Master thesis on Cognitive Systems and Interactive Media

Universitat Pompeu Fabra

Assessing State and Trait Anxiety Through Digital Phenotyping

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Supervisor: Klaudia Grechuta

Co-supervisor: Héctor López Carral

Host Research Group: SPECS

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Abstract

Mental health disorders place an immense burden on individuals and have significant personal and social impacts. This has been worsened by the effects of the COVID-19 pandemic, resulting in remote access to healthcare becoming more extensively studied and enforced. In recent years, digital phenotyping has been utilized in research to analyze and predict mental health outcomes. The aim of this project was to utilize passive mobile data to assess how anxiety impacts activity levels of individuals to help better understand their lived experiences. Potential differences between state and trait anxiety were assessed by comparing tracked and perceived activity levels. The results showed that individuals with low levels of both types of anxiety engaged in more physical activity compared to individuals with high anxiety levels. However, all participants displayed lower physical activity levels when experiencing high levels of state anxiety. Although the findings presented were very limited and lacked significance, if extended using a larger population, they could have the potential to aid in facilitating preventative interventions by detecting early signs of mental illness through evaluating possibly at-risk patients and informing the design of patient-tailored interventions.

Keywords: COVID-19; mental well-being; digital phenotyping; anxiety; activity level

1. Introduction

Problem Statement

Positive mental health is essential for facilitating a life that is built upon stability and social belonging and provides the groundwork for a high quality of life[1]. The impact of diminished mental well-being not only affects individuals in their personal lives but also on a widespread level that translates to families and societies, leading to potentially severe consequences such as suicide or destructive behaviors[2]. In 2017, it was reported that 3.67% of the worldwide population suffer from mental health or substance abuse disorders[3], however, the stigma that accompanies mental illnesses often results in underestimated, underdiagnosed or untreated conditions[2]. On average, 76–85% of the population with mental disorders globally do not receive treatment or adequate mental health services[4]. Due to COVID-19, this number has likely increased, with more people stating that they are experiencing symptoms associated with negative mental health, as early research has shown that unexpected events can have detrimental effects on mental well-being[5,6,7]. Understanding the impact of traumatic events is vital to providing the necessary mental health interventions.

The effect of COVID-19 on mental well-being

When the coronavirus disease 2019 (COVID-19), caused by the severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2), was declared a global pandemic, the disruption that followed was and continues to be unparalleled. Measures have been implemented across the globe that include lockdowns, social distancing, and the mandatory use of face masks[8]. These restrictions have caused psychological turmoil in many and have been shown to exacerbate existing conditions in patients with mental health disorders and cause emerging symptoms in those with no previous history[9]. Emerging research highlights these effects, indicating that the pandemic has increased stress, anxiety, depression, and post-traumatic stress[10,11,12,13]. Moreover, it has led to increased feelings of loneliness and worry as well as low tolerance for distress. The psychological effects surrounding significant events can persist long after the outbreak has taken place and cause negative thoughts that impact well-being[6]. Specifically, perceived threats, such as the pandemic in this case, mediate future anxiety through an increase in stress and vulnerability[14]. A lack of knowledge of the causes and symptoms of mental disorders, such as anxiety, can lead to a snowball effect of coinciding psychological issues such as behavioral, developmental, and emotional problems[15].

State of the Art

Anxiety

While anxiety represents a natural biological and physiological human response, it remains a topic of great ambiguity but continues to be the most prevalent mental disorder[3,16]. Its definition is often unclear in previous literature, despite many of its markers being distinctly identified and measured. It has been described as a type of physiological arousal in an unpleasant subjective state characterized by feelings of unease and worry[16]. Yet, despite the plethora of existing research, the measurement of emotional states can be complex and have made current definitions difficult to operationalize[16]. For example, Spielberger (1972) described it as an activation of the autonomic nervous system caused by tension[17], whereas other authors have stated that it derives from the anticipation of impending misfortune[18]. A lack of consensus on a single universal definition may lead to inconsistent testing as some characteristics are scientifically studied and others are inaccessible due to their introspective nature.

To analyze anxiety in a quantifiable and observable way, studies use its physical symptoms to assess the levels of panic that may occur. Affective states are typically accompanied by autonomic arousal, such as sweating, dizziness, or shortness of breath as well as somatic symptoms, like insomnia, restlessness, and muscle aches[19]. Moreover, the manifestation of anxiety through cardiovascular, respiratory, and neurological symptoms can lead to avoidant behaviors, appetite changes, and agitation[20]. While these effects are most notable in individuals diagnosed with an anxiety disorder, they can also be prominent in those experiencing temporary levels of anxiety[21].

Trait vs State Anxiety

Previous literature has made notable distinctions between trait anxiety (i.e., a stable personality characteristic), and state anxiety (i.e., a transitory or situationally dependent experience)[21]. Temporary feelings of anxiousness that vary in intensity and fluctuate over time reflect state anxiety while enduring depressive or anxious responses to stimuli in the form of stress, avoidance, anger, or attachment reflect trait anxiety. These effects amplify one another as state anxiety is heavily reliant on trait anxiety to determine an individual's predisposition to exhibit an anxiety response[22]. Although they differ drastically in terms of their long-term effects and personal experiences, there is a strong link between state affect and trait affect, and a tendency to withdraw; for example, spending more time at home[23]. Significant effects are seen which negatively impact performance[21], decrease attention[24], and lessen the degree in which individuals engage in or avoid social activities[23]. These findings, coupled with the physiological symptoms previously mentioned, show potential in passively measuring and assessing state and trait anxiety to assess mental illness in vulnerable populations. However, current work has prioritized active, self-reported data regarding a patient's emotions and behavior[25].

