

Digital Phenotyping for Stress, Anxiety and Mild Depression: A Systematic Literature Review

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Digital Phenotyping for Stress, Anxiety and Mild Depression: A Systematic Literature Review

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Abstract

Background: Unaddressed early stage mental health including stress, anxiety and mild depression can become burdens for individuals in the long term. Identifying milder symptoms before they become more serious is important and has motivated the use of digital phenotyping for that purpose. Digital phenotyping involves capturing continuous behavioural data via digital smartphone devices to monitor human behaviour and identify any abnormalities.

Objective: This systematic literature review asked: What is the evidence of effectiveness for digital phenotyping using smartphones, in identifying behavioural patterns related to stress, anxiety, and mild depression? In particular, which smartphone sensors are found to be effective and what are associated challenges?

Methods: We used the PRISMA process to identify 26 articles to assess the key smartphone sensors that are correlated with anxiety, stress and mild depression. Studies conducted with non-adult participants (e.g., teenagers, children) or with clinical populations were excluded. We also excluded personality and character measurement and phobia studies. As we were focused on the effectiveness of digital phenotyping with smartphones, results related to other wearable devices were excluded.

Results: The study length varied from two weeks to 8.5 months. The Android operating system was more commonly used than iOS. A range of passive sensors were used in the studies including Global Positioning System (GPS), Bluetooth, ambient audio, light sensor, accelerometer, microphone, illuminance, and WIFI. These were used to assess locations visited, mobility, speech patterns, phone usage such as screen checking and time spent in bed, physical activity, sleep, and aspects of social interactions such as number of interactions and response time. Students, employees, and adults were the most-studied populations. Students who experienced depression and stress visited fewer locations, became less social, and accrued increased screen time. Depressed adults were less likely to leave home and were less physically active whereas anxious adults left their home more often and were more active. Anxious adults visited more locations but avoided going to places where they needed to socially interact. In contrast to students and adults, less mobility was seen as positive for employees because less mobility in workplaces was associated with more positivity and higher performance. We saw that location, physical activity, and social interaction data were highly related to participants' mental health. Overall, sensing patterns through GPS, smartphone logs, audio, accelerometer, light, and keyboard were found to be significantly related to self-reported stress, anxiety and mild depression.

Conclusions: The focus was to understand whether smartphone sensors could be effectively used to detect behavioural patterns associated to stress and anxiety in non-clinical participants. The reviewed studies provide evidence that smartphone sensors are effective in identifying behavioural patterns associated to anxiety, stress and mild depression.

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Original Manuscript

Digital Phenotyping for Stress, Anxiety and Mild Depression: A Systematic Literature Review

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Abstract

Background: Unaddressed early stage mental health including stress, anxiety and mild depression can become burdens for individuals in the long term. Identifying milder symptoms before they become serious is important and has motivated the use of digital phenotyping for that purpose. Digital phenotyping involves capturing continuous behavioural data via digital smartphone devices to monitor human behaviour and identify abnormalities.

Objective: This systematic literature review asked: 1) What is the evidence of effectiveness for digital phenotyping using smartphones, in identifying behavioural patterns related to stress, anxiety, and mild depression? 2) In particular, which smartphone sensors are found to be effective and what are associated challenges?

Methodology: We used the PRISMA process to identify 36 articles (reporting on 39 studies) to assess the key smartphone sensors that are related with anxiety, stress and mild depression. Studies conducted with non-adult participants (e.g., teenagers, children) or with clinical populations were excluded. We also excluded personality and character measurement and phobia studies. As we were focused on the effectiveness of digital phenotyping with smartphones, results related to other wearable devices were excluded.

Results: We categorise studies into three major groups based on participant recruitment: students enrolled in universities, adults who were unaffiliated to any particular organisation and employees employed at an organisation. The study length varied from one week to three years. A range of passive sensors were used in the studies including: GPS, Bluetooth, accelerometer, microphone, illuminance, gyroscope, and WIFI. These were used to assess: locations visited, mobility, speech patterns, phone usage such as screen checking and time spent in bed, physical activity, sleep, and aspects of social interactions such as number of interactions and response time. 29 studies (74.4%) used machine learning models for prediction; most others used descriptive statistics. Students who experienced depression and stress visited fewer locations, became less social, and accrued increased screen time. Depressed adults were less likely to leave home and were less physically active whereas anxious adults were more active and left their home more often but avoided going to places where they needed to interact socially. In contrast to students and adults, less mobility was seen as positive for employees because less mobility in workplaces was associated with more positivity and higher performance. We saw that location, physical activity, and social interaction data were highly related to participants' mental health. Overall, sensing patterns through GPS, smartphone logs, audio, accelerometer, light, and keyboard were found to be significantly related to self-reported stress,

anxiety and mild depression.

Conclusion: The focus was to understand whether smartphone sensors could be effectively used to detect behavioural patterns associated to stress and anxiety in non-clinical participants. The reviewed studies provide evidence that smartphone sensors are effective in identifying behavioural patterns associated to anxiety, stress and mild depression.

