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Specific associations of passively sensed smartphone data with future symptoms of avoidance, fear, and physiological distress in social anxiety

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A R T I C L E I N F O

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A B S T R A C T

Background: Prior literature links passively sensed information about a person's location, movement, and communication with social anxiety. These findings hold promise for identifying novel treatment targets, informing clinical care, and personalizing digital mental health interventions. However, social anxiety symptoms are heterogeneous; to identify more precise targets and tailor treatments, there is a need for personal sensing studies aimed at understanding differential predictors of the distinct subdomains of social anxiety. Our objective was to conduct a large-scale smartphone-based sensing study of fear, avoidance, and physiological symptoms in the context of trait social anxiety over time.

Methods: Participants ($n = 1013$; 74.6 % female; M age = 40.9) downloaded the LifeSense app, which collected continuous passive data (e.g., GPS, communication, app and device use) over 16 weeks. We tested a series of multilevel linear regression models to understand within- and between-person associations of 2-week windows of passively sensed smartphone data with fear, avoidance, and physiological distress on the self-reported Social Phobia Inventory (SPIN). A shifting sensor lag was applied to examine how smartphone features related to SPIN subdomains 2 weeks in the future (distal prediction), 1 week in the future (medial prediction), and 0 weeks in the future (proximal prediction).

Results: A decrease in time visiting novel places was a strong between-person predictor of social avoidance over time (distal $\beta = -0.886$, $p = .002$; medial $\beta = -0.647$, $p = .029$; proximal $\beta = -0.818$, $p = .007$). Reductions in call- and text-based communications were associated with social avoidance at both the between- (distal $\beta = -0.882$, $p = .002$; medial $\beta = -0.932$, $p = .001$; proximal $\beta = -0.918$, $p = .001$) and within- (distal $\beta = -0.191$, $p = .046$; medial $\beta = -0.213$, $p = .028$) person levels, as well as between-person fear of social situations (distal $\beta = -0.860$, $p < .001$; medial $\beta = -0.892$, $p < .001$; proximal $\beta = -0.886$, $p < .001$) over time. There were fewer significant associations of sensed data with physiological distress. Across the three subscales, smartphone data explained 9–12 % of the variance in social anxiety.

Conclusion: Findings have implications for understanding how social anxiety manifests in daily life, and for personalizing treatments. For example, a signal that someone is likely to begin avoiding social situations may suggest a need for alternative types of exposure-based interventions compared to a signal that someone is likely to begin experiencing increased physiological distress. Our results suggest that as a prophylactic means of targeting social avoidance, it may be helpful to deploy interventions involving social exposures in response to decreases in time spent visiting novel places.

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Personal sensing, or the passive collection of data from networked smartphone sensors (Mohr et al., 2020), holds promise for personalizing digital mental health interventions, uncovering new treatment targets, and augmenting traditional clinical care (Wang and Miller, 2020). A growing number of studies have attempted to leverage personal sensing data to predict social anxiety symptoms, with findings indicating that a combination of call, text, accelerometer, and location based biomarkers reliably predict social anxiety severity ($r = 0.7$ (Jacobson et al., 2020); 85 % accuracy (Boukhechba et al., 2018)). Of these features, duration of time at home appears to be a particularly strong indicator (Boukhechba et al., 2018; Chow et al., 2017). Together, this growing body of literature supports the feasibility of identifying clinically relevant digital markers of trait social anxiety symptoms using passive smartphone data collection. However, these studies have been conducted primarily in small samples of university students (Jacobson et al., 2020; Boukhechba et al., 2018; Chow et al., 2017), raising questions about the generalizability of findings (Currey and Torous, 2022; Müller et al., 2021).

Additional challenges with personal sensing for social anxiety, particularly if there is an eventual goal of harnessing these data to personalize digital health interventions, include (1) understanding the time scale of prediction, and (2) parsing the heterogeneity of social anxiety symptoms. Regarding the former, we are unaware of any studies that consider how different lags between sensed data and symptom assessment may impact predictive power—a critical question for foundational work towards personalized interventions. Regarding the latter, social anxiety disorder is multifaceted; patients present with a range of symptoms across the domains of fear, avoidance, and physiological distress (Radomsky et al., 2006). However, this heterogeneity is unaddressed in most sensing studies, which examine relationships of smartphone data with social anxiety symptoms in aggregate. In a notable exception, again in a small sample of primarily university students, researchers demonstrated that the accuracy of symptom prediction from sensed data varied considerably across 7 different EMA-measured social anxiety outcomes (Rashid et al., 2020). The poorest prediction was found for social avoidance (Rashid et al., 2020).

Difficulties in predicting avoidance symptoms from sensed data are noteworthy in the context of the cognitive-behavioral model of social anxiety disorder (Rashid et al., 2020). The cognitive-behavioral model posits avoidance as a key driver of social anxiety symptoms, including fear of social situations (Clark and Wells, 1995; Hofmann, 2007; Rapee and Heimberg, 1997). Data from treatment studies support this notion; in cross-lagged models of treatment effects, behavioral avoidance is a stronger predictor of fear than vice versa (Aderka et al., 2013), and interventions that target avoidance early in the course of treatment (i.e., by session 2) have high effect sizes (>2) (Clark et al., 2003; Clark et al., 2006). Given the demonstrated centrality of avoidance symptoms in the maintenance and treatment of social anxiety, the ability to better predict avoidance from passively sensed data, and to distinguish passively sensed markers of avoidance relative to other social anxiety subdomains, would have important implications for mechanistic models and treatment of social anxiety.