Measures and Treatment

Anxiety is typically assessed using self-reported data, such as the Beck Anxiety Inventory or Generalized Anxiety Disorder Scale which evaluate the severity of anxiety in adults and adolescents[25]. Other methods have also been used in an attempt to measure vulnerability to anxiety, such as the State and Trait anxiety scale to further assess an individual's predisposition to react anxiously[25]. In more recent research, ecological momentary assessments, or the sampling of behaviors in real time, have been prioritized for their ability to examine the natural unfolding of biological and psychological processes overtime, typically through data-capturing devices[26]. This is often done by sending surveys at different random or planned intervals for patients to complete in their naturalistic settings. Despite the heavy reliance on self-reports, their susceptibility to external factors has been criticized due to diminished validity caused by biases, low recall accuracy, or incomplete information[25,27]. Another concern lies in people's introspective limits and their ability to accurately detect their own complex psychological or behavioral patterns in their everyday lives[23].

These methods, although widely used and thoroughly tested, are limited. Many studies focus on participants with existing mental health symptoms while little attention is given to individuals at risk[28]. The detection of cases of mental illness that have been unaccounted for can be improved by specifically recruiting "healthy" participants, however, only 4% of studies purposefully excluded patients currently being treated for mental health disorders[29]. Recruiting patients currently in treatment, while beneficial in gaining valuable knowledge, does not include those at risk of mental-ill health or those who may not be unaware of their symptoms. Recognizing and reporting symptoms can prove to be difficult for those with a mental illness[30]. Enhancing current practices by screening for individuals who are not diagnosed may decrease the likelihood of the onset of unexpected long-term effects derived from mental disorders[29]. With high rates of misdiagnosis and under-diagnosis, focus should be placed on detecting physical health concerns deriving from psychological states[30]. Characteristics of mild anxiety, such as subtle feelings of nervousness, can go unnoticed by many and monitoring its early signs using accurate and robust technological tools is imperative for preventative intervention.

Physical Activity Levels

The mental ill-health of an individual is not only linked to changes in biological states but also psychological ones that lead to the onset of negative mindsets and habits that are a detriment to well-being, such as social avoidance and solitude[20,23]. Growing bodies of research indicate that factors, including one's level of physical activity, can be impactful in improving the quality of life in general populations, including those with and without mental health disorders[31]. Despite this, past literature has focused on the study of the psychological effects of physical activity within clinical populations rather than those with no preexisting disorders[28]. The need to further investigate this topic is also enhanced by pandemic related confinements caused by COVID-19 showing significant negative impacts on physical activity levels[32]. A substantial decrease in moderate and vigorous physical activity by roughly 40% has been seen globally[32]. This decline in physical exertion, coupled with diminished psychological wellness, caused by the threat of the pandemic may affect subjective experiences of time[33]. These findings bring into question the accuracy of people's perceptions of their daily lives as self-report measures generally underestimate sedentary time when compared to device measures[34]. While self-reports can be extremely valuable, technological devices that extract passive movement data may offer objective measures of physical behaviors that can be used to make psychological inferences.

Digital Phenotyping

Digital phenotyping is the collection of mobile sensing data through smartphone or wearable technology to infer participant behavior gathered through movement, interaction, or activity[35]. Using passive data, digital phenotypes allow researchers to measure patient behavior within the context of healthcare[35]. Leveraging modern technology in digital phenotyping studies allows for the collection of real time information regarding many different variables simultaneously to provide robust proxies for measuring bodily functions. Digital tools provide new venues to identify and track symptoms and aid in early disease detection[36]. Although privacy risks have been reported, previous digital phenotyping research shows that people are generally cooperative and accepting of having digital phenotyping applications, such as mobile sensing apps, on their devices[37] and they can adopt these technologies with ease[38].

Popular passive data types employed to extract background information include location, accelerometer, social information, and screen time[39] to observe people's activity levels[40], location entropy[41], and positive and negative affect[42]. The use of digital phenotyping is enhancing the understanding of the relationship between behavior and mental health in individuals with bipolar disorder[43], anxiety and depression[44], and Alzheimer disease and dementia[45]. Specifically, the number of text messages, duration of phone calls, location/mobility data, and voice features extracted during phone calls have been shown to correlate with the level of anxious, depressive, and manic symptoms[43]. Other uses of digital phenotyping through gaming applications aim to detect early signs of Alzheimer disease and dementia[45]. Furthermore, digital phenotyping has been shown to accurately predict social anxiety disorders and differentiate them from other anxiety disorders[42]. Figure 1 depicts the correlation between predicted and observed social anxiety symptom severity by assessing accelerometer, text message, and call biomarkers. By providing researchers and patients with the adequate tools to monitor and track behaviors and bodily responses derived from mental health symptoms, an increase in awareness of one's own psychological and physical state follows[46]. Heightened self-awareness is essential in taking preemptive steps in healthcare and improving conscious action and implementing intervention strategies[46].

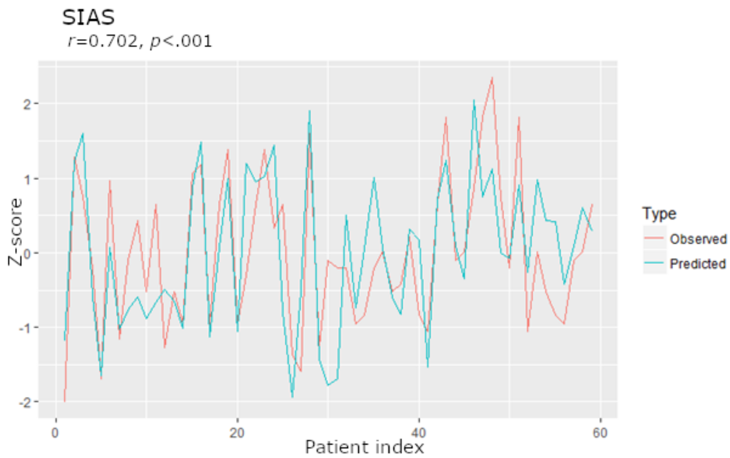

Figure 1: Predicted social anxiety disorder (SAD) severity and the observed SAD symptom severity for each participant. SIAS: social interaction anxiety scale.

In this project, the challenges surrounding mental health care will be addressed by investigating digital phenotypes of anxiety by analyzing GPS and accelerometer data extracted from smartphone sensors in an app called Sensus. Activity levels will be measured through the device and compared to participants' perceived activity. Assessing these differences and how they interact with an individual's anxiety levels can help improve current diagnostics and monitoring strategies for people at risk. The proposed project will be completed remotely due to COVID-19 constraints, however, providing remote services can prove to be advantageous in a climate that has highlighted the need for more accessible medical resources. Utilizing digital tools to create standardized and approved means of providing care and services remotely can only benefit the health care system by making it more available to those who need it.

