential (i.e., motivation and pleasure; MAP) deficits from the CAINS. The CAINS assesses these symptoms in the context of the previous week and experiences expected in the following week. Each CAINS item is rated on a scale from 0 to 4 and subscales are calculated as the mean of all included items (higher scores indicate greater severity of negative symptoms).

2.2.1.2. Social functioning. Social functioning at baseline, termination, and follow-up was assessed using both the Heinrichs Quality of Life Scale — Interpersonal Relations subscale (QLS-IR; Heinrichs et al., 1984) and the Birchwood Social Functioning Scale (SFS; Birchwood et al., 1990). The QLS-IR is a structured clinical interview that assesses social functioning within various social domains and types of relationships in the past 30 days. Each QLS-IR item is rated on a scale from 0 to 6 (higher scores indicate higher functioning); the QLS-IR total is the average of all items. The SFS is a well-validated self-report scale that includes 79 items assessing 7 social functioning domains (only total scores were included in the present analyses). Each SFS item is rated within a different range, and each domain is calculated as a sum of its included items. SFS total scores were calculated by taking the mean of all domain subscales, which were then standardized based on the sample used for scale validation (see Birchwood et al., 1990). Higher scores indicate better social functioning. The SCID-5, CAINS, and QLS-IR were administered by trained research assistants.

2.2.2. Ecological Momentary Assessment (EMA)

The digital intervention—the Motivation and Skills Support (MASS) smartphone app—involved selecting a single social goal (e.g., "Make a new friend by going to events") during the baseline visit and receiving twice daily reminders to work on this goal for 60 days, including a list of specific steps toward accomplishing the goal (see Procedures, below). As part of the intervention, participants were sent surveys during each push notification (twice daily). Participants answered questions related to their social activity and their progress on their social goal. In the current study, we focused on participants' reported social motivation and activity, specifically motivation to interact with others, motivation to work toward their social goal, and number of reported social interactions (i.e., "How many conversations did you have in person, by phone/text, or online, since the last survey?"; Table 1).

2.2.3. Mobility via Global Positioning System (GPS) geolocation

Geolocation was collected semi-continuously and passively via GPS throughout the intervention. GPS data were sampled approximately every 5 min. To preserve the phone battery, if a participant was determined to not have moved locations since the previous GPS reading (as determined using Wi-Fi data), the app would use the same GPS data as the previous reading; otherwise, it would capture a new GPS reading. If Wi-Fi was not active on the participant's phone, the app would automatically capture a new GPS reading. Mobility metrics were derived from GPS data using a publicly available R code that imputes missing data and calculates average values at the daily level (Barnett and Onnela, 2020). As this method is stochastic, data were sampled 10 times and each metric was averaged over the 10 samples. This amount of sampling was recommended by the code authors and provided sufficiently stable estimates, as demonstrated by negligible changes in estimates from additional sampling.

2.3. Study procedures

Participants were screened over the phone to determine eligibility, then attended three in-person visits: baseline (preintervention), termination (end of the 60-day intervention), and follow-up (three months after termination). Baseline visits consisted of informed consent, structured interviews assessing eligibility, structured clinical interviews and questionnaires assessing symptoms and functioning, demonstration of the app and other smartphone features, and selection of a social goal that the participant worked toward throughout the intervention. This social goal did not change over the course of the intervention; participants worked on different steps of the same goal throughout the 60 days. The intervention app integrated evidence-based psychosocial treatment approaches for schizophrenia drawn from research on affective, motivational, and cognitive science, targeting social motivation in real-time and in real-world settings with the intent to increase social functioning (Fulford et al., 2020). Social goals included in the MASS app involved creating new social connections and strengthening existing ones. Participants received push notifications to use the MASS app twice each day—one in the morning and one in the evening—as this was determined to be the most feasible and acceptable method based on participant feedback provided during pilot testing (Fulford et al., 2020). Administration of surveys was semirandom within blocks of 2.5 h; thus, time between surveys varied each day. Participants were instructed during their baseline visit to answer any questions asking for their experiences "since the previous survey" by reflecting on the period of time since when the previous survey should have been completed, to correct for the possibility of missed surveys or surveys that were never sent out of error. That is, when completing a morning survey, they were instructed to report on experiences since the prior evening, and when completing an evening survey, they were to report on experiences since that morning.

