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Digital Biomarkers of Anxiety Disorder Symptom Changes: Personalized Deep Learning Models Using Smartphone Sensors Accurately Predict Anxiety Symptoms from Ecological Momentary Assessments

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Abstract

Smartphones are capable of passively capturing persons' social interactions, movement patterns, physiological activation, and physical environment. Nevertheless, little research has examined whether momentary anxiety symptoms can be accurately assessed using these methodologies. In this research, we utilize smartphone sensors and personalized deep learning models to predict future anxiety symptoms among a sample reporting clinical anxiety disorder symptoms. Participants (N = 32) with generalized anxiety disorder and/or social anxiety disorder (based on self-report) installed a smartphone application and completed ecological momentary assessment symptoms assessing their anxiety and avoidance symptoms hourly for the course of one week (T = 2,007 assessments). During the same period, the smartphone app collected information about physiological activation (heart rate and heart rate variability), exposure to light, social contact, and GPS location. GPS locations were coded to reveal the type of location and the weather information. Personalized deep learning models using the smartphone sensor data were capable of predicting the majority of total variation in anxiety symptoms (R^2 = 0.748) and predicting a large proportion of within-person variation at the hour-by-hour level (mean R^2 = 0.385). These results suggest that personalized deep learning models using smartphone sensor data are capable of accurately predicting future anxiety disorder symptom changes.

Keywords

passive sensing; digital phenotyping; anxiety disorders; ecological momentary assessment; generalized anxiety disorder; social anxiety disorder

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Anxiety disorders occur in 7.3% of the population globally (Baxter et al., 2013). Moreover, large cohort studies over the past three decades have suggested that both anxiety disorders and anxiety symptoms are dramatically rising (American Psychiatric Association, 2018; Booth et al., 2016; Dorling, 2009; Duffy et al., 2019; Harman et al., 2002; Skaer et al., 2000; Twenge, 2000; Twenge et al., 2010; S. Xin et al., 2019; Z. Xin et al., 2010; Yang et al., 2014), with estimates suggesting that global prevalence has increased 45% over the past 40 years (Richter et al., 2019). Being the sixth leading cause of disability worldwide (Baxter et al., 2014), anxiety disorders cost the United States over $40 billion annually (Greenberg et al., 1999) and lead to a 43% increased risk of death from all causes (Walker et al., 2015).

In recent decades, researchers have increasingly recognized that anxiety disorders can best be studied by densely collecting data within the confines of daily life (Frank et al., 2017). Assessing behaviors and feelings intensively within daily life allows researchers to move beyond limitations of traditional assessments of anxiety disorders (Dogan et al., 2017; Newman et al., 2019), namely by studying phenomena in ecologically valid settings rather than in the lab and by utilizing longitudinal data rather than long retrospective reports of a given period. Yet, typical methods of densely collecting data in daily lives, such as using ecological momentary assessment strategies, are quite burdensome, repeatedly disrupting activities of daily life (Scollon et al., 2003). Thus, although intensive longitudinal data collected within daily life might hold promise in overcoming major weaknesses in assessing anxiety disorder symptoms, typical measurements result in immense participant burden.

An alternative method of assessing psychiatric disorders and symptoms in daily life includes utilizing passively collected smartphone and wearable sensor data, which can objectively monitor psychomotor patterns, location and environmental context, technology use, and social activity (Jacobson et al., 2019a, 2019b, 2020; Jacobson & O'Cleirigh, 2019; Wilhelm et al., 2019). In particular, prior research has examined the correlation between persons who experience higher anxiety disorder symptoms and passively collected smartphone sensor data in daily life, and it has shown that persons with higher anxiety levels were associated with: (1) making fewer phone unlocks (Rozgonjuk et al., 2018); (2) visiting fewer locations (Boukhechba, Chow, et al., 2018), particularly spending less time at spiritual locations (Huang et al., 2016; Saeb et al., 2017), work (Saeb et al., 2017), at others' homes, and traveling out-of-town (Boukhechba, Daros, et al., 2018) (each observed via GPS); and (3) having less intense physical activity movements (Boukhechba, Daros, et al., 2018). Studies have shown that these passively collected sensor data using machine learning could accurately predict trait worry severity ($r = 0.6$) (Jacobson & O'Cleirigh, 2019) and social anxiety severity ($r = 0.7$, 85% accuracy) (Boukhechba, Chow, et al., 2018; Boukhechba et al., 2017; Jacobson et al., 2020). This suggests that intensive longitudinal data collected passively from smartphone and wearable sensors may directly relate to anxiety symptom severity.

Nevertheless, despite the promising work emerging on assessing trait-level symptom severity, research examining within-person variability in anxiety symptoms via smartphone sensors and wearable sensors is quite sparse. Only two studies have been conducted. In particular, one study showed that those with higher social anxiety with greater negative affect on one day had a greater likelihood of spending time at home the following day (Chow et al., 2017). Another study predicted state affect in 20 healthy control participants and found that they were able to accurately predict changes in daily state anxiety using illuminance, acceleration, rotation and smartphone application activity logs (F-score = 74.2%) (Fukazawa et al., 2019). This suggests that smartphone sensors may be capable of capturing changes in anxiety symptoms across daily life.