In the present study, we aimed to evaluate the relationship between smartphone sensor-based behavioral markers and trait social anxiety symptoms of avoidance, fear, and physiological distress. Through a secondary analysis of data collected in a large sample, we examined sensed features' prospective relationships to each social anxiety subdomain severity, as well as their utility as distal or proximal predictors, using sensor data windows shifting from directly before the symptom assessment to 2 weeks prior (Fig. 1). Given the centrality of diminished positive experiences in social anxiety (Kashdan, 2007), and the role of

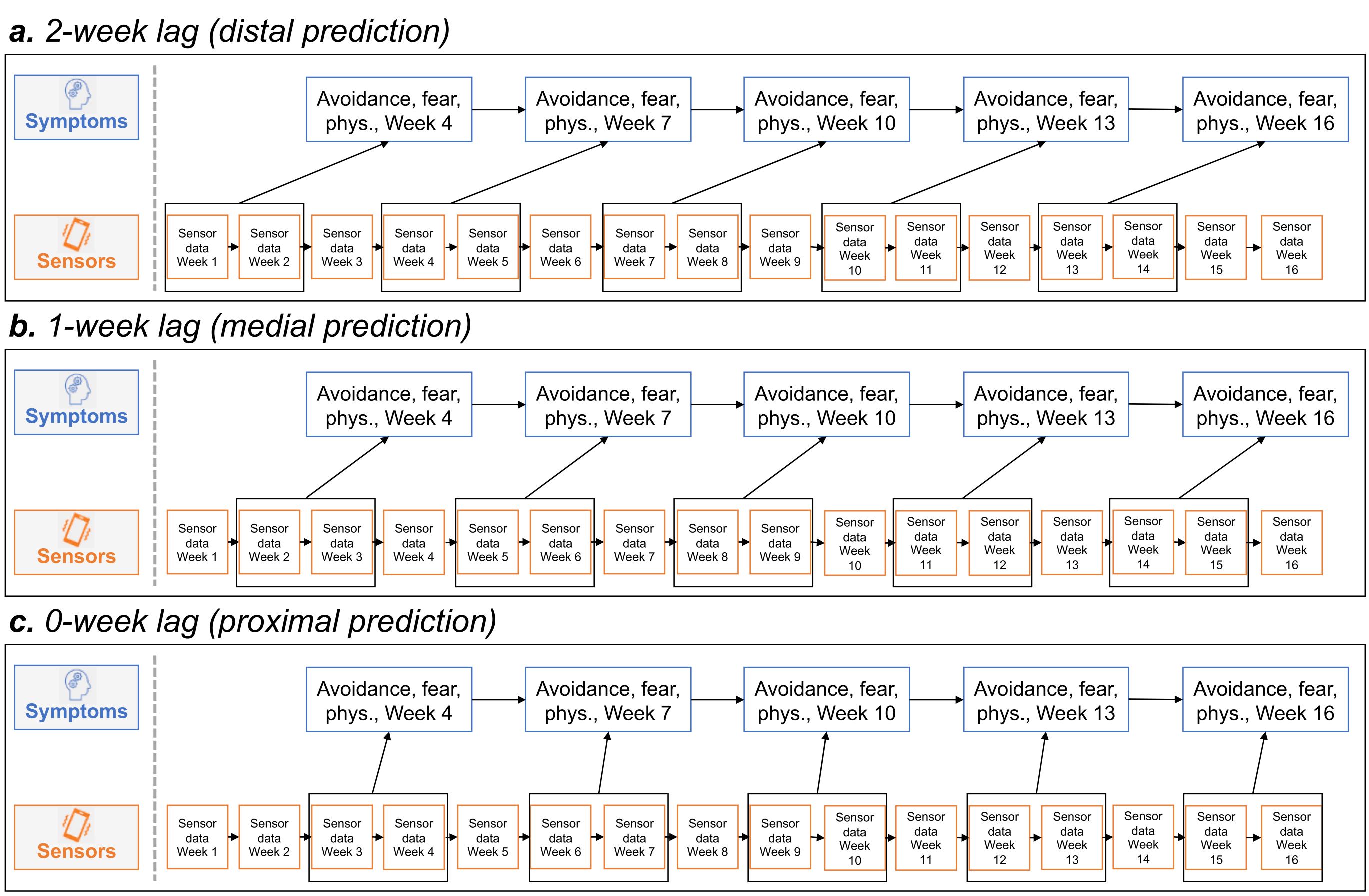

Fig. 1. Testing the influence of past-2-week sensor data on social anxiety symptom subdomains (avoidance, fear, and physiological distress) with a 2 week lag (distal prediction), 1 week lag (medial prediction), and 0 week lag (proximal prediction).

low positive affect in avoidance specifically (Trew and Alden, 2012), we hypothesized that avoidance symptoms would relate to decreased novelty-seeking and communication. We also expected that increased home duration would relate to one or more social anxiety subdomains, in line with previous literature (Boukhechba et al., 2018; Chow et al., 2017).

1. Methods

1.1. Participants

We recruited 1093 participants across 3 waves (Wave 1: July–September 2019; Wave 2: February–April 2020; Wave 3: January–April 2021). Recruitment sources included the following: ResearchMatch.org, a national health volunteer registry supported by the National Institutes of Health; Focus Pointe Global, a market research data collection company; and digital advertisements (e.g., posts on Instagram, Facebook, Twitter, Craigslist, etc.). We also recruited from the Center for Behavioral Intervention Technologies (CBITs) research registry, a database of people who have consented to be contacted for research. The registry was populated through a variety of means, including social media advertising and research participants who expressed interest in being contacted about future studies.