Expected Outcome

What we expect to find is that those with high trait anxiety scores will demonstrate more withdrawal tendencies such as lower activity levels and a lower number of places visited per day. Trait anxious individuals may generally experience a higher rate of anxiety, resulting in overall lower activity levels; however, in situations of increased anxiousness, both groups will exhibit more dissociation in their perceived activity levels. Furthermore, trait and state anxious individuals will significantly under-report when assessing their own activity levels in comparison to device measures when experiencing high anxiety versus low anxiety.

2. Methods

The aim of this study is to assess anxiety through perceived activity levels by using digital phenotyping. Gathering GPS and accelerometer information to compare from both the device and the participant is valuable as individuals often have flawed perceptions of their levels of physical activity. Previous research has shown that self-report measures generally underestimate sedentary time when compared to device measures[34]. Based on this information, the assumption can be made that those experiencing mental health disorders may have an even more heightened distortion of their daily activity. Therefore, we hypothesize that individuals will display dissociation in perceived activity levels when experiencing high anxiety and less when experiencing low or no anxiety. Furthermore, it is expected that those with higher anxiety scores will demonstrate withdrawal tendencies such as lower physical and social activity levels.

General Methodology Applied

Participants

Ten individuals were recruited to participate in the study through online means and using various social media platforms. The target population for this study was young adults between the ages of 20 and 30 that are currently residing in Spain. A specific age group was chosen with the expectation that they will have similar lifestyles and levels of activity. Being a current resident in Spain was also important to account for potential differences in COVID-19 movement restrictions and environmental factors such as weather changes, limited public transportation, or proximity to nature. Lastly, participants were required to have access to a mobile phone that could be carried throughout all their daily activities.

Measures

<u>State-Trait Anxiety Inventory</u>

The State-Trait Anxiety Inventory (STAI) is one of the most commonly used measures of trait and state anxiety[47,48]. The inventory has 20 items for assessing trait anxiety and

20 for assessing state anxiety. State anxiety items include: “I am tense; I am worried” and “I feel calm; I feel rested”. Trait anxiety items include: “I am inclined to take things hard” and “I tire quickly; I am a steady person.” All items are rated on a 4-point scale with higher scores indicating greater anxiety. The scale has been shown to have high internal consistency coefficients, test-retest reliability, and construct and concurrent validity[47,48]. Scores can range from 20–80 with higher scores indicating greater anxiety. Scores above 40 have been shown to detect clinically significant symptoms and have been used as a cut-off point to distinguish between high and low anxiety levels[48]. In this study, participants completed the Trait Anxiety Inventory upon enrollment and the State Anxiety Inventory was completed on a daily basis to account for their state affect.

International Physical Activity Questionnaire

The International Physical Activity Questionnaire (IPAQ) is a self-report measure of physical activity with a 27-item long form and a 7-item short form[49]. It covers job related physical activity (e.g. “How much time do you usually spend walking as part of your work?”), transportation (e.g. “How much time do you usually spend in a train, bus, tram, or other kind of motor vehicle?”), housework, maintenance, and caring for family (e.g. “How much time do you usually spend doing moderate physical activities inside your home?”); recreation, sport, and leisure time (e.g. “How much time do you usually spend doing vigorous physical activities in your leisure time?”), as well as time spent sitting (e.g. “How much time did you usually spend sitting on a weekday?”). IPAQ has been shown to have acceptable validity when assessing patterns and levels of physical activity[49]. Moreover, this questionnaire is particularly beneficial in this study as it captures most types of physical activity a person may engage in. Participants completed the long form of the IPAQ once they were enrolled, then completed the short form on a daily basis to assess their daily perceived activity levels.

Passive Biomarkers

For the duration of the study, accelerometer and GPS data was collected through a mobile app. Unlike other sensing agents, GPS modules tend to drain mobile batteries very quickly due to its computational load[50]. To account for this, the GPS probe was tested rigorously and the most reasonable data collection rate that did not sacrifice battery life was five minutes. Data was stored every five minutes or when there was a significant change in location to override the scheduled polls. Similarly, accelerometer data was also gathered by polling for major differences.

Experimental design and set-up

Sensus App

Sensus is a mobile crowdsensing app that is available on both iOS and Android that has been created to allow the gathering of passive data from participants[51]. It allows researchers to configure their own protocols and alter any probing information, such as which data to collect in the background, or configuration settings specific to the study. Sensus also supports scheduled and sensor-triggered surveys to collect active data. It secures and anonymizes data and integrates with data analysis environments such as R and MATLAB. The app has source code available online and was used to configure the study. Once completed, the study was distributed to participants via a link that they then entered and loaded into the Sensus app. Gathered data was collected and stored in a server for later retrieval and analysis.

Procedure

Participants were recruited through online means and told that this study examines how their thoughts and feelings interact with their level of activity. Detailed study enrollment instructions were sent to each participant with information regarding the timeline protocol, how to set up the app and study successfully, and their participant identification numbers. During this stage, they were instructed on the type of data that will be collected from their phones as well as what they will be expected to complete for the course of the experiment. Once the guidelines were followed and consent was provided in the form of entering their unique participant ID, the study immediately began. This prompted three enrollment surveys to be sent to their mobile devices. A demographic survey asked for their gender, age, location, level of activity, and prior diagnoses. The Trait Anxiety Inventory and the long version of the IPAQ were the second and third enrollment surveys to be completed. For the duration of 2 weeks, the app collected data in the background without any interference and the participant was sent the State Anxiety Inventory and the short version of the IPAQ to complete daily at

10PM. After the study was completed, the raw GPS and accelerometer data was accessed and analyzed. A visual timeline of the study is shown in Figure 2.