Participants were allowed the option to pause their participation in the study, including surveys and GPS collection, for up to an hour at a time. There was no limit to the number of times participants could pause their participation. Participants were provided with Samsung Galaxy S8 phones, which they were allowed to keep after the study ended. Data, call, and text plans were provided throughout the 60-day intervention. Termination and follow-up visits consisted of the same structured clinical interviews and questionnaires to assess changes in symptoms and functioning. For further details regarding the MASS app intervention and outcomes, see Fulford et al. (2021a) and Fulford et al. (2020).

2.3.1. Data analysis plan

We limited analysis of GPS metrics to five mobility variables that demonstrated limited overlap with each other, and which our group previously found to be associated with social isolation and loneliness (Fulford et al., 2021b): time spent at home; number of significant locations visited; probability of pausing, or remaining stationary; likelihood of following one's own typical daily routine (labeled as "circadian routine"); and average flight duration. Probability of pausing and circadian routine are both probability-related variables that lie on a scale from 0 to 1; these values were multiplied by 100 to aid in interpretation of coefficients and to avoid any issues with model

Table 2
Description of mobility variables included in analysis.

Variable name	Variable description	ICC	Mean (SD)
Home time	Hours spent at home per day (out of 24)	0.44	16.01 (7.55)
Significant locations	Number of significant locations visited per day	0.50	1.68 (0.87)
Probability of pausing	Probability of being stationary relative to time moving per day	0.32	81.10 (21.18)
Circadian routine	Likelihood of following one's own weekday routine (as determined by similarity of locations visited at different times of the day) in a given weekday	0.72	65.87 (25.30)
Average flight duration	Average duration of a flight (movement from one location to another), in minutes	0.23	28.38 (132.08)

Table 1
Description of EMA variables included in analysis.

Variable name	Variable description	Question text	Answer options	ICC	Mean (SD)
Social motivation	Motivation to interact with another person regardless of social goal motivation	"How much would you like to talk to or interact with someone right now?"	Not at all, A little, A moderate amount, Quite a bit, Extremely (range: 0–4)	0.65	2.09 (1.30)
Number of interactions	Number of social interactions experienced since the previous survey	"How many conversations did you have in person, by phone/text, or online, since the last time you filled out a survey?"	None, 1, 2, 3 or more (range: 0–3)	0.53	1.76 (1.07)
Goal motivation — presence	Presence of motivation to work toward one's social goal	"Would you like to take any steps toward the following social goal today?"	None for now (0), Yes (1) (binary variable)	0.46	0.59 (0.49)
Goal motivation — degree	Degree of motivation to work toward one's social goal	"How motivated are you to work on this step?" (Only presented if participant answered "Yes" to "Would you like to take any steps toward the following social goal today?")	Not at all motivated, A little motivated, Moderately motivated, Very motivated, As motivated as possible (range: 0–4)	0.69	2.67 (0.94)

identification. See Table 2 for a description of mobility metrics. See Supplemental materials for additional information regarding the calculation of these metrics.

EMA metrics were also aggregated at the daily level: variables assessing social motivation, number of social interactions since the previous survey, and degree of motivation to work on one's social goal were calculated by taking the average value of the two daily surveys. Daily values for the dichotomous variable assessing presence of desire to work toward one's social goal were calculated based on a "yes" response to at least one daily survey. If the participant responded "yes" to either survey, the daily value for this variable was set to 1; if the participant answered "no" both times, the value was set to 0. Thus, analyses included one value per participant per day for each survey as well as for each GPS mobility metric.