This paper reports on a secondary analysis of existing data (Meyerhoff et al., 2021; Meyerhoff et al., 2023; Liu et al., 2021; Stamatis et al., 2022). Because the parent study aims were centered on depression symptoms (Stamatis et al., in review), stratified sampling was conducted based on baseline Patient Health Questionnaire-8 (PHQ-8) scores. The PHQ-8 is a well-validated measure of depression with 88 % sensitivity and 88 % specificity, and is frequently used to identify clinically significant depression symptoms in decentralized clinical research (Kroenke et al., 2009). In Wave 1 and Wave 2, we recruited such that a minimum of 50 % experienced at least moderate depression symptoms (PHQ-8 $\geq$ 10), which was increased to 100 % of Wave 3 participants. Additional inclusionary criteria involved being at least 18 years old, a U. S. resident, and able to read English, as well as owning an Android smartphone with an active data and text messaging plan. We excluded participants with a history of bipolar disorder, manic, or hypomanic episode, schizophrenia, or other psychotic disorder.

1.2. Procedure and measures

All procedures were approved by the Northwestern University Institutional Review Board, and all participants provided informed consent prior to engaging in the 16-week study. Participants downloaded the LifeSense app (Audacious Software, 2018), which facilitated the collection of a range of passively sensed smartphone data (GPS, app and device use, and communication data; see Supplementary Table S1 for a list of sensors used and frequency acquired, consistent with Saeb et al., 2015). Participants completed the Social Phobia Inventory (SPIN) (Connor et al., 2000) via REDCap every three weeks (i.e., weeks 1, 4, 7, 10, 13, 16) (Harris et al., 2019; Harris et al., 2009). The three subscales of the SPIN, which measure fear, avoidance, and physiological arousal in the context of social anxiety, were used as the primary outcomes in this study and demonstrated high internal consistency in our sample (Supplementary Table S2). Participants were compensated up to \$142 for completion of assessments.

1.3. Analytic methods

We tested a series of multilevel linear regression models in R using the *lmerTest* package with maximum likelihood estimation (Kuznetsova et al., 2017). Multilevel models were selected in order to parse within-person versus between-person associations of sensed data and symptoms, with the idea that person-specific relationships would likely be most relevant to personalized digital health interventions. We evaluated the associations of clustered sensor features (see Supplement and Table S3 for details on clustering) across weeks with subsequent social anxiety subdomains. In order to understand the impact of prediction lag on the relationships between sensor data and social anxiety symptoms, we tested three different models for each outcome: (1) 2-week lag (Fig. 1a, "distal prediction"); (2) 1-week lag (Fig. 1b, "medial prediction"); (3) 0-week lag (Fig. 1c, "proximal prediction"). The sensed features were person-mean-centered such that for each feature, both a person mean term and a within-person deviation term were included in the model. Additional variables in the model included demographic covariates (age and gender), the effect of time (week), and the random effect of person.

2. Results

2.1. Demographic data

Data were available from 1013 participants (74.6 % female; mean age = 40.9 years [*SD* = 12.7]; see Table 1 for complete demographic data). The models included a total of 4617 avoidance scores (of 5065 possible; 8.85 % missing), 4638 fear scores (of 5065 possible; 8.43 % missing), and 4641 physiological distress scores (of 5065 possible; 8.37 % missing). There were no adverse events reported.

2.2. Sensor data

There were generally low rates of missing data across the sensed features: Application Launch, 8.5 % missing; Calls (Communication), 4.9 % missing; SMS (Communication), 6.8 % missing; GPS Location, 4.3 % missing. Given this, we filled impacted features with the average value of all participants across the past 14 days, such that we did not drop any participant from analyses for missing passive data.

2.3. Primary results

Table 2 contains results for all within- and between-person effects of sensor data on SPIN social avoidance over time. Results for sensor data on SPIN fear and physiological distress subscales can be found in Tables 3 and 4, respectively. For parsimony, in the text, we only describe sensed features with at least some significant relationships to social anxiety outcomes.

2.3.1. Avoidance

Communication, location, and phone use features predicted self-reported avoidance symptoms, with five out of the 14 sensed features showing at least one significant association. Participants who engaged in greater phone-based communication in comparison to other participants (i.e., between-person) were less likely to report social avoidance in the future and concurrently (distal $\beta = -0.882$, $p = .002$; medial $\beta = -0.932$, $p = .001$; proximal $\beta = -0.918$, $p = .001$). Similarly, communicating less relative to one's average communication (i.e., within-person) predicted future self-reported avoidance severity (distal $\beta = -0.191$, $p = .046$; medial $\beta = -0.213$, $p = .028$), though within-person communication did not relate to proximal self-reported avoidance. People who were frequently going to novel places were less likely to report future and concurrent social avoidance (between-person distal $\beta = -0.886$, $p = .002$; medial $\beta = -0.647$, $p = .029$; proximal $\beta = -0.818$, $p = .007$). However, within-person effects for this feature related to self-reported avoidance severity were non-significant. When people spent more time on gaming apps relative to their own average, they were more likely to report avoidance in the near future as well as concurrently (within-person medial $\beta = 0.148$, $p = .036$; proximal $\beta = 0.190$, $p = .007$), though the distal within-person effect and all between-person effects were non-significant.

Table 1
Demographic data.