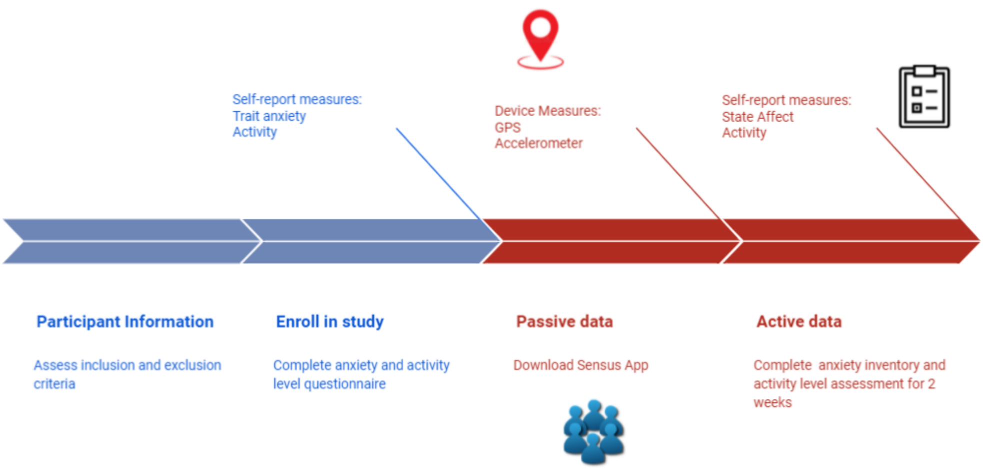

Figure 2: Timeline Protocol.

Data Analysis

Throughout the course of the two week period, three participants dropped out of the study and one participant was removed due to a lack of sufficient data, leaving six participants [mean age (SD) = 23.16 (0.75); 5 females (83.3%)] to complete data collection successfully. The demographic information for each participant is shown in Table 1. Due to issues with participants not carrying their phones or submitting daily surveys, as well as mistakenly closing the application, a vast amount of data was lost. A total of 84 observations were expected, however, 40 total days were removed due to participants closing the app leading to insufficient accelerometer and gps data, and 36 days were removed due to missing participant self-reports or survey entries. This resulted in 22 total observations across the 6 participants. The statistical programming language R was used to analyze the data and was extracted using the SensusR package which was developed to make the raw data more digestible.

Table 1: Demographics of the participants. Note that three participants had high trait anxiety levels at the start of the study.

Participant ID	Trait Anxiety	Gender	Age	City	Fitness Level	Mental Disorders
1	High	Female	23	Barcelona	Very physically active	Depression
2	High	Male	23	Barcelona	Somewhat physically active	No
3	Low	Female	22	Barcelona	Not physically active at all	No
5	Low	Female	24	Barcelona	Very physically active	No
9	Low	Female	23	Alcobendas	Somewhat physically active	No
10	High	Female	24	Donostia-San Sebastián	Very physically active	No

The number of places visited was extracted by comparing GPS data and times to analyze the data quantifiably by assessing their number of places visited per day. PowerBi and OpenStreetMap for R were used to visualize the GPS data. The home location was identified based on the most frequent appearance of localities during nighttime[23]. Figure 3 shows an example of one day of GPS data in which a participant went from Barcelona to Madrid and stopped at the red dots for a prolonged period of time. To gather an objective measure of the time spent on physical activity (denoted as non-sedentary movements including standing), the accelerometer data was used to compute the Euclidean Norm Minus One (ENMO) for each time window of 1 second, since data was not collected at a constant rate. Managing large amounts of raw accelerometer data may pose many challenges such as gravitational and noise components incorporated within the signals. To account for this, the ENMO is emerging as a metric for efficiently analysing this type of data while classifying intensity and sedentary behaviours to allow them to be comparable between studies. As suggested in prior research, only time intervals with an ENMO of 2.9 or more were considered to compute the total time spent on non-sedentary activities by subtracting a fixed offset value of 1 gravitational unit at each time point to correct for gravity[52].

Figure 3: A participant's GPS data during their travel from Barcelona to Madrid.

3. Results

Due to non-normally distributed data, the results were analyzed using violin plots as well as the Spearman R correlation coefficient. Although no significant results were obtained, there are clear trends within the final graphs that will be discussed. First, looking at the difference between individuals' own self-reports (Figure 4), the median self-reported time is greater for individuals with low levels of state/trait anxiety (μ = 120, μ = 100), compared to those with high levels (μ = 32.5, μ = 45). This indicates that those with low anxiety are generally engaging in more physical activity even though there is almost no difference between trait and state anxiety groups. To confirm the self-reported findings, the sensed data in Figure 5 shows similar results with the median accelerometer-tracked time being greater for individuals with low levels of state/trait anxiety (μ = 20, μ = 17.5), compared to those with high levels (μ = 1.5, μ = 6). Furthermore, the difference between high and low trait anxious individuals and the accelerometer tracked time is significant (p = 0.004), meaning participants with high trait anxiety are engaging in less physical activity. When comparing those with high levels of state and trait anxiety between both the self-reported and accelerometer-tracked plots in Figures 4 and 5, it is evident that overall physical activity is being over-reported, opposing the prediction made in the initial hypothesis. In order to understand if there is a difference between the self-reported time and the accelerometer-tracked time, Figure 6 shows the interaction of both times grouped by all four combinations of state and trait anxiety levels. A p-value of 0.17 shows no statistically significant relation, however, individuals with high/low and low/high state and trait anxiety have a much higher difference between what is sensed and what is reported in comparison to those with both low levels of anxiety.