To determine whether greater mobility was associated with more self-reported social interactions and greater social motivation, we used multilevel linear models that incorporated EMA self-report metrics as the outcome and GPS mobility variables as a Level 1 predictor. To determine whether baseline negative symptoms and social impairment were associated with mobility, we used multilevel models that incorporated GPS mobility variables as the outcome and baseline symptom and functioning scores (i.e., CAINS, QLS-IR, SFS) as a Level 2 predictor.

Data were detrended by incorporating time point as a Level 1 predictor in each model to account for effects related to time as well as any potential changes over time attributable to the intervention. Multilevel models were run using MPlus 8 software (Muthén and Muthén, 2017). Depending on the ICC of the variable used in our analysis, the expected power to detect large effect sizes ranged from 70 % to 99 %, and the expected power to detect medium effect sizes ranged from 30 % to 80 % (Bolger et al., 2012), based on a final sample of 26 participants (see below). Heteroscedasticity was tested using a Breusch-Pagan test (Breusch and Pagan, 1979). Models in which mobility metrics were included as outcome variables demonstrated heteroscedasticity ($p < 0.001$). After log transformation of mobility metrics, models remained significantly heteroscedastic ($p < 0.001$) and we therefore ran analyses with the non-transformed data; one exception was for average flight duration, which we log transformed to account for statistical outliers.

3. Results

Of the 31 individuals who completed the clinical trial, 26 were included in the current analysis (see Table 3). One participant was excluded from analyses because of a software malfunction that prevented GPS data from being collected. Two participants were excluded after preprocessing the GPS data using the aforementioned script, as the algorithm determined that there was an insufficient number of flights (i.e., data points captured during movement) to calculate mobility metrics. One of these two participants was missing most of their GPS data, and both participants demonstrated little to no deviation from their primary location. Two additional participants were excluded due to missing 40 or more days (i.e., two-thirds of the study) of GPS data. See Supplemental Materials for additional information regarding data completeness. See Fig. 1 for example geo-location heatmaps (i.e., time spent in various locations during the study).

3.1. Sample characteristics

Most participants received disability payments, though some worked a full- or part-time job. Participants did not significantly differ in any mobility metrics in terms of gender, study location, employment status, or diagnosis. Two participants had never used a smartphone before, though this variable was not included in group difference analyses given the small sample size. See Table 3 for additional sample characteristics.

Table 3
Participant demographics and sample characteristics ($n = 26$).

Variable	Values
Diagnosis, n (%)	
Schizophrenia	13 (50)
Schizoaffective disorder	13 (50)
Race, n (%)	
Asian American	9 (35.62)
Black or African American	4 (15.38)
White	10 (38.46)
Multiracial	3 (11.54)
Hispanic or Latinx ethnicity	1 (3.85)
Gender, n (%)	
Male	11 (42.31)
Female	14 (53.85)
Non-binary	1 (3.85)
Location, n (%)	
Boston	11 (42.31)
San Francisco	15 (57.69)
Age (years), mean (SD)	45.62 (11.44)
Illness duration (years), mean (SD)	22.34 (12.87)
Antipsychotic medication, n (%)	21 (80.77)
Marital status (married, cohabitating, or divorced), n (%)	4 (15.38)
Education (college graduate), n (%)	9 (34.62)
Employed (full- or part-time), n (%)	10 (38.46)
Disability (receive disability payments), n (%)	16 (61.54)
Smartphone history, n (%)	24 (92.31)
CAINS-MAP baseline score, mean (SD, observed range)	1.58 (0.79, 0.00–2.89)
QLS-IR baseline score, mean (SD, observed range)	2.81 (1.48, 0.75–5.50)
SFS scaled baseline score, mean (SD, observed range)	107.92 (7.32, 93.00–122.43)

Note. CAINS-MAP = Clinical Assessment Interview for Negative Symptoms — Motivation and Pleasure; QLS-IR = Quality of Life Scale — Interpersonal Relations; SFS = Social Functioning Scale.