Variable	All waves (*n* = 1013)	Wave 1 (*n* = 265)	Wave 2 (*n* = 332)	Wave 3 (*n* = 416)
Age in years, mean (sd)	40.91 (12.69)	38.89 (12.01)	43.06 (12.26)	40.48 (13.22)
Sex at birth, n (%)				
Female	756 (74.63 %)	207 (78.11 %)	241 (72.59 %)	308 (74.04 %)
Male	257 (25.37 %)	58 (21.89 %)	91 (27.41 %)	108 (25.96 %)
Gender identity, n (%)				
Woman	732 (72.26 %)	197 (74.34 %)	240 (72.29 %)	295 (70.91 %)
Man	253 (24.98 %)	58 (21.89 %)	91 (27.41 %)	104 (25.00 %)
Non-binary	15 (1.48 %)	6 (2.26 %)	1 (0.30 %)	8 (1.92 %)
Transgender	7 (0.69 %)	0 (0 %)	0 (0 %)	7 (1.68 %)
Unknown	6 (0.59 %)	4 (1.51 %)	0 (0 %)	2 (0.48 %)
Race, n (%)				
White	804 (79.37 %)	211 (79.62 %)	254 (76.51 %)	339 (81.49 %)
Black/African American	107 (10.56 %)	20 (7.55 %)	52 (15.66 %)	35 (8.41 %)
Asian	33 (3.26 %)	9 (3.40 %)	6 (1.81 %)	18 (4.33 %)
Native American/Alaska Native	10 (0.99 %)	3 (1.13 %)	4 (1.20 %)	3 (0.72 %)
More than one race	53 (5.23 %)	20 (7.55 %)	15 (4.52 %)	18 (4.33 %)
Unknown	6 (0.59 %)	2 (0.75 %)	1 (0.30 %)	3 (0.72 %)
Ethnicity, n (%)				
Hispanic/Latinx	78 (7.7 %)	25 (9.43 %)	19 (5.72 %)	34 (8.17 %)
Non-Hispanic/Non-Latinx	932 (92.0 %)	238 (89.81 %)	313 (94.28 %)	381 (91.59 %)
Unknown	3 (0.30 %)	2 (0.75 %)	0 (0 %)	1 (0.24 %)
Highest level education completed, n (%)				
Some high school, no diploma	14 (1.38 %)	3 (1.13 %)	4 (1.20 %)	7 (1.68 %)
High school/GED	77 (7.60 %)	12 (4.53 %)	28 (8.43 %)	37 (8.89 %)
Some college, no degree	233 (23.0 %)	42 (15.85 %)	72 (21.69 %)	119 (28.61 %)
Associate's degree	163 (16.09 %)	37 (13.96 %)	68 (20.48 %)	58 (13.94 %)
Bachelor's degree	312 (30.80 %)	94 (35.47 %)	99 (29.82 %)	119 (28.61 %)
Master's degree	174 (17.18 %)	59 (22.26 %)	53 (15.96 %)	62 (14.90 %)
Professional degree	19 (1.88 %)	7 (2.64 %)	5 (1.51 %)	7 (1.68 %)
Doctoral degree	19 (1.88 %)	11 (4.15 %)	2 (0.60 %)	6 (1.44 %)
Unknown	1 (0.10 %)	0 (0 %)	1 (0.30 %)	0 (0 %)
Marital status, n (%)				
Single/never married	338 (33.37 %)	95 (35.85 %)	106 (31.93 %)	137 (32.93 %)
Domestic partnership	158 (15.60 %)	45 (16.98 %)	51 (15.36 %)	62 (14.90 %)
Married	335 (33.07 %)	88 (33.21 %)	107 (32.23 %)	140 (33.65 %)
Separated	32 (3.16 %)	5 (1.89 %)	12 (3.61 %)	15 (3.61 %)
Divorced	143 (14.12 %)	29 (10.94 %)	55 (16.57 %)	59 (14.18 %)
Unknown	7 (0.69 %)	3 (1.13 %)	1 (0.30 %)	3 (0.72 %)
Household income, n (%)				
<$10,000	67 (6.61 %)	12 (4.53 %)	23 (6.93 %)	32 (7.69 %)
$10,000–19,999	90 (8.88 %)	19 (7.17 %)	33 (9.94 %)	38 (9.13 %)
$20,000–39,999	212 (20.93 %)	40 (15.09 %)	66 (19.88 %)	106 (25.48 %)
$40,000–59,999	206 (20.34 %)	55 (20.75 %)	69 (20.78 %)	82 (19.71 %)
$60,000–99,999	242 (23.89 %)	83 (31.32 %)	78 (23.49 %)	81 (19.47 %)
>$100,000	169 (16.68 %)	48 (18.11 %)	58 (17.47 %)	63 (15.14 %)
Unknown	27 (2.67 %)	8 (3.02 %)	5 (1.51 %)	14 (3.37 %)
Employment, n (%)				
Employed	643 (63.47 %)	206 (77.74 %)	211 (63.55 %)	226 (54.33 %)
Unemployed	135 (13.33 %)	21 (7.92 %)	42 (12.65 %)	72 (17.31 %)
Disability	104 (10.27 %)	15 (5.66 %)	33 (9.94 %)	56 (13.46 %)
Retired	49 (4.84 %)	10 (3.77 %)	16 (4.82 %)	23 (5.53 %)
Other	78 (7.70 %)	12 (4.53 %)	29 (8.73 %)	37 (8.89 %)
Unknown	4 (0.39 %)	1 (0.38 %)	1 (0.30 %)	2 (0.48 %)
Baseline SPIN				
Minimal (0–20), n (%)	418 (41.26 %)	120 (45.28 %)	174 (52.41 %)	124 (29.81 %)
Mild (21–30), n (%)	175 (17.28 %)	54 (20.38 %)	47 (14.16 %)	74 (17.79 %)
Moderate (31–40), n (%)	166 (16.39 %)	48 (18.11 %)	35 (10.54 %)	83 (19.95 %)
Severe (41–50), n (%)	142 (14.02 %)	24 (9.06 %)	39 (11.75 %)	79 (18.99 %)
Very Severe (>50), n (%)	107 (10.56 %)	19 (7.17 %)	35 (10.54 %)	53 (12.74 %)

2.3.2. *Fear*

A similar set of features predicted the fear subscale, and again, five out of the 14 sensed features showed at least one significant association to fear. As with avoidance, people who communicated more via phone/text relative to other participants were less likely to report future and concurrent fear (between-person distal $\beta = -0.860$, $p < .001$; medial $\beta = -0.892$, $p < .001$; proximal $\beta = -0.886$, $p < .001$). Within-person effects of communication on fear were non-significant. People who were frequently going to novel places were less likely to report future fear symptoms (between-person distal $\beta = -0.483$, $p = .047$), though this association was nonsignificant for medial and proximal prediction, and within-person associations of this feature to fear severity were non-significant. Unique to predicting fear was a within-person association between home duration and lower next-week/concurrent fear symptoms (medial $\beta = -0.213$, $p = .009$; proximal $\beta = -0.241$, $p = .005$), which was not observed for distal prediction, nor at the between-person level. Also unique to fear was an association between increased between-person app-based messaging and fear (distal $\beta = 0.578$, $p = .029$; medial $\beta = 0.555$, $p = .039$; proximal $\beta = 0.636$, $p = .018$; non-significant within-person), and between increased within-person social media use and next-week fear symptoms (medial $\beta = 0.153$, $p = .018$).