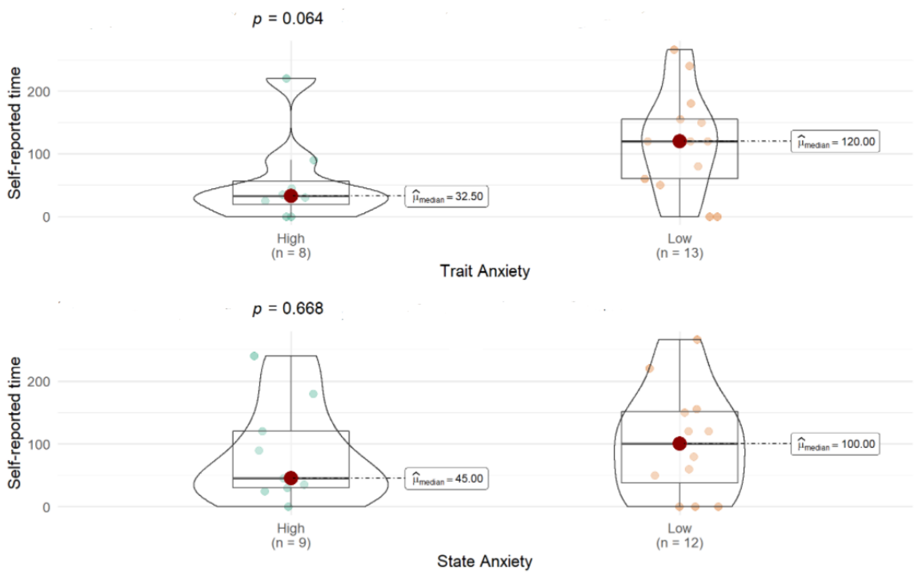

Figure 4: Self-reported time spent on physical activities grouped by levels of state/trait anxiety.

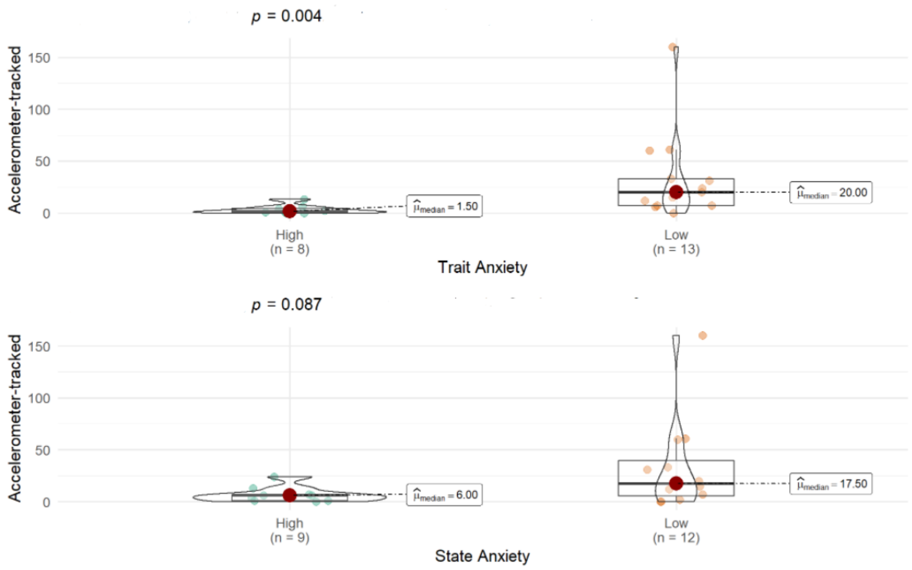

Figure 5: Accelerometer-reported time grouped by levels of state/trait anxiety.

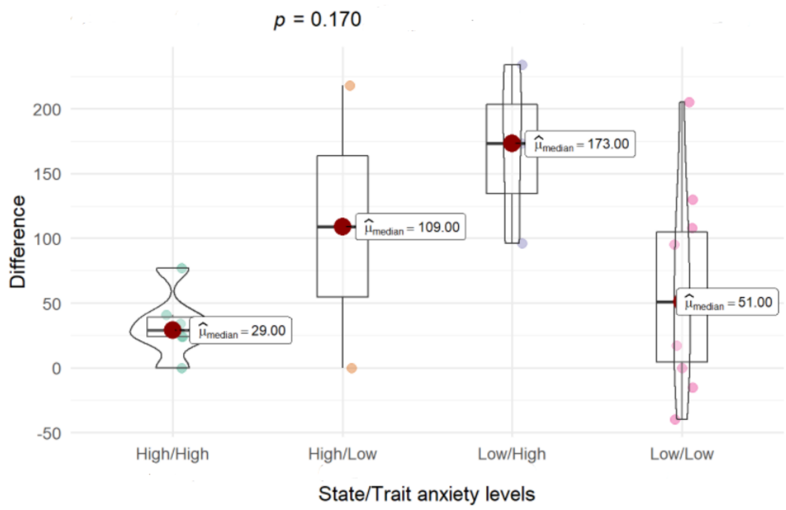

Figure 6: Difference between self-reported and accelerometer-tracked times, grouped by all four combinations of state and trait anxiety levels.

The trends seen within the violin plots show similar results to those in the Spearman R correlations. It is apparent that individuals with high levels of anxiety had lower activity levels. The correlations in Figure 7 between mean state and trait anxiety scores and average accelerometer-tracked time is negative and statistically not significant (R = -0.31, p = 0.544; R = -0.67, p = 0.148). Similarly, Figure 8 also shows negative and insignificant results between mean state and trait anxiety scores and self-reported times (R = -0.49, p = 0.329; R = -0.46, p = 0.354). The primary similarity between graphs is the consistent negative correlation between variables. Although no significant results were obtained, as mean state/trait anxiety scores increase, activity levels decrease. In our hypothesis and based on past literature[41], we also expected that higher levels of state and trait anxiety would impact the number of places visited per day. Figure 9 shows that this expectation was not met as the correlation between average state and trait anxiety scores and the average number of places visited is negative and statistically not significant (R = -0.12, p = 0.827; (R = 0.00, p > .999). The weak correlations within the results presented are heavily associated with the low number of participants and the lack of data points. With a larger number of subjects, a stronger correlation could be visible and provide for a more concrete framework to base future research on.