Still to date, there are no studies that predict momentary changes in anxiety and avoidance symptoms using smartphone sensor data among those at clinical levels of anxiety. These movements are particularly important, as they may enable the ability to build targeted just-in-time adaptive interventions. A just-in-time adaptive intervention is a framework to deliver interventions within the context of daily life, adapting to a user's changing needs and receptivity across time (Nahum-Shani et al., 2018). Here, being able to predict when a person is at an acutely increased risk of increases in anxiety and avoidance symptoms may enable targeted interventions during individuals' moments of greatest need.

The current study attempts to use passively collected smartphone sensor data to predict moment-to-moment changes in anxiety and avoidance symptoms among persons reporting clinical levels of generalized anxiety disorder and social anxiety disorder. Additionally, building on the research that personalized models of anxiety disorders may facilitate translation of personalized treatments (Fisher, 2015; Fisher et al., 2017, 2018), we utilized personalized deep learning models to predict momentary changes in anxiety and avoidance symptoms. We hypothesized that these personalized deep learning models based on passively collected smartphone sensor data could predict momentary changes in anxiety and avoidance symptoms.

Method

Participants

Participants were 32 undergraduate students (50 % female; 65.62% White/Caucasian, 3.12% Black/African American, 12.50% Hispanic/Latina/Latino, 12.50% Asian/Asian American, 3.12% Multiracial/Multiethnic, and 3.12% other race or ethnicity; mean age = 19.56, age range = 18-27) who screened positive for generalized anxiety disorder or social anxiety disorder via the Generalized Anxiety Disorder Questionnaire (GAD-Q) and the Social Phobia Diagnostic Questionnaire (SPDQ).[1] Participants were recruited from a psychology subject pool. An additional 29 persons completed the screens but did not screen positive for either generalized anxiety disorder or social anxiety disorder and thus were not eligible for the current study.

Generalized Anxiety Disorder Questionnaire (GAD-Q-IV; Newman et al., 2002).—The GAD-Q-IV was administered once at baseline. This 14-item self-report scale assesses and diagnoses generalized anxiety disorder based on the Diagnostic and Statistical Manual

[1]In designing the study, we chose to target those with generalized anxiety disorder and social anxiety disorder because we hoped to assess forms of anxiety that are often experienced as dimensional in nature. Both social anxiety and generalized anxiety disorder are commonly reflected by graded forms of anxiety. In our conceptualization, panic attacks as might be seen in panic disorder and/or agoraphobia tend to be much more intense in nature for a much shorter duration.

of Mental Disorders 5 criteria (American Psychiatric Association, 2013). Prior research has shown that the measure has 89% specificity and 83% sensitivity in identifying generalized anxiety disorder compared to social anxiety disorder, panic disorder, and non-anxious controls, and has strong interrater agreement compared to structured interviews (kappa = 0.67 with a structured interview; Newman et al., 2002). Results have shown high convergence between using the GAD-Q-IV diagnostic scoring criteria with sensitivity of 89% and specificity of 82% in a psychotherapy seeking sample (Moore et al., 2014).

Social Phobia Diagnostic Questionnaire (SPDQ) (SPDQ; Newman et al., 2003).—The SPDQ was administered at the study baseline. The SPDQ is a 25-item self-report measure to assess social anxiety disorder, as defined in the Diagnostic and Statistical Manual of Mental Disorders versions 5 criteria (American Psychiatric Association, 2013). The SPDQ has shown high concordance with clinical interviews (85% specificity; 82% sensitivity; kappa = 0.66) (85% specificity; 82% sensitivity; kappa = 0.66; Newman et al., 2003). Likewise, other studies have also shown that the SPDQ has good convergent validity with other social anxiety symptom measures in transdiagnostic samples (where the SPDQ has been treated as the gold-standard instrument, and other social anxiety measures have demonstrated 77-78% sensitivity and 77% specificity in a transdiagnostic sample; McAleavey et al., 2012).

Ecological Momentary Assessment Anxiety and Avoidance Items.—To measure momentary feelings of anxiety, the following ecological momentary assessment items were administered from the items from the Positive Affect Negative Affect Schedule - Expanded Edition (PANAS-X) Fear Subscale: (1) How nervous do you feel right now? and (2) How shaky do you feel right now?. Additionally, the item from the Multidimensional Experiential Avoidance Questionnaire (MEAQ)'s behavioral scale was adapted to fit the momentary assessment paradigm (Gámez et al., 2011). Particularly, the question: "I go out of my way to avoid uncomfortable situations" was modified to ask: "Since the last prompt, to what extent did you try to get out of one more unpleasant situations?". A second item was then constructed to ask: "Since the last prompt, to what extent did you go out of your way to avoid one or more uncomfortable situations?"[2] The behavioral avoidance measure on the MEAQ was found to be related to anxiety (r range .45 - .52) and other types of avoidance (r range .45-,60). On average, the participants completed 62.72 prompts (SD = 13, min = 44, max = 89, approximately 64% of all EMAs). Note that the current analyses used a composite of both avoidance and anxiety symptoms.

Ecological Momentary Assessment Depressed Affect Items.—To determine whether the current investigation exhibited discriminant validity in predicting anxiety and avoidance symptoms, the current investigation also assessed momentary depressed affect during the same ecological momentary assessments. To measure momentary feelings of depression, the following ecological momentary assessment items were administered from the items from the Positive Affect Negative Affect Schedule - Expanded Edition (PANAS-X)

[2]We chose to modify the single item from the MEAQ into a pair of items to enhance the reliability of the measurement and because persons with anxiety disorders do not often label their own behaviors as "avoidant" and may instead tend to report their behaviors as "getting out" of an unpleasant situation, which may still function as avoidance.