3.2. Relationship between motivation and EMA-reported social behavior

Multilevel models assessing the relationship between EMA-reported social motivation and social behavior were run to examine whether self-reported motivation and behavior were related outside the context of mobility. Greater motivation to interact with others ($b = 0.16$, SE = 0.03, $p < 0.001$), but not participants' level of motivation to work toward their social goal ($b = 0.02$, SE = 0.05, $p = 0.78$), was associated with more EMA-reported social interactions at the daily level. Additionally, greater levels of motivation to interact with others was significantly associated with greater motivation to work toward one's social goal ($b = 0.12$, SE = 0.03, $p < 0.001$). As such, participants tended to engage in more social interactions and express motivation to work toward their goal on days in which they were more motivated to talk to others in general. Further analyses regarding EMA variables and clinical assessments of social functioning were reported previously (Fulford et al., 2020).

3.3. Mobility, social drive and EMA-reported social behavior

As we predicted, findings suggested a general pattern whereby greater mobility was associated with greater EMA-reported social behavior. Less time spent at home ($b = -0.02$, SE = 0.004, $p < 0.001$), more locations visited during the day ($b = 0.10$, SE = 0.04, $p < 0.01$), lower likelihood of being stationary ($b = -0.004$, SE = 0.001, $p < 0.001$), and lower likelihood of following one's daily routine ($b = -0.01$, SE = 0.001, $p < 0.001$) were all associated with significantly more self-reported social interactions at the daily level (Table 4). However, no mobility metrics were significantly associated with either measure of social drive (i.e., motivation to either pursue a social goal or interact with others; Table 4).

Our prediction that greater baseline social impairment would be associated with lower GPS mobility was supported in two models.

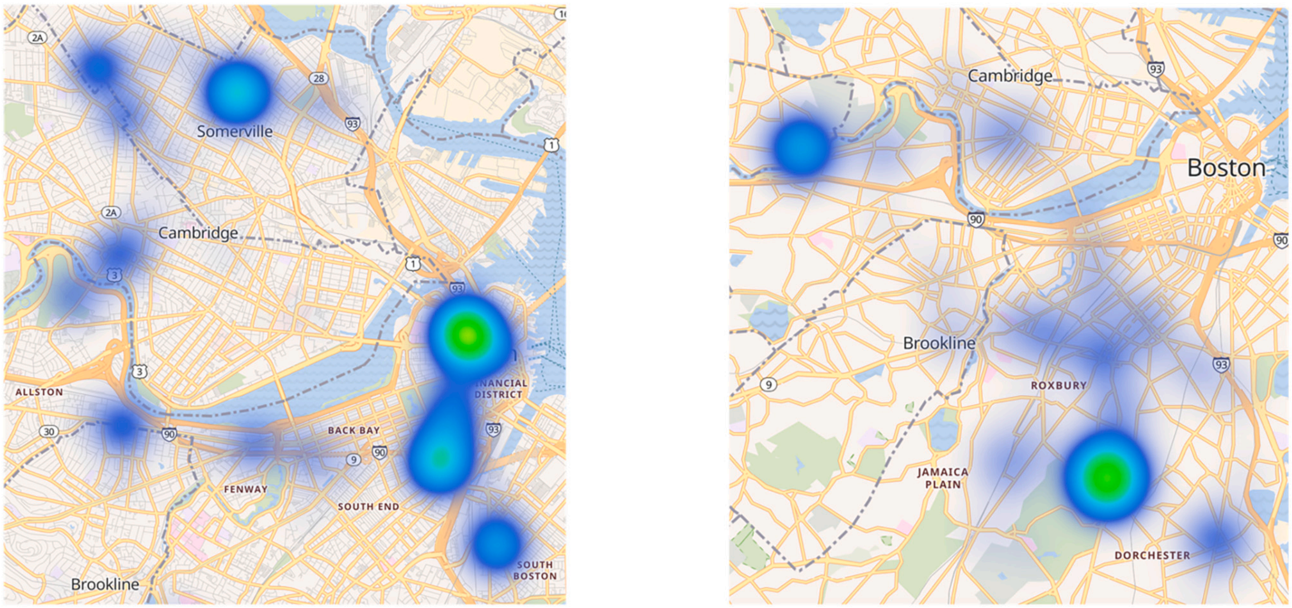

Fig. 1. Heat maps generated for two sample participants showing their movement and frequently visited locations.