2.3.3. *Physiological distress*

Overall, fewer phone-based features predicted physiological distress, with only two of 14 sensed features having at least one significant association with this physiological distress. When people spent more time on gaming apps relative to their own average (within-person), they were more likely to report concurrent and future symptoms of physiological

Table 2
Multilevel model results predicting avoidance from sensing data across shifting prediction windows.

Predictor	Sensing predicting avoidance with 2-week lag (R^2 = 0.091)			Sensing predicting avoidance with 1-week lag (R^2 = 0.088)			Sensing predicting avoidance with 0-week lag (R^2 = 0.092)		
	Estimate	*SE*	*p-value*	*Estimate*	*SE*	*p-value*	*Estimate*	*SE*	*p-value*
Home duration - B	−0.058	0.282	0.836	0.065	0.278	0.816	0.013	0.275	0.961
Home duration - W	0.023	0.103	0.822	−0.026	0.103	0.802	0.025	0.108	0.818
Circadian movement - B	−0.590	0.369	0.110	−0.277	0.376	0.461	−0.605	0.366	0.098
Circadian movement - W	0.074	0.073	0.314	0.048	0.071	0.498	0.049	0.074	0.504
Location variability - B	0.443	0.312	0.155	0.270	0.316	0.394	0.472	0.310	0.128
Location variability - W	−0.111	0.154	0.472	0.140	0.152	0.358	0.103	0.155	0.509
More frequent venues - B	−0.482	0.320	0.132	−0.485	0.314	0.123	−0.435	0.316	0.169
More frequent venues - W	−0.061	0.074	0.415	0.009	0.074	0.898	0.041	0.075	0.583
Less frequent venues - B	**−0.886**	**0.292**	**0.002****	**−0.647**	**0.295**	**0.029***	**−0.818**	**0.302**	**0.007****
Less frequent venues - W	0.045	0.071	0.529	0.063	0.069	0.360	0.014	0.067	0.829
GPS variability and mobility - B	0.145	0.354	0.682	0.018	0.344	0.958	−0.083	0.345	0.811
GPS variability and mobility - W	−0.070	0.059	0.236	**−0.123**	**0.059**	**0.038***	0.034	0.060	0.567
Call and text communication - B	**−0.882**	**0.281**	**0.002****	**−0.932**	**0.288**	**0.001****	**−0.918**	**0.288**	**0.001****
Call and text communication - W	**−0.191**	**0.096**	**0.046***	**−0.213**	**0.097**	**0.028***	−0.088	0.094	0.349
App-based messaging - B	0.532	0.316	0.093	0.497	0.322	0.122	0.572	0.322	0.076
App-based messaging - W	0.073	0.080	0.364	−0.055	0.079	0.490	**−0.173**	**0.079**	**0.028***
Social media - B	−0.160	0.287	0.576	−0.052	0.287	0.856	−0.085	0.283	0.763
Social media - W	0.010	0.083	0.900	0.103	0.082	0.206	0.096	0.081	0.240
Screen-on time - B	−0.030	0.241	0.902	−0.282	0.322	0.382	−0.154	0.331	0.643
Screen-on time - W	0.032	0.061	0.595	−0.024	0.054	0.652	−0.035	0.055	0.522
Browser - B	0.116	0.279	0.677	0.223	0.280	0.427	0.290	0.281	0.302
Browser - W	−0.062	0.078	0.428	−0.025	0.076	0.737	0.048	0.076	0.526
Email - B	0.180	0.271	0.508	0.152	0.276	0.584	0.177	0.272	0.517
Email - W	0.067	0.081	0.409	0.023	0.077	0.766	0.017	0.078	0.826
Game - B	0.152	0.278	0.584	0.146	0.276	0.597	0.121	0.277	0.662
Game - W	0.067	0.070	0.333	**0.148**	**0.070**	**0.036***	**0.190**	**0.070**	**0.007****
Launcher - B	−0.445	0.303	0.143	−0.394	0.309	0.202	−0.437	0.313	0.163
Launcher - W	−0.072	0.082	0.375	−0.021	0.083	0.803	−0.003	0.084	0.976
Age	**−1.710**	**0.238**	**<0.001*****	**−1.675**	**0.238**	**<0.001*****	**−1.685**	**0.236**	**<0.001*****
Male (vs. female)	**−0.548**	**0.231**	**0.018***	**−0.573**	**0.233**	**0.014***	**−0.542**	**0.231**	**0.019***
Urban (vs. rural)	**−1.040**	**0.230**	**<0.001*****	**−1.051**	**0.230**	**<0.001*****	**−1.062**	**0.229**	**<0.001*****
Study week	**−0.140**	**0.031**	**<0.001*****	**−0.153**	**0.030**	**<0.001*****	**−0.153**	**0.030**	**<0.001*****
(Intercept)	11.501	0.223	<0.001***	11.500	0.224	<0.001***	11.500	0.223	<0.001***

Note. B = between; W = within; * $p < .05$, ** $p < .01$, *** $p < .001$. Features highlighted in bold have at least one significant relationship to the outcome.

distress (distal $\beta = 0.091$, $p = .028$; medial $\beta = 0.105$, $p = .012$; proximal $\beta = 0.147$, $p < .001$), though all between-person effects were non-significant. When people spent more time on app-based messaging relative to their own average (within-person), they were more likely to report future physiological distress (distal $\beta = 0.095$, $p = .045$; medial $\beta = 0.098$, $p = .037$), though this association was non-significant for proximal prediction and at the between-person level.