Sadness Subscale: (1) "How sad do you feel right now?" and (2) "How lonely do you feel right now"?

Passive Sensing Data.—The following features were passively collected from participants including: (1) raw location based information: (1a) GPS coordinates (Latitude, Longitude), (1b) location Accuracy, (1c) location Speed, and (1d) whether the location-based information was based on GPS or Wi-Fi (86% of all location measures were based on GPS); (2) location type based on Google Places location type (e.g. University, gym, bar, church); (3) local weather information, including (3a) temperature, (3b) humidity, (3c) precipitation, (2) light level, (3) heart rate information: (3a) average heart rate and (3b) heart rate variability; and (4) outgoing phone calls.

The sensing data was indexed once per hour to match the ecological momentary assessment design and the device was not sampled more frequently to prevent excessive battery drain. The app used the GPS when the users had it enabled, and, if the GPS was disabled, the app collected location-based information from Wi-Fi. The type of location was based on the nearest location based on the Google Places API, and the local weather was determined based on the National Weather Service API.

Heart rate was assessed by asking subjects to press their finger against the rear-facing camera for 30 seconds. During this time, the application measured the rapid changes in color of their finger. Here the application noted the timing of the varying degrees of redness in the image, with high redness values corresponding to a pulse. The average heart rate was calculated based on the average heart beats per minute, and heart rate variability was based on the root mean square of successive differences of these beats. Results have shown that these methods have high convergence with traditional measures ($r = .98 – 1.00$ with heart rate, and $r = .90-.97$ in RMSSD) (Bolkhovsky et al., 2012).

Procedure

Participants were recruited from an undergraduate student subject pool. Participants were granted participation course credit for participating in the study and were recruited via an online portal. Participants were required to own an Android-based phone. Participants then attended a first study section and were asked to install the "Mood Triggers" application on their phones. Mood Triggers is an application which collects ecological momentary assessment data and passive sensing data and gives users feedback about which features most strongly predict their anxiety and depressed mood; however, for this study, the personalized feedback was disabled to not influence the naturalistic course of the symptom changes. Participants were also asked to input the hours that they would be awake over the following seven days, by inputting their bedtimes and wakeup times. Following the introductory session, the participants were prompted to rate their anxiety and avoidance symptoms once per hour and participate in the heart rate assessment for the times that they indicated that they would be awake (these times were based on the hours in which they indicated that they would be awake; participants also completed other measures outside the bounds of the current study). Participants then returned to the laboratory where their data was downloaded from their phone approximately eight days later.

Planned Analyses

The current design utilized personalized deep-learning models designed to incorporate temporal patterns within time series. Deep learning models are a subfield of machine learning, and the development of these methods was influenced by the way transmission occurs within biological systems (and as such are often called artificial neural networks). There are many configurations of deep learning models, and the current project uses long short-term memory networks (LSTM), a type of recurrent neural networks. Unlike traditional models applied within the social sciences used to predict time series outcomes (e.g., variations of vector autoregressive integrative moving average models), multi-layered LSTMs allow for non-linearity, higher order interactions, as well as long and short-term dependencies in temporal data. The current models were analyzed using idiographic (i.e., person-specific methods, $N = 1$) methods such that each model was tailored to predict an individual's unique associations between their smartphone sensor data and future changes in their anxiety and avoidance.

In contrast to traditional recurrent neural networks, LSTMs allow for the transmission of gradients to continue without changes; which dramatically reduces the likelihood of exploding or vanishing gradients (i.e., it facilitates the ability for the network to learn while retaining the ability to retain long-term dependencies) (Bengio et al., 1994; Hochreiter & Schmidhuber, 1997, 1996). LSTMs are considered the state-of-the-art for time series applications (Fan et al., 2019; Greff et al., 2017). Based on pilot data and past work incorporating deep learning from passive sensor data (Jacobson et al., 2021), the exponential linear unit (ELU) activation function was used for all intermediate layers, which allows for both linearity among numbers greater than 0 and non-linearity in numbers below negative 0 [via exp(x)-1] (Clevert et al., 2016). The current research deployed four hidden layer LSTMs of 100 nodes each. A ridge penalization was set to 0.001 for each hidden layer. A normal initialization was performed for each hidden layer as consistent with He and colleagues (2015). The Adam optimizer was used (Kingma & Ba, 2017). To account for missing data, all analyses were based on data from multiple imputation using random forest to account for non-linearities and interactions between sensors and outcomes (Stekhoven & Bühlmann, 2012).

A sliding window for cross-validation was performed, such that only a single subject's past data was trained to predict the next-hour symptom dynamics based on the passive sensing data (i.e. only past data predicted the future data) with the first model being trained on the data from the first 24 hours predicting the next hour. The primary metric of the current study included the robust coefficient of determination in anxiety and avoidance symptoms (i.e., robust R^2) (Renaud & Victoria-Feser, 2010) and their bootstrapped confidence intervals across persons and individually within-persons. See Figure 1 for a graphical depiction of the model development.