Table 4
Multilevel models of mobility as predictor of social motivation and behavior.

Outcome	Predictor	Unstandardized estimate	Standard error (SE)	Confidence interval	*p*-Value
Social motivation	Home time	−0.004	0.004	−0.01, 0.004	0.37
	Significant locations	−0.02	0.04	−0.09, 0.06	0.65
	Probability of pausing	<0.001	0.001	−0.003, 0.002	0.85
	Circadian routine	−0.001	0.002	−0.004, 0.002	0.59
	Average flight duration	−0.004	0.02	−0.04, 0.04	0.85
Number of interactions	Home time	−0.02	0.004	−0.02, −0.01	<0.001***
	Significant locations	0.10	0.04	0.03, 0.16	0.006**
	Probability of pausing	−0.004	0.001	−0.01, −0.002	0.001**
	Circadian routine	−0.01	0.001	−0.01, −0.005	<0.001***
	Average flight duration	0.01	0.02	−0.03, 0.04	0.76
Desire to work on goal (Y/N)+	Home time	0.99	0.02	0.96, 1.02	
	Significant locations	1.04	0.14	0.80, 1.36	
	Probability of pausing	1.00	0.01	1.00++, 1.01	
	Circadian routine	1.00	0.01	0.98, 1.01	
	Average flight duration	0.94	0.07	0.82, 1.08	
Degree of motivation to work on goal	Home time	−0.003	0.004	−0.01, 0.004	0.42
	Significant locations	0.02	0.04	−0.05, 0.08	0.65
	Probability of pausing	<0.001	0.001	−0.002, 0.003	0.91
	Circadian routine	−0.001	0.002	−0.01, 0.002	0.40
	Average flight duration	−0.01	0.02	−0.05, 0.03	0.59

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
\+ Odds ratio reported in place of unstandardized estimate.
\++ Value < 1.00 when observed with finer resolution.

Greater social functioning at baseline (as assessed via QLS-IR) was associated with less daily time spent at home ($b = -2.05$, SE $= 0.70$, $p < 0.01$; see Fig. 2) and a lower likelihood of following daily routines ($b = -6.60$, SE $= 2.97$, $p < 0.05$). However, no other baseline clinical measures (symptoms or functioning) were related to mobility (Table 5).

To correct for multiple comparisons, we also adjusted the false discovery rate using the Benjamini-Hochberg procedure (Benjamini and Hochberg, 1995). All significant results survived this correction at a 0.05 level with the exception of the association between QLS-IR and Circadian Routine.

4. Discussion

In this study, we explored the utility of smartphone-derived mobility metrics as markers of social motivation and EMA-reported social behavior in people with schizophrenia. Findings suggested that passively collected mobility metrics showed more consistent relationships with self-reported social behavior than with social drive. Furthermore, mobility showed some associations with lower social functioning at baseline. Overall, passive markers of mobility derived from smartphones and other mobile devices could serve as indicators of important social outcomes in people with schizophrenia.

4.1. Motivation, mobility, and self-reported behavior

Social interactions were more likely to occur on days when participants distributed their time across various locations and spent less time at home, likely due to increased opportunities for social interaction