2.3.4. Demographic effects

Higher social anxiety severity was found for younger people (β: [1.225–1.866], p: [<0.001 - <0.001]), women (β: [0.254–0.573], p: [0.004–0.047]), and people living in rural areas (β: [0.407–1.062], p: [<0.001–0.001]).

2.3.5. Time effects

There was a significant fixed effect of time, such that people reported decreasing avoidance and fear severity over the course of the study (β: [−0.067 to −0.153], p: [<0.001–0.008]). Physiological distress did not significantly change over time.

2.3.6. Overall variability explained

The models explained a modest amount of overall variability in avoidance (distal $R^2 = 0.091$; medial $R^2 = 0.088$; proximal $R^2 = 0.092$), fear (distal $R^2 = 0.118$; medial $R^2 = 0.116$; proximal $R^2 = 0.120$), and physiological distress (distal $R^2 = 0.094$; medial $R^2 = 0.092$; proximal $R^2 = 0.094$) symptom severity.

3. Discussion

The objective of the present study was to identify passively sensed digital indicators of self-reported social avoidance, and to determine whether distinct sensed data predict avoidance relative to other social anxiety symptom subdomains (i.e., fear, physiological discomfort). We found that similar features—namely, reduced call/text based communication and novelty-seeking—predicted both self-reported avoidance and fear symptoms, but that novelty-seeking was more strongly related to self-reported social avoidance over time. Fewer smartphone-based sensed features predicted physiological distress.

Our findings around reduced novelty-seeking in communication and movement associated with self-reported social avoidance and fear align with the inhibitory learning framework (Sewart and Craske, 2020; Craske et al., 2014). In the context of this model, talking to others less or visiting fewer novel locations may result in short-term relief associated with a reduction in social anxiety threats; the person takes this relief as evidence that these behaviors protect them from social anxiety, increasing the likelihood of avoidance in the future and strengthening the core fear of social situations. From a treatment perspective, developing a new inhibitory meaning of a conditioned stimulus—which exists alongside, but does not replace the original danger meaning—underlies the efficacy of exposure therapy. In a clinical context, early identification of sensed changes in real-world behavior that are suggestive of poor inhibitory learning, such as decreased communication and exploration, may signal a need for increased exposure to feared situations. Our results around reduced novelty-seeking in communication and movement also correspond with earlier mobile sensing research that found that students with higher scores on social anxiety visited a lower variety of places and had a narrower range of activities (Boukhechba et al., 2017).

The greater similarity of sensed features associated with self-reported avoidance and fear relative to physiological distress is consistent with past literature on the conceptualization and treatment of social

Table 3
Multilevel model results predicting fear from sensing data across shifting prediction windows.

Predictor	Sensing predicting fear with 2-week lag (R^2 = 0.118)			Sensing predicting fear with 1-week lag (R^2 = 0.116)			Sensing predicting fear with 0-week lag (R^2 = 0.120)		
	Estimate	*SE*	*p-value*	*Estimate*	*SE*	*p-value*	*Estimate*	*SE*	*p-value*
Home duration - B	−0.030	0.234	0.898	0.064	0.230	0.780	0.041	0.228	0.857
Home duration - W	−0.101	0.082	0.217	**−0.213**	**0.082**	**0.009****	**−0.241**	**0.086**	**0.005****
Circadian movement - B	−0.388	0.306	0.205	−0.175	0.312	0.575	−0.434	0.303	0.153
Circadian movement - W	0.037	0.058	0.525	−0.002	0.057	0.968	−0.056	0.059	0.345
Location variability - B	0.447	0.259	0.085	0.333	0.263	0.205	0.490	0.257	**0.057**
Location variability - W	−0.085	0.122	0.484	0.162	0.121	0.181	0.152	0.123	0.217
More frequent venues - B	−0.455	0.265	0.087	−0.437	0.260	0.094	−0.419	0.262	0.110
More frequent venues - W	−0.055	0.059	0.353	−0.048	0.059	0.413	−0.056	0.060	0.350
Less frequent venues - B	**−0.483**	**0.242**	**0.047***	−0.302	0.244	0.217	−0.435	0.250	0.083
Less frequent venues - W	0.025	0.056	0.662	0.015	0.055	0.779	0.015	0.053	0.776
GPS variability and mobility - B	0.048	0.294	0.871	−0.046	0.286	0.872	−0.102	0.287	0.723
GPS variability and mobility - W	−0.031	0.047	0.511	−0.069	0.047	0.145	0.073	0.048	0.126
Call and text communication - B	**−0.860**	**0.234**	**<0.001*****	**−0.892**	**0.239**	**<0.001*****	**−0.886**	**0.240**	**<0.001*****
Call and text communication - W	−0.005	0.076	0.943	−0.054	0.077	0.484	−0.048	0.075	0.520
App-based messaging - B	**0.578**	**0.264**	**0.029***	**0.555**	**0.268**	**0.039***	**0.636**	**0.269**	**0.018***
App-based messaging - W	0.041	0.064	0.518	−0.042	0.063	0.505	−0.028	0.063	0.653
Social media - B	−0.073	0.238	0.760	0.027	0.238	0.909	0.017	0.235	0.943
Social media - W	0.086	0.066	0.194	**0.153**	**0.065**	**0.018***	0.073	0.065	0.262
Screen-on time - B	−0.099	0.201	0.622	−0.195	0.267	0.466	−0.066	0.275	0.811
Screen-on time - W	0.028	0.048	0.560	−0.001	0.043	0.988	−0.057	0.043	0.193
Browser - B	0.026	0.230	0.911	0.109	0.232	0.639	0.174	0.233	0.456
Browser - W	−0.108	0.062	0.081	−0.030	0.060	0.622	0.003	0.060	0.955
Email - B	0.102	0.227	0.653	0.070	0.232	0.762	0.080	0.228	0.725
Email - W	−0.011	0.064	0.870	−0.013	0.061	0.827	0.019	0.062	0.762
Game - B	0.172	0.231	0.455	0.175	0.229	0.444	0.127	0.229	0.580
Game - W	−0.011	0.055	0.845	0.065	0.056	0.243	0.083	0.056	0.138
Launcher - B	−0.370	0.252	0.142	−0.338	0.256	0.188	−0.409	0.260	0.116
Launcher - W	−0.019	0.065	0.767	−0.034	0.066	0.612	−0.044	0.067	0.514
Age	**−1.866**	**0.197**	**<0.001*****	**−1.834**	**0.198**	**<0.001*****	**−1.833**	**0.196**	**<0.001*****
Male (vs. female)	**−0.544**	**0.192**	**0.005****	**−0.554**	**0.193**	**0.004****	**−0.533**	**0.192**	**0.006****
Urban (vs. rural)	**−0.784**	**0.191**	**<0.001*****	**−0.794**	**0.191**	**<0.001*****	**−0.798**	**0.191**	**<0.001*****
Study week	**−0.067**	**0.025**	**0.008****	**−0.075**	**0.024**	**0.002****	**−0.075**	**0.024**	**0.002****
(Intercept)	8.818	0.185	<0.001***	8.814	0.186	<0.001***	8.814	0.185	<0.001***