In addition, the discriminant validity of the model predictions to anxiety and avoidance symptom severity was examined by controlling for concurrent depressed affect in a robust linear regression. This included examining (1) whether the standardized regression coefficient was still significant, and (2) whether there were stronger relationships between anxiety and predicted anxiety than between depression and concurrent anxiety (as reflected by the strength of standardized beta weights). Lastly, the strength of the relationship between the predicted anxiety and observed anxiety was compared to the predicted anxiety and depressed affect.

Historically, deep-learning models have been considered black-box solutions that lack model interpretability, which fundamentally represents a barrier to science wherein the goal is not only prediction, but also understanding system dynamics. Nevertheless, major advancements have been made in model interpretability within deep-learning models based on SHapley Additive explanations (SHAP), a reverse-engineering strategy based on game theory (Lundberg & Lee, 2017). SHAP uses perturbations in a trained model's features to examine changes in model predictions. SHAP was used to derive personalized variable importance to determine which variables were making the greatest contributions to model predictions.

Results

Total Performance Across Persons

First, the total performance of the model in predicting hour-to-hour momentary anxiety and avoidance symptoms was evaluated. The results showed that a large proportion variation was explained in hourly anxiety and avoidance symptoms (robust $R^2 = 0.748$, 95% CI [0.728, 0.766], see Figure 2).

Total Performance Within Persons

Next, the idiographic model performance was evaluated. The results suggested that the mean individual-level performance was robust R^2 of 0.385 across persons (see Figures 3 and 4). With only 1 participant having a variance explained with a lower bootstrapped confidence interval closely approximating 0, the models were capable of predicting some degree of individual variation in future anxiety and avoidance symptoms in 97% of participants. As suggested in Figures 3 and 4, the models tend to exhibit similar levels of performance across a broad range of anxiety and avoidance symptom severity. In a total of 28% of persons, the majority of variance was explained (i.e., robust $R^2 \geq 0.500$), 63% of the individuals had a variance explained greater than 0.300, and 94% of persons a variance explained greater than 0.100. There was a small non-significant positive correlation between anxiety symptom severity (based on a composite measure of generalized and social anxiety symptom severity) and model performance ($r = 0.24$, $p = .185$).

Discriminant Validity of Predictions

Based on the results of follow-up robust linear models, (1) deep learning model predictions were still strongly related to future anxiety when controlling for concurrent depressed affect (standardized regression coefficient for deep learning predictions = 0.093, $SE = 0.004$, $t = 21.524$, $p < .001$), (2) the deep learning model predictions of anxiety had much stronger relationships to observed anxiety compared to concurrent depressed affect (standardized egression coefficient for momentary depressed affect = 0.034, $SE = 0.004$, $t = 7.932$, $p < .001$), and (3) the relationship between predicted anxiety and observed anxiety was also much higher (mean $R^2 = 0.384$) compared to the mean R2 of predicted anxiety and observed depressed affect (mean $R^2 = 0.189$). These results suggest strong discriminant validity of the predictions to avoidance and anxiety symptoms.

Variable Importance

Lastly, the variable importance of each model was examined using Shapley values (see Figure 5). Being indoors was consistently among the top features associated with anxiety and avoidance symptom severity. In particular, being indoors was the most important feature for 47% of participants, precipitation was the top feature for 12% of participants, temperature in degrees was the top feature for 12% of participants, and humidity was the top feature for 6% of participants. Taken together, location-based factors appeared to be a salient feature in making predictions about anxiety and avoidance symptoms. The mean variable importance of being indoors tended to be higher in persons with social anxiety disorder (mean importance = 80%) compared to persons with generalized anxiety disorder (mean importance = 66%). Nevertheless, the results also suggest strong person-specific patterns in the data (e.g., spending time at parks was the most important feature for one participant).

Discussion

The current research utilized smartphone sensor data gathered within the context of daily life to predict momentary anxiety and avoidance symptoms among persons reporting clinical levels of anxiety symptoms. The current research suggests that hour-to-hour changes in anxiety and avoidance symptoms can be accurately predicted using personalized deep learning models. The group-level performance suggested that the models were able to predict the majority of the total variation (including both within and between-person variation) in anxiety and avoidance symptoms, explaining approximately 75% of the total variation across and within persons. Notably, these predictions showed strong discriminant validity to depressed affect, suggesting that these models are mostly specific to avoidance and anxiety symptoms.

Perhaps more importantly, the results also suggested that personalized models could predict a substantial proportion of within-person variation with an average of approximately 39% of fluctuations in anxiety and avoidance symptoms being explained, and a large proportion of variation (greater than 30%) in anxiety and avoidance symptoms being capable of being predicted within most persons in the sample (this would be considered a large effect within the social sciences; Cohen, 2013). This suggests that these personalized models may have the potential to predict a substantial proportion of variation in momentary anxiety and avoidance symptoms across most persons. In addition, there was a small ($r = 0.24$, non-significant) positive relationship between baseline anxiety symptom severity and model performance suggesting that the current strategies may be effective across a range of symptom severity.

