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Capturing behavioral indicators of persecutory ideation using mobile technology

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ABSTRACT

Most existing measures of persecutory ideation (PI) rely on infrequent in-person visits, and this limits their ability to assess rapid changes or real-world functioning. Mobile health (mHealth) technology may address these limitations. Little is known about passively sensed behavioral indicators associated with PI. In the current study, sixty-two participants with schizophrenia spectrum disorders completed momentary assessments of PI on a smartphone that also passively collected behavioral data for one year. Results suggested that PI was prevalent (n = 50, 82% of sample) but had infrequent incidence (25.2% of EMA responses). PI was also associated with changes in several passively sensed variables, including decreases in distance traveled ($M_{kilometers} = -1.20$, SD = 18.88), time spent in a vehicle ($M_{minutes} = -4.15$, SD = 49.59), length of outgoing phone calls ($M_{minutes} = -0.79$, SD = 13.13), time spent proximal to human speech ($M_{minutes} = -6.26$, SD = 153.03), and an increase in time sitting still ($M_{minutes} = 4.04$, SD = 94.69). The present study suggests changes associated with PI may be detectable by passive sensors, including reductions in moving or traveling, and time spent around others or in self-initiated phone conversations. These constructs might constitute risk for PI.

1. Introduction

Persecutory delusions are among the most common (Bebbington and Freeman, 2017; Coid et al., 2013; Freeman and Garety, 2014), impairing (Bowie et al., 2006), and treatment-resistant (Freeman et al., 2016a; Garety et al., 2015) of all psychotic symptoms. They are associated with rehospitalization (Castle et al., 1994), social isolation (Kuipers et al., 2006; Smith et al., 2006), and disruption of functioning (Bowie et al., 2006). Treating persecutory delusions is challenging. Medications demonstrate low adherence rates (Leucht et al., 2013), and psychosocial interventions have limited effect on these beliefs' intractability (Bell et al., 2006; Freeman, 2007). Though impairing and treatment-resistant, persecutory delusions are not static (Freeman, 2016, 2007; Freeman et al., 2002; Zubin and Spring 1977). Persecutory ideation (PI) comprises a continuum from infrequent, changeable, non-disruptive thoughts about being harmed (Verdoux et al., 1998; Verdoux and Van Os, 2002) to severe delusions (Fusar-Poli et al., 2017; Paolini et al., 2016). PI emerges in response to environmental stressors (Lataster et al., 2013; Lincoln et al., 2015; Myin-Germeys et al., 2003), concurrent with elevations in worry (Freeman and Garety, 1999), negative self-beliefs (Ben-Zeev et al., 2009; Vorontsova et al., 2013), or anomalous sensory experiences (So et al., 2017). It may be possible, with improved assessment of these PI risk factors to intervene early to prevent or mitigate severe episodes (Reininghaus et al., 2016a).

It is challenging to effectively assess PI and its related risk factors in an ongoing manner. Many leading assessment strategies, including in-person self-report measures or clinical interviews (Bell et al., 2017), have considerable limitations. Changes in PI occur on a brief time scale

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(Ben-Zeev et al., 2012b, 2011), and often only in one's lived environment outside the clinic or office (Ben-Zeev et al., 2012a). In-person measures quantify variability between respondents but not changes that occur over time within a single individual. A number of technologies – pagers with accompanying journals (Lataster et al., 2013; Peters et al., 2012; Thewissen et al., 2011, 2008), palm pilots or PDAs (Ben-Zeev et al., 2011), and more recently mobile phones (Depp et al., 2010) – have been used to deploy a mobile data collection technique called ecological momentary assessment, or EMA (Bell et al., 2017; Granholm et al., 2008). These approaches appear feasible in participants with significant PI and have helped identify a number of risk factors, including reduced self-esteem (Thewissen et al., 2011), increased negative affect (Lataster et al., 2013), and aberrant sensory experiences (Broyd et al., 2017; Reininghaus et al., 2016b). Novel interventions have been developed to target these and related domains (Combs et al., 2007a,b; Freeman et al., 2017, 2016b, 2015; Lahera et al., 2013; Roberts et al., 2014). However, EMA still relies on patient self-report, which is susceptible to minimization, demand characteristics, and poor insight (Sabbag et al., 2012). EMA also places a requirement on patients to complete frequent assessments, which can be perceived as disruptive or burdensome.