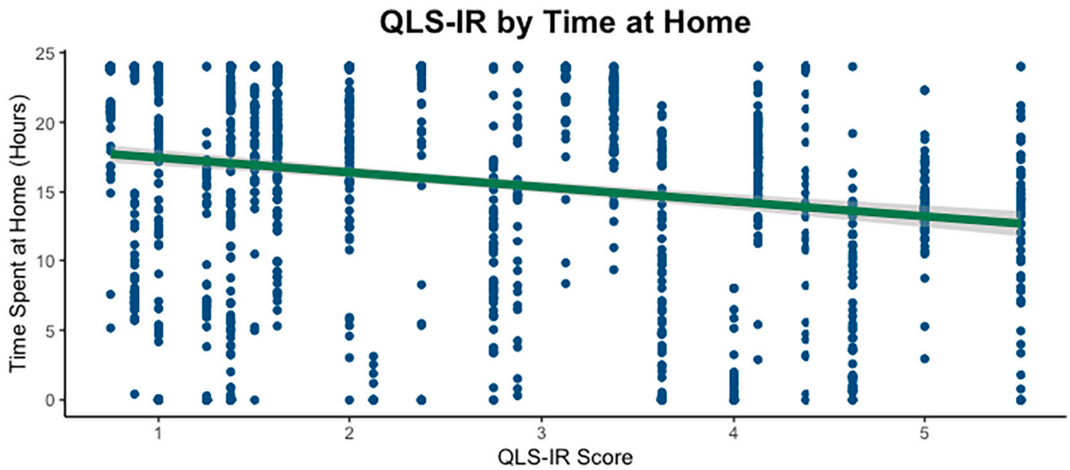

Fig. 2. Linear relationship between social functioning (QLS-IR) at baseline and daily time spent at home. Each vertical column of datapoints represents one individual participant.

Table 5
Multilevel models of baseline clinical measures as predictors of mobility. Results presented as *b* (SE).

Outcome	CAINS-MAP	QLS-IR	SFS Total
Home time	1.34 (1.55)	−2.05 (0.70)**	−0.20 (0.15)
Significant locations	−0.29 (0.20)	0.10 (0.10)	0.01 (0.02)
Probability of pausing	1.08 (3.44)	−2.03 (1.71)	0.07 (0.34)
Circadian routine	1.36 (6.39)	−6.60 (2.97)*	−0.42 (0.50)
Average flight duration	1.54 (13.47)	−2.66 (6.84)	−0.74 (1.32)

Note. CAINS-MAP = Clinical Assessment Interview for Negative Symptoms — Motivation and Pleasure; QLS-IR = Quality of Life Scale — Interpersonal Relations; SFS = Social Functioning Scale.
* $p < 0.05$.
** $p < 0.01$.

outside one's home. This was expected, given our prediction that greater activity (i.e., GPS mobility metrics) would be associated with more social behavior (i.e., self-reported number of interactions).

More social interactions were also associated with lower likelihood of following a daily routine. In people who engage in role-based activities such as work or school, less structured time (e.g., a day off from work) may provide more opportunities for social activities. However, less than half of our participants were employed, and prior research suggests that people with schizophrenia generally spend less time in structured activities than people without schizophrenia, although this was not measured within our study (Granholm et al., 2020; Hayes and Halford, 1996; Hodgekins et al., 2015; Shimitras et al., 2003). Additionally, mobility metrics did not significantly differ among participants based on employment status. It may be that participants who aimed to increase their social behavior intentionally changed their daily routine. Alternately, social interactions experienced during unstructured time may be more memorable and therefore more likely to be reported via EMA surveys.

Of note, the association of increased social interactions with decreased likelihood of following one's typical routine was somewhat unexpected given previous findings linking higher likelihood of following a daily routine with higher functioning and lower symptom severity, including decreased loneliness. One study posited that following a routine may reflect engagement in social activities with close others (Fulford et al., 2021b). Another study suggested that disruptions to social rhythms may be associated with factors that moderate symptoms and functioning (Henson et al., 2020). However, neither paper explored the mechanisms moderating this association in depth, and other factors that may be specific to social interactions or our social intervention may have affected the association between adherence to routines and functioning.