The personalized variable importance within the current study corroborates and extends prior descriptive nomothetic work linking daily behaviors captured from smartphone sensor data to trait levels of anxiety. In particular, the current findings corroborate the importance of physical location. Specifically, the current findings suggest that spending more time indoors was among the single strongest predictor of momentary changes in anxiety and avoidance symptoms, which is consistent with prior research suggesting that visiting fewer locations is related to trait levels of anxiety (Boukhechba, Chow, et al., 2018). The current work also found that anxiety and avoidance symptoms tended to be more impacted by time spent indoors in persons with social anxiety disorder compared to persons with generalized anxiety disorder, suggesting that anxiety and avoidance symptoms may be more location-bound in social anxiety disorder than generalized anxiety disorder. Nevertheless, there were strong individual differences in the variable importance across persons, as the local weather conditions also appeared to be strongly informative in making predictions within the current models for some persons. Notably, this corroborates prior research showing a strong association between weather and individual level anxiety for a patient with panic disorder (Bos et al., 2012). Likewise, other research has found relationships between anxiety and weather variables, including sunny days, precipitation, and temperature (Howarth & Hoffman, 1984). Taken together, the current study tends to show that there tends to be some common variables, namely location-derived features, which tend to be among the most important factors in predicting moment-to-moment symptom changes, but there are large individual differences suggesting potential for heterogeneity in the maintenance of these symptom changes (Fisher, 2015; Fisher et al., 2017, 2018; Jacobson & Chung, 2020).

In predicting large proportions of variation in anxiety and avoidance symptoms among persons at clinical levels of anxiety, these results suggest that personalized deep learning models paired with unobtrusive passively collected smartphone data may have the potential to inform just-in-time adaptive interventions (Nahum-Shani et al., 2018). In particular, if these personalized models predict an individual is at an increased risk of acute changes in their anxiety symptoms, it may facilitate a notification prompt and delivery of behavioral interventions using mobile technology so that these interventions can be weaved into the context of persons' daily lives (Mohr et al., 2013; Schueller et al., 2017).

Regarding the delivery method of the just-in-time adaptive intervention, these models may plausibly capture causal associations, but the current models only validate smartphone sensor data as a prognostic indicator. Here passively collected sensor data appear to be prognostic, but future research would need to be conducted to determine whether these models are indeed uncovering causal associations. If causal associations are being uncovered, it might motivate not only the timing but also the delivery target of the just-in-time adaptive interventions (e.g., persons at an increased risk of heightened future avoidance and anxiety symptoms could be recommended to spend more time outdoors). Even if these associations are not causal, but rather only prognostic of future changes, these models could still inform the timing of delivery of just-in-time adaptive interventions.

The current research also contains several areas for future extensions. Although the current research deployed instruments which assess DSM-5 diagnostic criteria for anxiety disorders, this work relied on self-report instruments. Future work should extend this work to examine whether the current methods might generalize to persons assessed using psychiatric interviews from clinicians. Additionally, the current sample did not target all forms of anxiety disorders, and future research should examine whether the current methods could be used with other anxiety disorders, such as panic disorder. Similarly, although the current sample reported clinical levels of generalized anxiety disorder or social anxiety disorder, participants were recruited from undergraduate populations, and future research should examine whether the current methods may generalize to persons seeking treatment. Additionally, future research should evaluate the feasibility and efficacy of integrating these passive computational methods to enhance just-in-time adaptive interventions to target moment-to-moment changes in persons with anxiety disorders.

In sum, the current paper finds strong relationships between passively collected smartphone sensor data and hourly changes in anxiety and avoidance symptoms among undergraduates experiencing clinical levels of generalized anxiety disorder and social anxiety disorder symptoms. The findings imply that changes in anxiety and avoidance symptoms are capable of being predicted using passively collected data from devices carried in persons' daily lives. The current work also suggests that there are person-specific differences in what predicts future changes in anxiety and avoidance symptoms. Nevertheless, the research also suggests that, for a large number of persons, spending time indoors predicted future changes in anxiety and avoidance symptoms (especially for persons with social anxiety disorder). The current work could inform the development of both the momentary intervention content and timing of just-in-time adaptive interventions to treat anxiety disorders. Importantly, this line of work could inform the delivery of personalized tailored interventions, driving both the timing and content delivery of digital treatments delivered within the fabric of persons' daily lives. In sum, this work has the potential to enhance the efficacy of scalable personalized interventions.

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Highlights

- Smartphones can capture social interaction, movement, physiology, and the environment.
- Smartphone data and deep learning can predict rapid changes in avoidance and anxiety
- Deep learning models and smartphones may promote just-in-time adaptive interventions