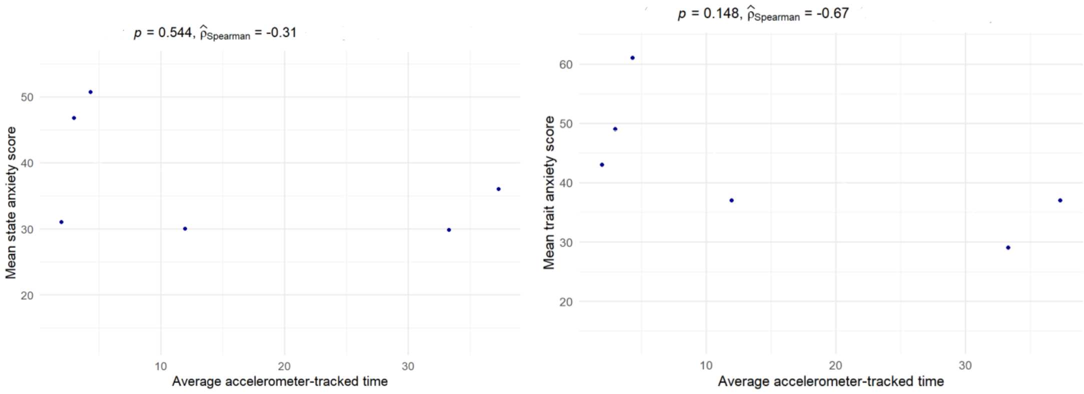

Figure 7: Correlation between mean state/trait anxiety scores and average accelerometer-reported time.

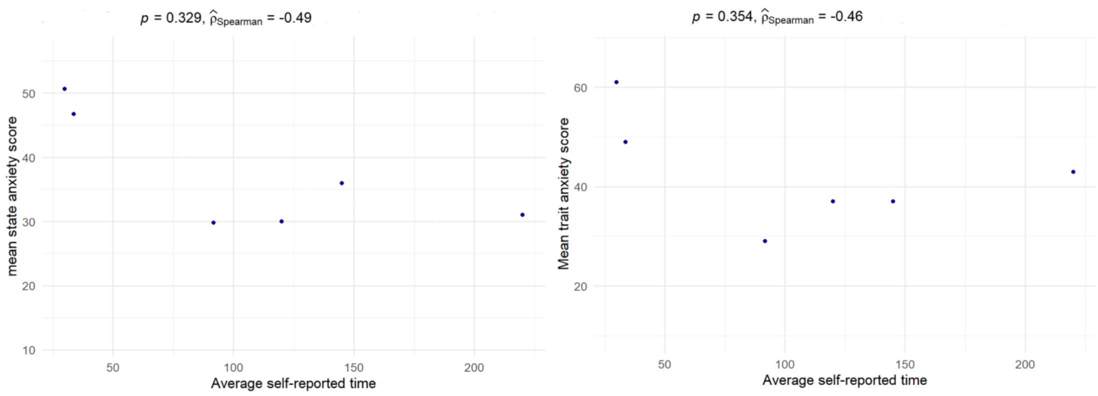

Figure 8: Correlation between mean state/trait anxiety scores and average self-reported time.

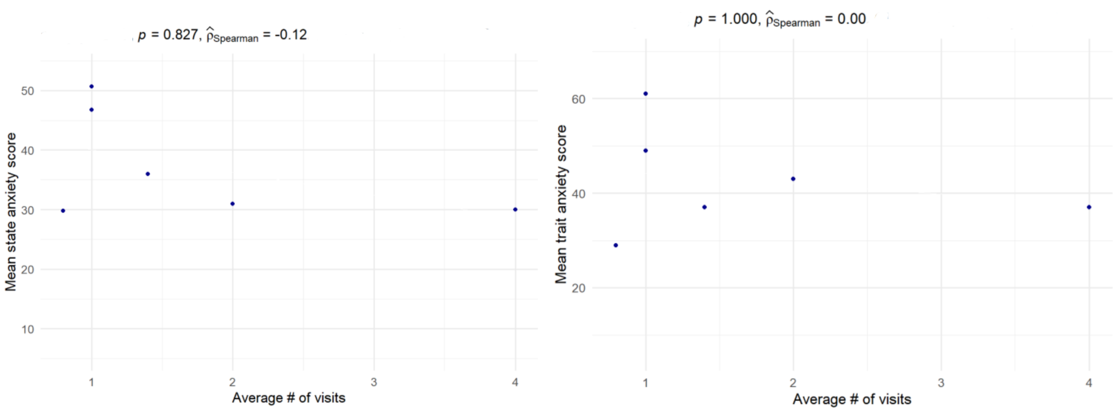

Figure 9: Correlation between the average number of places visited and mean state/trait anxiety scores.

4. Discussion

Principal Findings

To summarize the initial predictions and findings, we first hypothesized that those with higher trait anxiety scores will demonstrate lower activity levels and although no significance was found, participants did tend to have lower physical activity levels when experiencing high levels of state anxiety. This trend was also seen in individuals with low levels of both types of anxiety as they engaged in more physical activity compared to individuals with high anxiety levels. Additionally, both groups were expected to experience more dissociation in perceived activity levels when anxious and less when not. However, the difference between self-reported and accelerometer-reported times and participants' anxiety levels was not significant, therefore there is insufficient evidence to deduce that that a relationship exists until further experimentation is conducted. Finally, no significant relation was found between the number of places visited and anxiety scores.

Limitations

The findings presented make light of several limitations and provide direction for future research. First, the results were derived from a modest sample size. Factors such as time and location made it difficult to gather an adequate number of individuals leading to a limited set of participants. Conducting the study on a larger scale may allow for more representative findings that consider not only the research question but also other moderating factors. Second, COVID-19 restrictions varied significantly in different countries around the world. Due to these differences, the population pool was limited to individuals residing in Spain to ensure that rules inhibiting movement or social interaction was the same between all participants. Third, an abundance of data was lost due to participants not carrying their phones with them at all times as instructed, forgetting to submit daily surveys, and closing the application completely which prevented background data collection for several days. Furthermore, many technical difficulties such as battery life, corrupted data files, and software bugs led to a significant decrease in the amount of data collected. Lastly, no causal relationships can be made between digital phenotyping and the onset of anxiety due to the correlational nature of the results. As with any academic research, many external variables may have influenced the data collected. However, prolonging the study period can account for some by revealing a true representation of participants' day-to-day life.