Despite the unexpected lack of association between mobility and social motivation more broadly, greater social motivation was associated with more social interactions at the daily level as reported through the EMA surveys. This indicates that in people with SZ, desire for social interaction did indeed track with social behavior. Because mobility was associated with amount of social interaction but not motivation, it may be that social interaction is associated with mobility and social motivation through different mechanisms. One possibility is that social interactions increased with mobility as a result of behavior that served a non-social purpose. For example, a trip to the store may result in a social interaction with the store clerk, but a participant might not report that they are specifically motivated to interact with the store clerk. Previous studies of quality and quantity of social interactions indicate that people with SZ may have similar numbers of social interactions as people without SZ, but the interactions they have may be of a lower quality (e.g., less meaningful engagement; (Abel et al., 2021; Fulford et al., 2021b). Collecting information about the quality of social interactions may help to clarify the relationship between mobility and social motivation and behavior. Based on these findings, interventions to increase mobility in people with schizophrenia may not be very effective for also increasing motivation and pleasure in social relationships.

4.2. *Negative symptoms and social functioning*

Higher baseline social functioning as assessed via the QLS-IR was associated with less time spent at home and lower probability of following a daily routine throughout the study, though the latter relationship did not survive correction for multiple comparisons. The QLS-IR integrates quality of social relationships, degree and frequency of social interactions, social initiative and withdrawal, and instrumental support (Heinrichs et al., 1984). In line with our finding that less time at home was associated with more social interactions, it may be that higher social functioning was at least partly a reflection of more interactions during the study. Similarly, a lower probability of following one's daily routine was associated with increased social interactions, which may have contributed to increased social functioning.

The SFS, a self-report scale of social functioning, was unrelated to mobility. While the SFS is considered a gold standard assessment used in many treatment outcome studies (Burns and Patrick, 2007), the QLS-IR was originally designed as a measure of the deficit syndrome (Abplanalp et al., 2021; Cramer et al., 2000; Rocca et al., 2014), and its items may be more strongly tied to observable behavior, like mobility, than the subjective impressions given in the SFS. Additionally, the QLS-IR may provide a more accurate representation of social behavior because it is interview-rated, rather than self-reported. Thus, geolocation-based mobility may again be more strongly related to objective social behavior than subjective social experiences.

We did not find a relationship between mobility and baseline negative symptoms, inconsistent with prior findings (Depp et al., 2019; Raugh et al., 2020). However, three factors may play an important role in this discrepancy. First, the CAINS assesses symptoms that are more closely related to the EMA questions probing social drive, which we found to be less strongly associated with GPS mobility than questions probing self-reported social behavior. Second, the scales used in clinician ratings include a broad range of domains that contribute to the constructs of negative symptoms. For example, the CAINS Motivation and Pleasure (MAP) scale assesses both anticipatory motivation and consummatory pleasure within the same scale. It is possible that mobility may be related to one or more of these domains without being related to these constructs as a whole. Lastly, our sample size was smaller than previous studies that found significant associations between mobility metrics and negative symptoms, so it is possible that we simply did not have the statistical power to detect effects.

4.3. Limitations

There are several limitations of this study to note. Our sample size was small, which limited our statistical power to detect small to moderate effects. Additionally, a limitation of GPS-based mobility data is the assumption that such mobility reflects the participant's behavior; however, participants may not keep their phone on their person at all times. There is also the problem of missing data: if a participant turns their phone off, the phone battery dies, or the software malfunctions, GPS cannot be collected. For some participants, this resulted in loss of GPS data. It is also possible that GPS data was disproportionally absent during times of either greater or lower mobility and/or social behavior. Participants also had the option to pause GPS collection, though we did not collect data on the rates/durations of pauses. GPS was also collected continuously rather than in a location-triggered method, which may have biased our metrics toward including more flights that were shorter or less obvious than those observed in studies using location-triggered GPS collection.

In addition to the technological limitations of collecting GPS data, we also faced conceptual limitations in our interpretation of mobility metrics. For example, we could not determine whether a person was alone or with someone else during a flight or a pause, which types of locations or modes of transportation were used, and what types of activities (e.g., leisure, work, structured vs. unstructured) the participant engaged in during flights and pauses. Future studies using this method of passive data collection should include objective and subjective measures of these characteristics to more fully answer these questions.