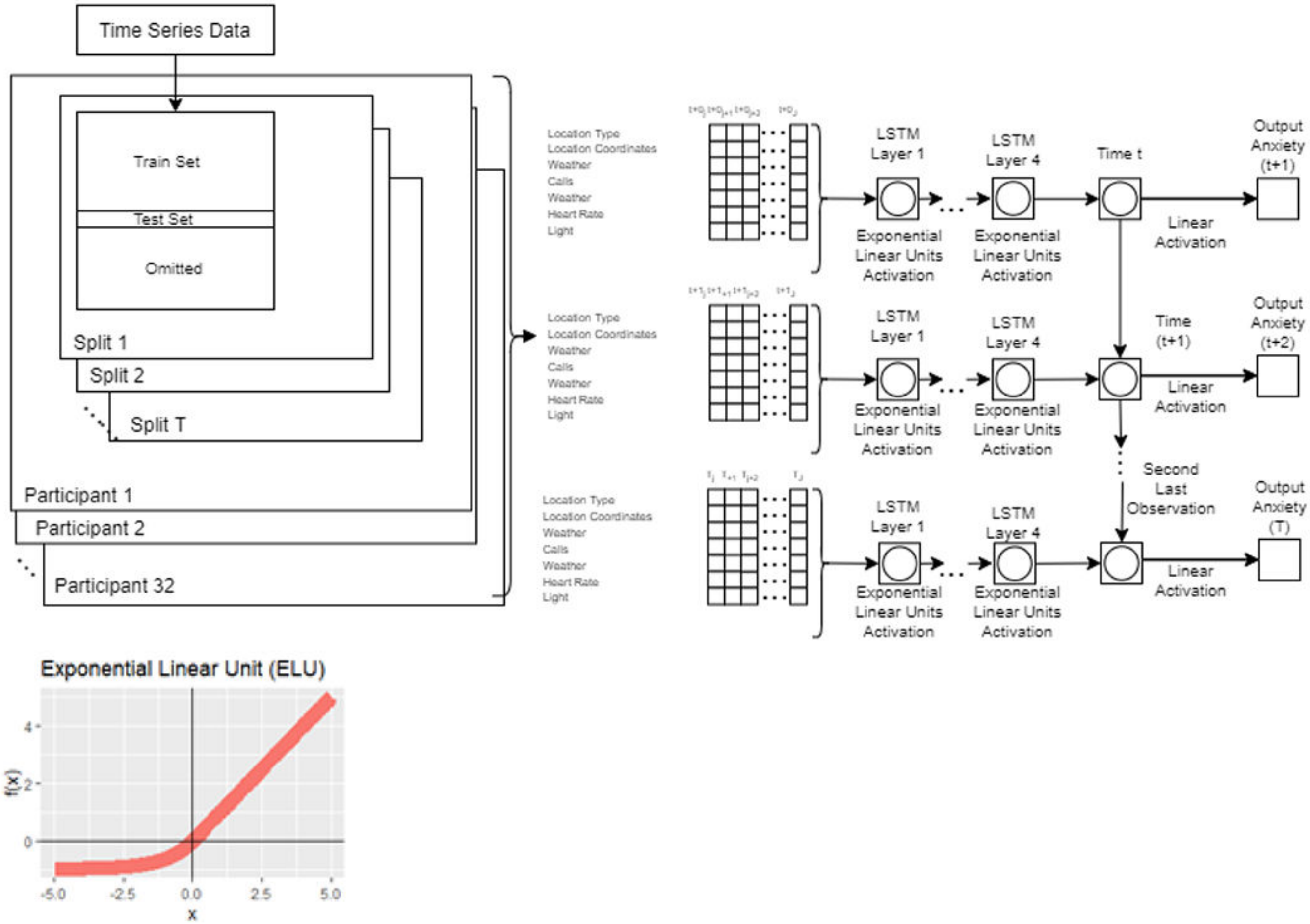

Figure 1.

This figure depicts the model training and testing architecture for the current project. All data were used based on idiographic models with past data predicting the future held-out data using only the sensor data. We utilized the exponential linear unit activation function at each hidden layer and a linear activation to make the predictions in the last layer.