Conclusion

Despite the limitations presented, this research topic holds great potential in making inferences regarding people's everyday experiences and can be improved upon to provide beneficial mental health interventions. While none of the initial hypotheses were met in terms of significant values, this study extends past literature utilizing passive smartphone sensor data to detect patterns of anxiety. With the rise of mental health disorders due to the recent pandemic, taking advantage of digital phenotyping may substantiate previous findings. It may also provide a framework to identify those in need of help but are unaware of their current state or are afraid of seeking help. As anxiety disorders become more prevalent, the need to develop novel methods of assessing psychological ill-health have become crucial. Leveraging modern technology within the realm of research and healthcare can demonstrate its importance in providing adequate care.

3. Bibliography

1. Tennant, R., Hiller, L., Fishwick, R., Platt, S., Joseph, S., Weich, S., Parkinson, J., Secker, J. & Stewart-Brown, S. The Warwick-Edinburgh mental well-being scale (WEMWBS): Development and UK validation. *Health and Quality of Life Outcomes*. **5**(1), 63–74 (2007).

2. Baumann, A. E. Stigmatization, social distance and exclusion because of mental illness: The individual with mental illness as a 'stranger'. *International Review of Psychiatry*, **19**(2), 131-135 (2007).

3. Ritchie, H. & Roser, M. Mental Health. *Our World in Data* (2018). Available at: https://ourworldindata.org/mental-health.

4. Mental disorders. *World Health Organization* (2019). Available at: https://www.who.int/en/news-room/fact-sheets/detail/mental-disorders.

5. Maunder, R., Hunter, J., Vicent, L., Bennett, J., Peladeau, N., Leszcz, M., Sadavoy, J., Verhaeghe, L.M., Steinberg, R. & Mazzulli, T. The immediate psychological and occupational impact of the 2003 SARS outbreak in a teaching hospital. *CMAJ*. **168**(10), 1245–1251 (2003).

6. Holman, E. A. & Silver, R. C. Future-oriented thinking and adjustment in a nationwide longitudinal study following the September 11th terrorist attacks. *Motivation and Emotion*. **29**(4), 385-406 (2005).

7. Perrin, P. C., McCabe, O. L., Everly Jr, G. S. & Links, J. M. Preparing for an influenza pandemic: mental health considerations. *Prehospital and disaster medicine*. **24**(3), 223 (2009).

8. Coronavirus. *World Health Organization.* Available at: https://www.who.int/health-topics/coronavirus#tab=tab_1.

9. Cullen, W., Gulati, G. & Kelly, B.D. Mental health in the COVID-19 pandemic. *QJM Monthly Journal of the Association of Physicians*. **113**(5), 311–312 (2020).

10. Liu, C.H., Zhang, E., Wong, G.T.F., Hyun, S. & Hahm, H. Factors associated with depression, anxiety, and PTSD symptomatology during the COVID-19 pandemic: Clinical implications for U.S. young adult mental health. *Psychiatry*

Research. **290**, 1–7 (2020).

11. Ho, C. S., Chee, C. Y. & Ho, R. C. Mental health strategies to combat the psychological impact of COVID-19 beyond paranoia and panic. *Ann Acad Med Singapore*. **49**(1), 1-3 (2020).

12. Zhang, Y. & Ma, Z. F. Impact of the COVID-19 pandemic on mental health and quality of life among local residents in Liaoning Province, China: A cross-sectional study. *International journal of environmental research and public health*. **17**(7), 2381 (2020).

13. Ornell, F., Schuch, J. B., Sordi, A. O. & Kessler, F. H. P. "Pandemic fear" and COVID-19: mental health burden and strategies. *Brazilian Journal of Psychiatry.* **42**(3), 232-235 (2020).

14. Paredes, M. R., Apaolaza, V., Fernandez-Robin, C., Hartmann, P. & Yañez-Martinez, D. The impact of the COVID-19 pandemic on subjective mental well-being: The interplay of perceived threat, future anxiety and resilience. *Personality and individual differences*. **170** (2020).

15. Reupert, A. & Maybery, D. Families affected by parental mental illness: A multiperspective account of issues and interventions. *American Journal of Orthopsychiatry*. **77**(3), 362-369 (2007).

16. Sarason, I. G., Sarason, B. R. & Pierce, G. R. Anxiety, cognitive interference, and performance. *Journal of Social Behavior & Personality*. **5**(2), 1–18 (1990).

17. Spielberger, C. D. *Anxiety: Current trends in theory and research*. (Elsevier, 2013).

18. Kring, A. M., Davison, G. C., Neale, J. M. & Johnson, S.L. *Abnormal psychology* (John Wiley & Sons Inc, 2007).

19. Gelenberg, A. J. Psychiatric and Somatic Markers of Anxiety: Identification and Pharmacologic Treatment. *Primary care companion to the Journal of clinical psychiatry.* **2**(2), 49–54 (2000).

20. Perrotta, G. Anxiety disorders: definitions, contexts, neural correlates and strategic therapy. *Journal of Neurology and Neuroscience*. **6** (2019).

21. Meijer, J. Stress in the relation between trait and state anxiety. *Psychological reports*. **88**, 947–964 (2001).

22. Endler, N. S. & Kocovski, N. L. State and trait anxiety revisited. *Journal of anxiety disorders*. **15**(3), 231-245 (2001).

23. Chow, P.I., Fua, K., Huang, Y., Bonelli, W., Xiong, H., Barnes, L.E. & Teachman, B.A. Using Mobile Sensing to Test Clinical Models of Depression, Social Anxiety, State Affect, and Social Isolation Among College Students. *J Med Internet Res*. **19**(3) (2017).

24. Pacheco-Unguetti, A. P., Acosta, A., Callejas, A. & Lupiáñez, J. Attention and anxiety: Different attentional functioning under state and trait anxiety. *Psychological science*. **21**(2), 298-304 (2010).

25. Suslow, T., Hußlack, A., Bujanow, A., Henkelmann, J., Kersting, A., Hoffmann, K. T., Egloff, B., Lobsien, D. & Günther, V. Implicitly and explicitly assessed anxiety: No relationships with recognition of and brain response to facial emotions. *Neuroscience*. **408**, 1–13 (2019).

26. Robinaugh, D. J., Brown, M. L., Losiewicz, O. M., Jones, P. J., Marques, L. & Baker, A. W. Towards a precision psychiatry approach to anxiety disorders with ecological momentary assessment: the example of panic disorder. *General psychiatry*. **33**(1) (2020).