Passive sensing of behavior – the automatic collection of data with existing smartphone features (e.g. sound, motion and tracking of calls/texts) – might provide a more sustainable option. Sensing appears to be feasible, acceptable to individuals with SMI, and informative to illness course (Ben-Zeev et al., 2016; Wang et al., 2016). Passive sensors provide frequent observations that do not require active user participation. Existing models (Freeman, 2016) suggest that PI may manifest behaviorally. Individuals experiencing PI report that they are more likely to isolate, stay home, and avoid or escape situations that they perceive to be potentially threatening (Freeman et al., 2007, 2001). Passive sensing technologies can be deployed to indicate whether individuals have left home, traveled extended distances, or spent time around others. Little is known about what passively sensed behavioral indicators might be associated with PI. The ability to detect PI passively using sensors could facilitate more timely and targeted treatment delivery while posing minimal patient burden.

In the current study, we examined data collected via an integrated mobile health system over the course of an entire year to (1) quantify between- and within-person variability in PI, (2) evaluate pre-existing models of indicators of PI (e.g. worry, negative self-beliefs and anomalous perceptions) with EMA gathered over a longer timespan than extant studies, and (3) identify passively sensed indicators of PI.

2. Methods

2.1. Participants

Participants were recruited from outpatient treatment programs at a large psychiatric hospital in New York. Inclusion criteria were (1) being 18 years or older; (2) having a diagnosis of schizophrenia, schizoaffective disorder, or psychosis not otherwise specified; and (3) the occurrence of an inpatient psychiatric hospitalization, daytime psychiatric hospitalization, outpatient crisis management visit, or short-term psychiatric hospital emergency room visit within the last 12 months. Individuals were excluded if they (1) had hearing, vision, or motor impairment making smartphone operation impossible (determined using a demonstration smartphone during screening); (2) had a reading level below the 6th grade (determined using the reading section of the Wide Range Achievement Test) (Wilkinson and Robertson, 2004); or (3) were unable to provide informed consent (i.e. pass a competency screener).

2.2. Procedure

All participants were given a Samsung Galaxy S5 Android smartphone with an unlimited data, call and text plan for one year. They were asked to carry the phone with them during the course of the study and to make sure to charge the device each night. This device had an integrated mobile health assessment system called CrossCheck pre-installed. CrossCheck comprised EMA self-report scales and multimodal behavioral sensing data from sensors that are come pre-installed on most smartphones (Ben-Zeev et al., 2017; Wang et al., 2017, 2016).

Table 1
Overview of EMA items gathered by CrossCheck examined in the present study.

EMA item
Prompt: Just checking in to see how you've been doing over the last few days.
Have you been SOCIAL?
Have you been bothered by VOICES?
Have you been SEEING THINGS other people can't see?
Have you been feeling STRESSED?
Have you been worried about people trying to HARM you?
Have you been SLEEPING well?
Have you been DEPRESSED?

0 = Not at all; 1 = A little; 2 = Moderately, 3 = Extremely.

2.3. Ecological momentary assessment (EMA)

CrossCheck prompted participants to complete a brief, 10-item self-report measure three times per week (i.e. each Monday, Wednesday and Friday during the study period), with the prompt, "Just checking in to see how you've been doing over the last few days." Response options for each items ranges from 0 (*not at all*) to 3 (*extremely*). PI was assessed with the following EMA item: "Have you been worried about other people trying to HARM you?". In addition to symptoms of psychosis, EMA items also assessed mental health (e.g., stress, depression, hopefulness, calmness, clarity of thought), and functioning (e.g., socialization, sleep). These items are listed in Table 1.

2.4. Multimodal behavioral sensing measures

Physical activity. Physical activity is assessed by multiaxial accelerometers through Google Activity Recognition Application Programming. While these data are collected continuously, CrossCheck generates a rating of each activity every 10 s when the user is moving and every 30 min if the device is still. For the present analysis, physical activity variables were represented as the amount of time (in total hours per day) that the individual was engaged in a number of activities, including sitting still, moving on foot, and riding in a vehicle.

Geospatial activity. Global positioning system (GPS), Wi-Fi, and cellular tower location services allow for time-stamped estimates of participants' approximate location. Each new location detected via the positioning system allows for a calculation of distances traveled and locations. For the present analysis, this included the number of discrete locations visited as well as distance traveled (in kilometers). In light of several extreme values in the case of atypical travel (e.g. long flights), the distance traveled variable was adjusted (> 95th percentile, and < 5th percentile replaced with the 95th and 5th percentile value respectively).