Note. B = between; W = within; * $p < .05$, ** $p < .01$, *** $p < .001$. Features highlighted in bold have at least one significant relationship to the outcome.

anxiety subdomains. Namely, past studies support a reciprocal relationship between avoidance and fear for social anxiety and indicate that physiological distress may change independently from these two (Aderka et al., 2013; Heeren and McNally, 2016). Our findings extend this literature by suggesting that a similar set of smartphone-based sensed features around communication and behavioral novelty-seeking may track concurrent changes in self-reported avoidance and fear. Conceptually, social fear contributes to the behavioral avoidance of *external* social stressors and vice versa (Kashdan et al., 2014), whereas the physiological distress subscale may reflect experiential avoidance, or the tendency to avoid unpleasant *internal* experiences (Hayes et al., 1996). In this context, our finding of an association of within-person increases in gaming and physiological distress may reflect attempts to distract from unpleasant internal emotions. More broadly, the fewer significant findings of sensed behavior associated with physiological symptoms may reflect that physiological changes in treatment would likely occur over a slower time frame after repeated behavioral change (i.e., exposure).

Broadly, the current study has implications for identifying novel targets associated with core components of social anxiety (i.e., avoidance) and personalizing adaptive interventions. The prospective, within-person associations of reduced call and text-based communication with self-reported avoidance suggest that it may be fruitful to deploy prophylactic exposure-based techniques when within-person increases in these sensed features are detected. Further, research indicates that behavioral avoidance maintains fear of social situations, such that increased avoidance precipitates increased fear (Aderka et al., 2013). While prior studies have linked time spent at home with broad social anxiety symptoms (Boukhechba et al., 2018; Chow et al., 2017), it was unknown whether spending time at home reflected a consequence or leading indicator of symptoms, nor how general vs. specific this association was to social anxiety subdomains. That within-person increases in time spent at home precipitated fear of social situations in our study suggests that increased home duration may signal a person-specific opportunity for exposure-based interventions in an attempt to reduce maladaptive behavior (i.e., staying home) that reduces immediate fear but maintains social anxiety in the long term (Hofmann, 2007; Rapee and Heimberg, 1997). Together, these findings suggest that attempts to personalize social anxiety interventions may benefit from a focus on decreases in communication and increases in time spent at home.

The current study has strengths and limitations that point to avenues for future research. Whereas past sensor studies of social anxiety have generally relied on small samples of university students (Boukhechba et al., 2017), our study involved a large community sample of adults, enabling the exploration of sensed feature relationships to more specific social anxiety subdomains. The amount of variance explained in the current data was relatively low, ranging from 9 to 12 % across different outcomes and time periods; however, it was still higher than what was observed for GAD-7/PHQ-8, as reported in another paper describing primary outcomes (Stamatis et al., in review). This is notable given that the present study represents a secondary analysis of data originally collected with depression as a primary outcome, and in a group of people oversampled for depressive symptoms. Additionally, the second wave of data was collected during the COVID-19 lockdown period, which may influence observed behavioral patterns. Future studies should collect more mobile sensor data during the non-pandemic time and specifically recruit for social anxiety to increase robustness. Another means of increasing generalizability will be to recruit users of both Android and iOS devices, given that there may be differences in these groups in terms of phone use and demographics. Further, while we

Table 4
Multilevel model results predicting physiological distress from sensing data across shifting prediction windows.