Although we collected data in two different locations, it is important to note that these findings may not generalize to all regions. For example, the San Francisco and Boston areas both have a public transportation system that may not be available to people in other regions. Similarly, findings may be different in cities and towns with different population density, as this may limit opportunities for both mobility and social activity. Participants' limited access to locations and transportation, as well as other external factors that may influence one's mobility and behavior (e.g., socioeconomic status or other environmental contributors), may also differ within cities.

The temporal specificity of this analysis is another limitation. Participants completed EMA surveys twice a day at most, and often once per day given roughly 60 % adherence overall (see Supplemental Materials for adherence statistics). Thus, we felt daily statistics were an ideal temporal resolution for providing unbiased estimates. Calculation of GPS metrics at the daily level also may have affected relationships among mobility and baseline assessments.

Additionally, data were collected from a study testing a novel treatment that aimed to increase participants' motivation. Although we did not find a significant change in motivation over the course of the study across the participants, our sample may have been biased by participants who were hoping to increase their social motivation. We also caution against the generalization of these findings to all individuals with schizophrenia, as there is substantial within-group variation in social interactions and mobility, and we may not have captured those on the lower end of functioning within our sample. Additionally, it may be possible that individuals with extremely high or low motivation might demonstrate different associations among these variables, which we may not have captured in our sample.

This study also lacked a control group, an objective measure of social behavior, and a measure of general behavior (i.e., non-social activities performed throughout the day), all of which would have improved our ability to interpret our findings. Data were collected prior to the COVID-19 pandemic, and as such, may not reflect any changes in social functioning processes that may have occurred as a result of the pandemic. Lastly, as is often the case with mobility data, the statistical models in which GPS was included as an outcome variable demonstrated heteroscedasticity, potentially biasing outcomes of the linear models we tested.

4.4. Conclusions

Greater mobility in general was related to objective social behavior (i.e., number of social interactions) in the context of a clinical trial targeting social motivation and functioning. In contrast, mobility was not significantly associated with any measures of social drive, including motivation to talk to others or pursue a social goal. Mobility therefore seems to be a valuable tool in examining objective social behavior—but not subjective social motivation—in a passive, unobtrusive way, thus putting less burden on the participant. This study supports the use of geolocation mobility data in research and interventions related to social behavior in schizophrenia. These findings are an important first step in establishing mobility metrics as a valuable tool for understanding behavior in daily life for this population, including tracking changes in behavior that may occur due to intervention and may go beyond those observed or reported during treatment sessions. As a passive measure, mobility can provide useful real-time and real-world information without creating substantial participant burden or requiring physical visits to a clinic or laboratory. We hope to see its use in further research examining the benefits of mobility on improvements in clinical outcomes.

CRediT authorship contribution statement

Contributions of each author to this manuscript are detailed below:

Jessica L. Mow participated in data collection, performed data analyses, conducted the literature review, and was the primary writer of this manuscript.

Dr. David E. Gard was a principal investigator of the clinical trial through which these data were collected, and provided feedback on drafts of this manuscript.

Dr. Kim T. Mueser was a co-investigator of the clinical trial through which these data were collected, and provided feedback on drafts of this manuscript.

Dr. Jasmine Mote played a key role in study design; participated in data collection, management, and analysis; and contributed to drafts of this manuscript.

Kathryn Gill was the research coordinator for the portion of the study conducted at Boston University, and contributed to study design, data collection and management, and feedback on drafts of this manuscript.

Lawrence Leung was the research coordinator for the portion of the study conducted at San Francisco State University, and contributed to study design, data collection and management, and feedback on drafts of this manuscript.

Tairmae Kangarloo assisted with cleaning and analyzing the GPS data used in this study, and provided feedback on drafts of this manuscript.

Dr. Daniel Fulford was a principal investigator of the clinical trial through which these data were collected, and provided feedback throughout study design, data collection, analyses, and manuscript writing. He contributed to drafts of this manuscript.

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Declaration of competing interest

The authors have no conflicts of interest to disclose.

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Appendix A. Supplementary data

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