Speech frequency and duration. CrossCheck applies a speech detection algorithm to quantify the amount of time during which speech is present or absent by activating the smartphone microphone. The device microphone is automatically activated every 3 min to assess surrounding sound. This system does not record raw audio on the device, but instead, classifies this data in real time according to whether speech is recorded, logging the start and end times. Speech duration (overall time classified as speech being present, measured in hours) is calculated and assessed in the present analysis.

Device use measures. CrossCheck automatically logs telecommunication activity, SMS text message logs, as well as number and duration of phone calls. In order to protect participant privacy, no written or audio content of these messages or calls is recorded. In the present study, number of calls and SMS messages placed are assessed.

2.5. Data analytic plan

We used an exploratory analytic framework that included (1) quantifying PI descriptively and (2) identifying its momentary digital indicators. First, descriptive statistics, including means, standard deviations, and item frequencies were examined to quantify the frequency, severity, and within- and between-person variability of PI. Second, potential indicators were identified from Freeman's updated *cognitive model of persecutory ideation* (Freeman, 2016), with the expectation of positive relationships to indicators of negative affect, worry, anomalous perceptual experiences, and sleep disturbances, and negative relationships to social and physical activity. Multilevel models with repeated EMA observations nested within person were used to examine between-participant and within-participant indicators of PI. Person-mean centering was used to create two variables for each indicator: (1) the mean daily value for each participant across days (i.e., between-participants effect) and (2) a person-mean centered variable with each participant's mean value subtracted from each daily value (i.e., within-participants effect). In calculating these variables and all models, data were selected on days in which participants provided an EMA response related to PI. Models involving passive sensing variables selected days in which 19 or more hours of data (consistent with prior sensing work; Wang et al., 2016) were recorded by the relevant sensor (e.g. for the speech variable, the audio sensor). The between- and within-person variables for each indicator were simultaneously entered as fixed effects in multilevel models, such that within-participant variability was statistically separated from between-participant variability.[1] Separate multilevel models were fit for each indicator (with each model including the within- and between-person variable) to prevent model overfitting and to accommodate the exploratory nature of the analyses, as this is – to our knowledge – the first study using passive sensing to identify characteristics that emerge alongside PI. Models were fit with restricted maximum likelihood and included fixed and random participant-level intercepts. To better characterize significant effects in models (the coefficients of which are reported in Table 2), we also compared the means of significant correlates during periods when PI was reported (at any level) versus periods when PI was reported as "not at all."

3. Results

The majority (n = 45) of the 62 randomized participants fully completed the study. One participant did not begin participation after randomization. On average, CrossCheck generated a data entry for 262.80 days (SD = 97.17) per participant, and on average, participants provided 84.52 (SD = 45.79) responses to the EMA persecutory ideation item. Within those days, passive sensors varied with regard to the hours of data they collected per day on average, as audio (M_{hours} = 17.81, SD = 9.03) and location sensors (M_{hours} = 17.12, SD = 9.51) logged more data than activity sensors (M_{hours} = 12.65, SD = 8.55). As mentioned, to reduce the impact of these missing data, models involving passive sensors selected days on which CrossCheck logged 19 or more hours of data. EMA responses were provided on slightly less than one third of the days for which participants' devices logged data ($M_{EMA\%}$ = 31.48% SD = 10.65%). If a participant were to respond to all EMAs when they were prompted (three times per week), this value would equal approximately 42.8%.

3.1. Frequency and distribution of PI

PI varied considerably within and between participants during the study period. Fifty participants (82%) reported at least "a little" PI on one or more occasions, whereas 11 (18%) reported none for the duration of the study. Among participants who endorsed PI at least once, the majority (n = 39, 78%) still reported having none on a majority of days. At the aggregate level, the overall mean PI severity score across all participants and time points was relatively low; about three quarters (75%) of all responses across participants were zero, and fewer were spread across the responses of "a little" (16%), "moderately" (6%), and "extremely" (4%).

3.2. Ecological momentary assessment indicators

Between-participant differences. All EMA indicators demonstrated between-participant relationships to PI (*ps* < .01, see Table 2). Average PI reported was higher for participants who on average reported elevated rates of depression, stress, hearing voices, seeing things, and reduced rates of reporting feeling social and sleeping well.