Predictor	Sensing predicting phys. with 2-week lag (R^2 = 0.094)			Sensing predicting phys. with 1-week lag (R^2 = 0.092)			Sensing predicting phys. with 0-week lag (R^2 = 0.094)		
	Estimate	*SE*	*p-value*	*Estimate*	*SE*	*p-value*	*Estimate*	*SE*	*p-value*
Home duration - B	−0.003	0.155	0.987	0.021	0.153	0.893	0.030	0.152	0.842
Home duration - W	−0.088	0.061	0.155	−0.049	0.061	0.421	0.034	0.064	0.595
Circadian movement - B	−0.319	0.204	0.117	−0.227	0.208	0.276	−0.257	0.202	0.204
Circadian movement - W	0.008	0.044	0.849	0.047	0.042	0.264	0.079	0.044	0.071
Location variability - B	0.030	0.172	0.862	−0.005	0.175	0.978	0.056	0.172	0.745
Location variability - W	−0.094	0.092	0.306	0.040	0.091	0.657	0.071	0.092	0.440
More frequent venues - B	−0.012	0.177	0.946	−0.040	0.174	0.817	−0.082	0.175	0.639
More frequent venues - W	−0.039	0.044	0.379	0.002	0.044	0.966	0.021	0.045	0.636
Less frequent venues - B	−0.216	0.161	0.180	−0.112	0.162	0.492	−0.145	0.167	0.384
Less frequent venues - W	0.035	0.042	0.404	0.040	0.041	0.327	0.026	0.040	0.508
GPS variability and mobility - B	0.154	0.195	0.432	0.090	0.190	0.637	0.026	0.191	0.891
GPS variability and mobility - W	−0.011	0.035	0.746	−0.059	0.035	0.096	−0.006	0.036	0.864
Call and text communication - B	−0.171	0.155	0.272	−0.223	0.159	0.161	−0.242	0.159	0.129
Call and text communication - W	−0.058	0.057	0.305	−0.097	0.058	0.091	−0.072	0.056	0.198
App-based messaging - B	0.112	0.176	0.522	0.125	0.178	0.482	0.158	0.179	0.377
App-based messaging - W	**0.095**	**0.048**	**0.045****	**0.098**	**0.047**	**0.037****	0.063	0.047	0.183
Social media - B	−0.291	0.158	0.066	−0.239	0.158	0.132	−0.247	0.157	0.115
Social media - W	−0.089	0.050	0.073	−0.070	0.049	0.151	−0.044	0.049	0.369
Screen-on time - B	0.137	0.134	0.309	0.029	0.178	0.870	0.110	0.183	0.547
Screen-on time - W	−0.062	0.036	0.084	0.006	0.032	0.848	0.023	0.033	0.481
Browser - B	−0.130	0.154	0.398	−0.084	0.154	0.587	−0.068	0.155	0.662
Browser - W	0.014	0.046	0.755	0.001	0.045	0.984	−0.004	0.045	0.933
Email - B	0.096	0.151	0.525	0.091	0.154	0.555	0.091	0.152	0.549
Email - W	0.010	0.048	0.841	−0.022	0.046	0.625	−0.020	0.046	0.667
Game - B	0.064	0.153	0.675	0.064	0.152	0.673	0.100	0.152	0.514
Game - W	**0.091**	**0.041**	**0.028****	**0.105**	**0.042**	**0.012****	**0.147**	**0.042**	**<0.001********
Launcher - B	−0.275	0.167	0.100	−0.263	0.170	0.122	−0.297	0.173	0.086
Launcher - W	0.003	0.049	0.946	−0.026	0.050	0.606	−0.025	0.050	0.622
Age	**−1.239**	**0.131**	**<0.001********	**−1.231**	**0.131**	**<0.001********	**−1.225**	**0.131**	**<0.001********
Male (vs. female)	**−0.254**	**0.128**	**0.047****	**−0.271**	**0.128**	**0.035****	**−0.266**	**0.128**	**0.037****
Urban (vs. rural)	**−0.409**	**0.127**	**0.001******	**−0.407**	**0.127**	**0.001******	**−0.409**	**0.127**	**0.001******
Study week	−0.008	0.019	0.657	−0.009	0.018	0.613	−0.010	0.018	0.572
(Intercept)	4.324	0.123	<0.001***	4.328	0.123	<0.001***	4.328	0.123	<0.001***

Note. B = between; W = within; * $p < .05$, ** $p < .01$, *** $p < .001$. Features highlighted in bold have at least one significant relationship to the outcome.

examined affective symptoms dimensionally, we did not include interview-based diagnostic or symptom severity measures. The patterns observed here may differ among people with a confirmed diagnosis. With any work in personal sensing, careful consideration of user privacy and data security is essential, including ensuring that participants understand the sensitivity of the data being collected, that data are encrypted during transmission, that data are stored and maintained on secure servers, and that participants have prospective control over their data, including the right to have their data deleted (Ross et al., 2023).

4. Conclusions

As the largest passive sensing study of social anxiety symptoms to date, this work highlights the importance of communication, location, and app use features in predicting distinct subdomains of social anxiety. Reduced communication and novelty-seeking may be prospective indicators of social avoidance and fear, whereas distinct smartphone-based features predict physiological distress in the context of social situations.

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CRediT authorship contribution statement

C.A.S.: Conceptualization, Methodology, Writing – Original Draft; T. L.: Writing – Original Draft; J.M.: Conceptualization, Writing – Review & Editing; Y.M.: Methodology, Formal analysis, Writing – Original Draft, Visualization; Y.M.C.: Methodology, Formal analysis, Writing – Review & Editing; C.J.K.: Software, Data Curation, Writing – Review & Editing; B.L.C: Writing – Review & Editing; L.H.U.: Investigation, Writing – Review & Editing; D.C.M.: Conceptualization, Investigation, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Caitlin A. Stamatis has received salary and equity support from Akili Interactive Labs and Google. Jonah Meyerhoff has accepted consulting fees from Boehringer Ingelheim. David C. Mohr has accepted honoraria and consulting fees from Otsuka Pharmaceuticals, Optum Behavioral Health, Centerstone Research Institute, and the One Mind Foundation, royalties from Oxford Press, and has an ownership interest in Adaptive Health, Inc.

Data availability

The data that support the findings of this study may be made available from the corresponding author upon reasonable request and execution of appropriate data use agreements and human subjects authorization. All code is publicly available on Colab: https://colab.research.google.

com/drive/1L9JE7nChMRZqVR8udU4xGQRGICnky4j6.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.invent.2023.100683.

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