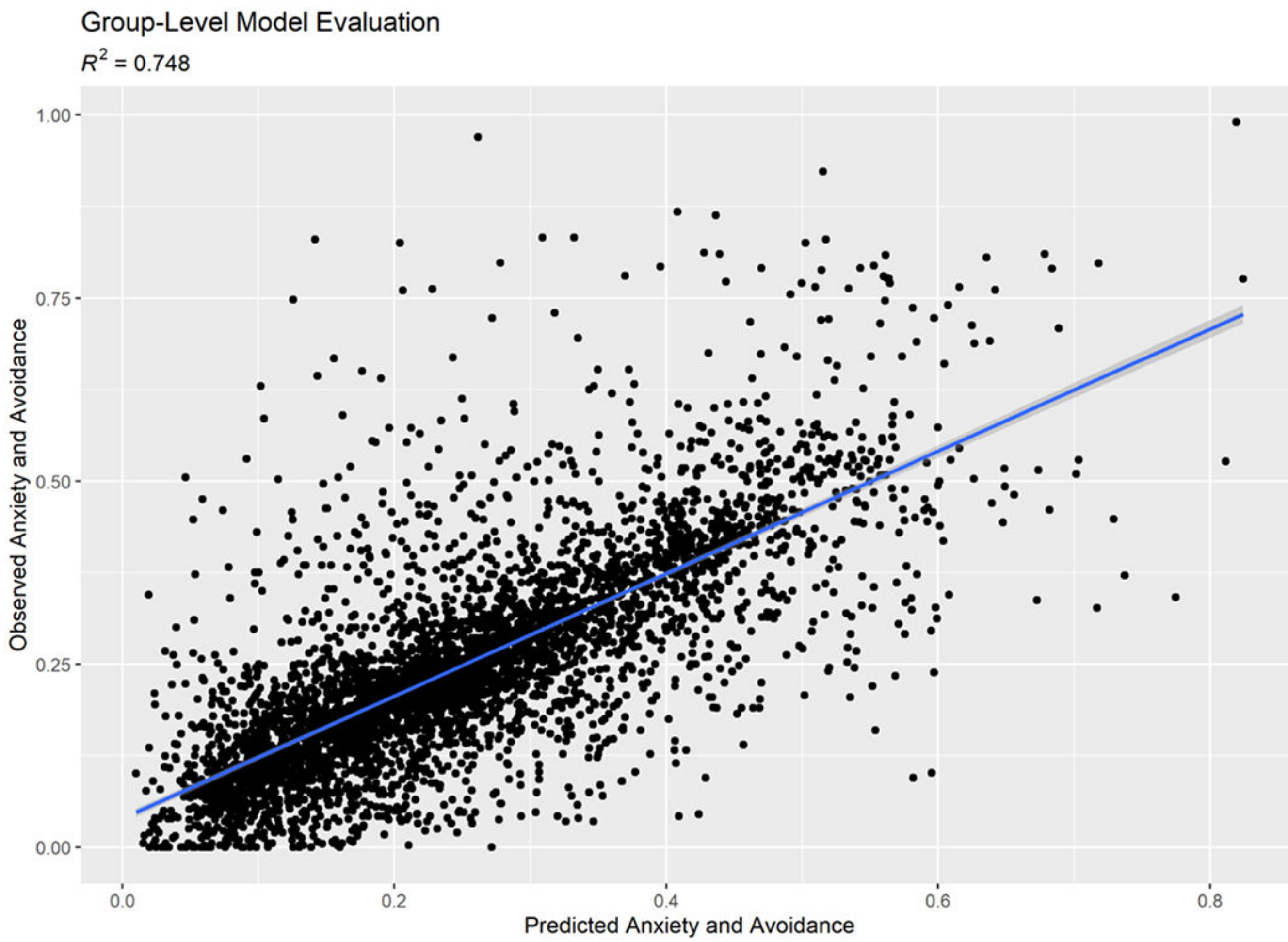

Figure 2.

This plot depicts the group-level predictions of the predicted anxiety and avoidance symptoms based on the passive sensor data. By evaluating performance at the group-level this plot includes both within-person and between-person variance.

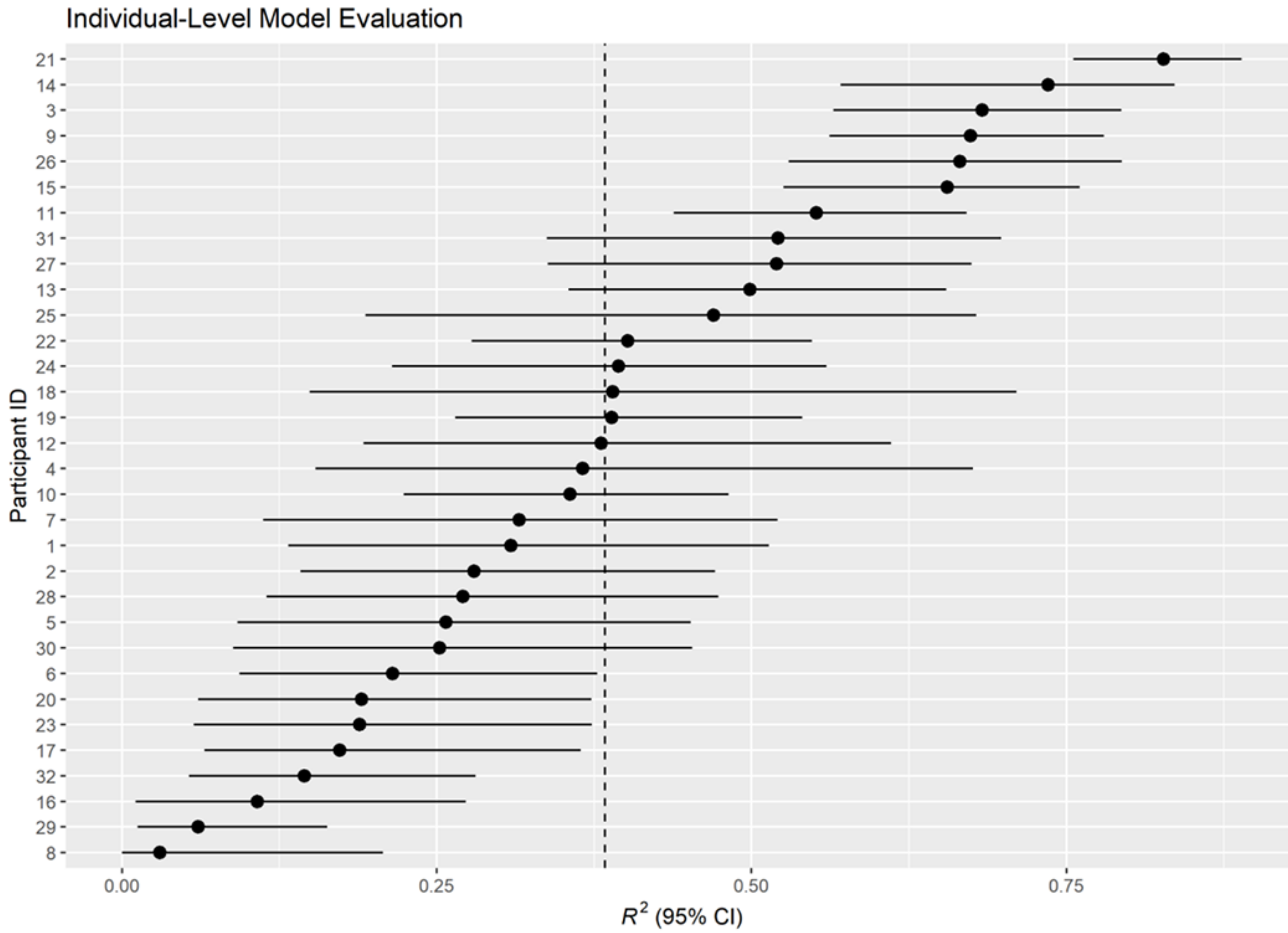

Figure 3.