Within-participant differences. When examining within-participant changes, we similarly found significant relationships between all EMA indicators and PI, and most but not all were in the expected direction. Reports of increases in depression, stress, hearing voices, and seeing things all were related to reports of PI, as expected. However, additionally, there were small but significant positive relationships with reports of feeling social and sleeping well, such that these variables were associated with increased PI (rather than decreased PI as we expected).

3.3. Passive sensing

Between-participant differences. No between-participants passive sensing variables were significantly related to PI (see Table 2).

Within-participant differences. Several within-participant passive sensing variables were associated with greater PI in a manner generally consistent with study hypotheses (see Table 2). When individuals reported PI, they demonstrated an increase relative to typical behavior in time sitting still ($M_{minutes}$ = 4.04, SD = 94.69) and a decrease in distance traveled ($M_{minutes}$ = −1.20 km, SD = 18.89) and time spent in a vehicle ($M_{minutes}$ = −4.15, SD = 49.59). Participants' social behavior was affected as well, as those reporting greater PI spent significantly less time around speech ($M_{minutes}$ = −6.26, SD = 153.03) and on outgoing phone calls ($M_{minutes}$ = −0.79, SD = 13.13).

4. Discussion

Our study adds to a growing body of evidence supporting the feasibility and utility of mobile technologies to assess psychotic symptoms. As participants responded to EMA prompts over the course of a 12-month data collection period, present results provide support for the scalability of integrated mobile assessment. Results suggest that PI is non-static and occurs in a manner that is consistent with existing conceptual models of PI (Freeman, 2016). In our sample, PI was a common but dynamic phenomenon. While the majority of participants reported at least some occurrences of PI at some point during the data collection period, most of those individuals reported it in less than half of their EMA entries. Three quarters of all EMA entries across all participants reported no PI. This is consistent with stress-vulnerability models of psychosis (Zubin and Spring 1977) suggesting that psychotic symptoms fluctuate over time.

EMA variables generally demonstrated relationships to behavioral indicators related to domains described in existing models of PI. As hypothesized, individuals who reported more PI tended to report being

[1] For passive sensing variables, to aid in interpretability of findings, persecutory ideation variables are multiplied by 100 such that parameter estimates represent a hundredth of a point change in the outcome for one point change in the indicator.

Table 2
Between and within-participants predictions of persecutory ideation from EMA and passively sensed variables.

Between-participant differences				Within-participant changes			
	B	SE	p		B	SE	*p*
EMA Self-Report				***EMA Self-Report***			
Depressed	0.45	0.09	< .000***	Depressed	0.29	0.01	< .000***
Stressed	0.33	0.08	< .000***	Stressed	0.34	0.01	< .000***
Voices	0.79	0.10	< .000***	Voices	0.41	0.01	< .000***
Seeing Things	0.92	0.10	< .000***	Seeing Things	0.50	0.01	< .000***
Social	−0.22	0.08	.008**	Social	0.07	0.01	< .000***
Sleeping	−0.38	0.08	< .000***	Sleeping	0.06	0.01	< .000***
Passive Behavioral Sensing				***Passive Behavioral Sensing***			
Activity and Location				*Activity and Location*			
Still	−1.75	3.24	.59	Still	1.35	0.67	.04*
Vehicle	4.16	9.02	.65	Vehicle	−3.92	1.23	.001**
On foot	1.15	9.40	.90	On foot	−1.28	1.64	.44
Distance	0.40	0.43	.36	Distance traveled	−0.20	0.05	< .001***
Locations visited	4.70	9.56	.63	Locations visited	−0.97	0.93	.30
Social				*Social*			
Speech	−0.20	2.82	.94	Speech	−0.65	0.32	.04*
Calls out	−12.34	29.85	.68	Call out	−6.08	2.83	.03*
SMS out	−0.43	0.51	.40	SMS out	−0.02	0.05	.71

^$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$.
For passive sensing variables, to aid in interpretability of findings, persecutory ideation variables are multiplied by 100. All time-related predictors entered in hours. Distance is measured in kilometers.

more depressed and stressed, more severe auditory and visual hallucinations, and being less social or sleeping less well. Further, PI tended to increase within-individuals as they experienced worse depression, stress, voices, and seeing things. Notably, two unexpected findings emerged when examining within-participants changes associated with PI: small but significant *increases* in self-reported socializing and sleeping well. It's possible that reports of PI might coincide with more intense affective states in general, differing from non-acute phases of illness characterized primarily by negative symptoms (Strauss et al., 2010). Alternately, these patterns might reflect that PI coincides with the participants' perception of increased social contact (e.g. *I feel paranoid because I have been social*) or greater time spent in bed avoiding others.