27. Perez-Pozuelo, I., Spathis, D., Clifton, E.A. & Mascolo, C. Wearables, smartphones, and artificial intelligence for digital phenotyping and health. *Digital Health*. 33-54 (2021).

28. Tyson, P., Wilson, K., Crone, D., Brailsford, R. & Laws, K. Physical activity and mental health in a student population. *Journal of mental health*. **19**(6), 492-429 (2010).

29. Rice, D.B. & Thombs, B.D. Risk of bias from inclusion of currently diagnosed or treated patients in studies of depression screening tool accuracy: a cross-sectional analysis of recently published primary studies and meta-analyses. *PLoS One*, **11**(2) (2016).

30. McCabe, M. P. & Leas, L. A qualitative study of primary healthcare access, barriers and satisfaction among people with mental illness. *Psychology, Health and Medicine*. **13**(3), 303-312 (2008).

31. Demont-Heinrich, C. The association between physical activity, mental health and quality of life: a population-based study. *health*. **800**, 886-7689 (2009).

32. Wilke, J., Mohr, L., Tenforde, A.S., Edouard, P., Fossati, C., González-Gross, M., Sánchez Ramírez, C., Laiño, F., Tan, B., Pillay, J.D. & Pigozzi, F. A pandemic within the pandemic? Physical activity levels substantially decreased in countries affected by COVID-19. *International Journal of Environmental Research and Public Health*, **18**(5) (2021).

33. Bar-Haim, Y., Kerem, A., Lamy, D. & Zakay, D. When time slows down: The influence of threat on time perception in anxiety. *Cognition and Emotion*, **24**(2), 255-263 (2010).

34. Prince, S.A., Cardilli, L., Reed, J.L., Saunders, T.J., Kite, C., Douillette, K., Fournier, K. & Buckley, J.P. A comparison of self-reported and device measured sedentary behaviour in adults: a systematic review and meta-analysis. *International Journal of Behavioral Nutrition and Physical Activity*. **17**(1), 1-17 (2020).

35. Huckvale, K., Venkatesh, S. & Christensen, H. Toward clinical digital phenotyping: a timely opportunity to consider purpose, quality, and safety. *NPJ digital medicine*. **2**, 88 (2019).

36. Jain, S.H., Powers, B.W., Hawkins, J.B. & Brownstein, J.S. The digital phenotype. *Nat Biotechnol*. **33**(5), 462-3 (2015).

37. Wang, R., Chen, F., Chen, Z., Li, T., Harari, G., Tignor, S., Zhou, X., Ben-Zeev, D. & Campbell, A.T. StudentLife: Using smartphones to assess mental health and academic performance of college students. *Mobile Health.* 7-33 (2017).

38. Taquet, M., Quoidbach, J., Fried, E.I. & Goodwin, G. M. Mood homeostasis before and during the coronavirus disease 2019 (COVID-19) lockdown among students in the Netherlands. *JAMA Psychiatry* (2020).

39. Melcher, J., Hays, R. & Torous, J. Digital phenotyping for mental health of college students: a clinical review. *Evidence-based mental health*. **23**(4), 161-166 (2020).

40. Hays, R., Keshavan, M., Wisniewski, H. & Torous, J. Deriving symptom networks from digital phenotyping data in serious mental illness. *BJPsych open*. **6**(6) (2020).

41. Boukhechba, M., Chow, P., Fua, K., Teachman, B. A. & Barnes, L. E. Predicting Social Anxiety From Global Positioning System Traces of College Students: Feasibility Study. *JMIR mental health*. **5**(3) (2018).

42. Jacobson, N. C., Summers, B. & Wilhelm, S. Digital Biomarkers of Social Anxiety Severity: Digital Phenotyping Using Passive Smartphone Sensors. *Journal of medical Internet research*. **22**(5) (2020).

43. Faurholt-Jepsen, M., Bauer, M. & Kessing, L.V. Smartphone-based objective monitoring in bipolar disorder: status and considerations. *International journal of bipolar disorders*. **6**(1), 1-7 (2018).

44. Canzian, L. & Musolesi, M. Trajectories of depression: unobtrusive monitoring of depressive states by means of smartphone mobility traces analysis. In *Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing*. 1293-1304 (2015).

45. Polzer, N. & Gewald, H. A Structured Analysis of Smartphone Applications to Early Diagnose Alzheimer's Disease or Dementia. *Procedia Computer Science*. **113**, 448–453 (2017).

46. Jack, K. & Smith, A. Promoting self-awareness in nurses to improve nursing practice. *Nursing Standard (through 2013),* **21**(32), 47-52 (2007).

47. Spielberger, C. D. State‐Trait Anxiety Inventory: Bibliography (2nd, Editio ed.) (1989).

48. Spielberger, C. D., Gorsuch, R. L., Lushene, R., Vagg, P. R. & Jacobs, G. A. Manual for the State-Trait Anxiety Inventory. *Consulting Psychologists Press.* (1983).

49. Hagströmer, M., Oja, P. & Sjöström, M. The International Physical Activity Questionnaire (IPAQ): a study of concurrent and construct validity. *Public health nutrition*. **9**(6), 755-762 (2006).

50. Chen, K., Tan, G., Cao, J., Lu, M. & Fan, X. Modeling and improving the energy performance of GPS receivers for location services. *IEEE Sensors Journal*. **20**(8), 4512-4523 (2019).

51. Xiong, H., Huang, Y., Barnes, L. E. & Gerber, M. S. Sensus: a cross-platform, general-purpose system for mobile crowdsensing in human-subject studies. *In Proceedings of the 2016 ACM international joint conference on pervasive and ubiquitous computing.* 415-426 (2016).

52. Bakrania, K., Yates, T., Rowlands, A.V., Esliger, D.W., Bunnewell, S., Sanders, J., Davies, M., Khunti, K. & Edwardson, C.L. Intensity thresholds on raw acceleration data: Euclidean norm minus one (ENMO) and mean amplitude deviation (MAD) approaches. *PloS one*. **11**(10) (2016).