This figure depicts the individual-level performance of the models. Here the mean R^2 of the model performance was 0.385 across persons. The majority (63%) of the individuals had a variance explained greater than 0.3. These results suggest that the models had a strong relationship between predicted and observed hour-to-hour symptom changes.

Figure 4.

This model predicts the composite measure of both anxiety and avoidance symptoms on the y-axis (termed “Anxiety”). This plot also depicts the predicted and observed anxiety and avoidance values for each model. These results demonstrate strong correspondence between predicted and observed hour to hour symptom changes.

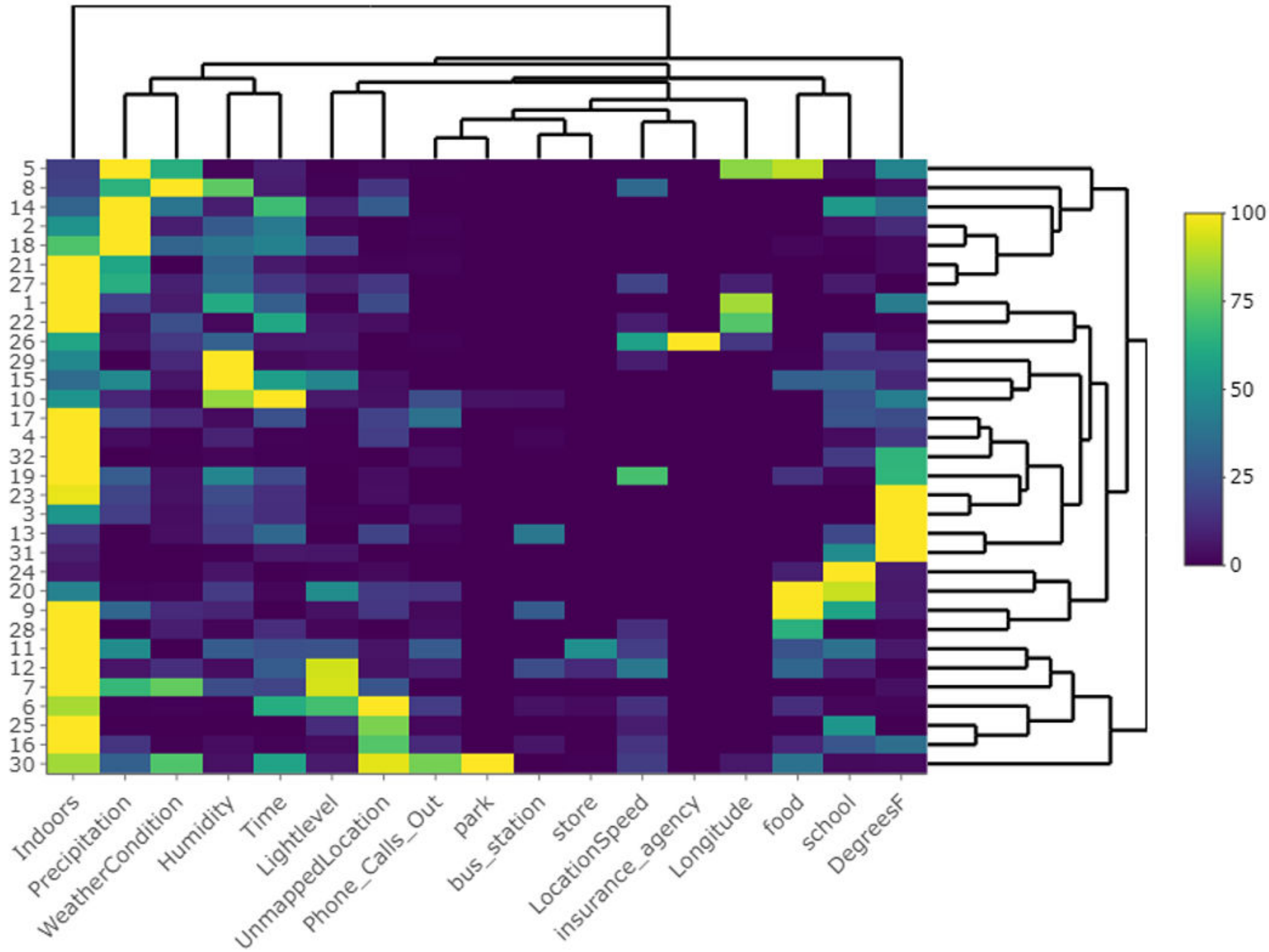

Figure 5.
This model depicts the variable importance of each feature. The x-axis reflects the feature, the y-axis reflects the participant ID, and the color reflects the feature importance. Time reflects the relative time in the study in hours. Many categories reflected here correspond to the location type (e.g., store, park, insurance agency, food, school). Being indoors was the most important feature, which was derived from the device's location accuracy and source of location data. This figure suggests that there was wide heterogeneity across persons in the features which most strongly influenced predictions, with the most consistent feature being time spent indoors.