Third, several passive sensing indicators similarly adhered to existing models of PI. Experimental (Freeman and Garety, 1999; Vorontsova et al., 2013) and EMA (Bell et al., 2017; Ben-Zeev et al., 2011; Peters et al., 2012; Thewissen et al., 2011, 2008) studies have suggested that certain behaviors are linked to the emergence and maintenance of PI; the present study provides additional support assessing these behaviors directly and in the moment. When experiencing PI, affected individuals tend to self-report avoiding potentially threatening situations to maintain safety, and the tendency to do this is associated with heightened distress (Freeman et al., 2007). The present study suggests that traces of these safety behaviors may be detectable by passive sensors, including reductions in activity, traveling (particularly in a vehicle), time spent with others and in self-initiated phone conversations. Importantly, the characteristics linked to PI in the present study were those that represented within-participant change, rather than between-participants averages. This provides additional support for stress-vulnerability models of PI. It also suggests that existing assessment strategies that provide aggregate estimates over extended periods miss potentially important within-participants changes. Person-centered assessments provided by mHealth might detect changes with greater granularity and improve the ability of providers to quickly detect risk.

This study is not without limitations. These results provide an exploratory examination of in-the-moment passively sensed indicators associated with PI. Given the correlational nature of our analyses, it is possible that related psychiatric symptoms (e.g. mood symptoms) or a third unknown or unmeasured variable (e.g. medication side effects) partially accounted for or affected identified relationships. This might be further complicated if specific factors correlated with a participants' decreased likelihood to respond to EMA items. Also, while our data allow examination of several key pieces of cognitive models of PI, they are not exhaustive. Several other phenomena that have been suggested to play a role in the emergence and maintenance of PI – e.g. aberrant salience (Reininghaus et al., 2016b), cognitive biases (Dudley et al., 2016), hostile attribution bias (Buck et al., 2017, 2016; Dennis R Combs et al., 2007a,b) – were not examined. Further, it was also the case that our measure of PI was brief and narrow, operationalized only as harm, when PI often comprises a range of varied concerns. There is a need for more extensive psychometric validation of differing forms of EMA, which is lacking given the relative novelty of such approaches. Last, relationships between passive sensing variables and PI, though significant, were small. It is possible that examining in-the-moment indicators of psychotic symptoms across individuals may obscure idiosyncrasies that more closely track their emergence. For example, other CrossCheck studies have demonstrated that rather than having consistent patterns across individuals, each person might present with their own specific “relapse signature” (Ben-Zeev et al., 2017) that could be identified and used in clinical risk prediction.

Overall, the present study provides replication and support of several components of existing models of PI (Freeman, 2016; Freeman et al., 2002) and introduces a new methodology that adds a dimension to the assessment of PI. These findings contributes to evidence supporting individuals with paranoia engaging with mobile assessments including EMA and passive sensing. Proximally, these results suggest that there might be value in closely monitoring changes in behavior, particularly travel and contact with others. More distally, these results add to the growing support for the development of integrated mobile health systems in routine clinical care. Such systems may be feasible, scalable, and particularly well-suited for the treatment of PI, as PI appears to fluctuate over time and coincide with specific behavioral changes that these systems can detect.

Conflicts of interest

Dr. Ben-Zeev has an intervention content licensing and consulting agreement with Pear Therapeutics. Dr. Campbell is a consultant for Verily Life Sciences. Dr. Choudhury is a co- founder and holds equity stake at HealthRhythms Inc. Dr. Kane has been a consultant for or received honoraria from Alkermes, Eli Lilly, EnVivo Pharmaceuticals (Forum), Forest (Allergan), Genentech, H. Lundbeck. Intracellular Therapies, Janssen Pharmaceutica, Johnson and Johnson, LB Pharmaceuticals, Merck, Minerva, Neurocrine, Otsuka, Pierre Fabre, Reviva, Roche, Sunovion, Takeda, LB Pharmaceuticals and Teva. He has received grant support from Otsuka, Lundbeck and Janssen, and participated in Advisory Boards for Alkermes, Intracellular Therapies, Lundbeck, Neurocrine, Otsuka, Pierre Fabre, Takeda, Teva. Dr. Kane is also a shareholder in Vanguard Research Group and LB Pharmaceuticals, Inc. The other authors have no other potential conflicts to disclose.

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