Keywords: Digital phenotyping; Passive sensing; Stress; Anxiety; Depression; PRISMA



Introduction

Digital phenotyping is "the moment-by-moment quantification of the individual level human phenotype in situ using data from personal digital devices" [1]. Digital phenotype applies the concept of phenotype, in other words, the observable characteristics resulting from the genotype and the environment, to conceptualise observable patterns in individuals' digital data. In the last decade, digital phenotyping studies have been able to compare typical and atypical patterns in daily activities to correlate atypical behaviour and negative emotion [2,3]. Behavioural patterns include variation in mobility, frequency of being in various locations, and sleeping patterns. With smartphones, user data can be stored, managed, interpreted, and captured in enormous amounts [1,4,5]. This can be done actively or passively. Active data collection requires the user to self-report and complete surveys, while passive sensing collects data automatically without user input [5]. Most studies combine active and passive sensing to more accurately detect and predict behavioural abnormalities. Modern smartphone analytics can be used for the discovery of commonalities and abnormalities about user behaviour. The ease of using passive sensing makes it an ideal data gathering method for mental health studies [6-8] and as a sign of mental health [9].

Digital phenotyping has been successful in early detection and prediction of behaviours related to neuropharmacology [10], cardiovascular diseases [11], diabetes [12], and major severe injuries like spinal cord injury [13], motivating further adoption. Digital phenotyping has also proven useful for detection of severe mental health disorders such as schizophrenia [14,15], bipolar [16], and suicidal thoughts [17]. Digital phenotyping has been so successful for specialised, clinical populations that it is increasingly considered for mass market use with non-clinical populations. Digital phenotyping applications and software tools have been used to capture employee information, such as their screen time and clicking patterns [18]. However, there are not many digital phenotyping studies that have specifically looked at detection or prediction of mild stress and anxiety.

Individuals with stress and anxiety can develop chronic mental health symptoms that impact their mobility, satisfaction with life, and social interaction [19,20]. When these symptoms are not detected early, they worsen and the impact is more significant [21-23] increasing the need for medication and hospitalisation. This makes mild mental health symptoms a valid target for digital phenotyping, as its goal is to enable early detection followed by early treatment. Smartphones are increasingly ubiquitous [24Error: Reference source not found] which makes them an optimal platform for digital phenotyping. We constrain our systematic literature search to the more challenging problem of detection of mild mental health symptoms with only the use of smartphone sensors and exclude studies that added additional wearable sensors. In general, we believe that additional wearables might increase effectiveness of digital phenotyping for detecting mild anxiety, stress, and depression. Given the ubiquity of smartphones, we ask: What is the effectiveness of digital phenotyping using smartphone sensors for the detection of mild anxiety, stress, and depression?

Objectives

The objective of this systematic literature review is to better understand current uses and results of the use of digital phenotyping for detection and prediction of mild behavioural patterns related to stress, anxiety, and mild depression. The two research questions are:

1. What is the evidence of effectiveness for digital phenotyping using smartphones in identifying behavioural patterns related to stress, anxiety, and mild depression?
2. In particular, which smartphone sensors are found to be effective and what are the associated challenges?

In these research questions, we consider statistically significant associations between sensor patterns and behavioural patterns as evidence of effectiveness.

Methods

Type of Studies

This review followed PRISMA guidelines [25]. In the first round of screening records, one author excluded records that were not relevant to the research questions. Another author reran the queries for confirmation. Studies were included in this review if they were conducted to measure and detect stress, anxiety, or mild depression, even if they included other variables such as job performance, promotion, or discrimination. We included studies where the data collection was done through smartphones with an iOS or Android operating system. If data collection method was done with wearable devices, those results were excluded. We included studies where participants were adults aged 18 and above and were from a non-clinical population. The studies conducted with non-adult participants (e.g., teenagers and children) are excluded. Given our research questions, if the studies' participants have or have had any severe mental health disorder, such as schizophrenia, bipolar disorder, or psychosis, they were not included. We also excluded personality and character measurement and phobia studies. The primary research language was English. Studies included were conducted from 2010 to 2023 September. Peer-reviewed conference articles and journal articles were included. The data that we wished to extract was: the study Aim, Data Collected, the Operating System for the smartphone used in data collection, Behavioural Patterns identified, surveys used for Verification, and Sample Size. Three authors reviewed the reports independently to extract data and confirm extracted data. After the first round of data extraction, one author re-examined the reports to extract the Predictive Modelling used. These data are presented in tables within the results section. We noticed that participants within studies fell into one of three major groups (students, adults and employees) based on participant recruitment. For the studies that recruited adults enrolled in universities, we refer to their participants as 'students'. For the studies that recruited adults unaffiliated to any particular organisation, we refer to their participants as 'adults'. For the studies that recruited adults employed at a particular organisation, we refer to their participants as 'employees'.

Search Strategy

Three databases were queried: Web of Science, Association for Computing Machinery (ACM), and PubMed. PubMed is a medicine-based database, ACM is a technology-based database, and Web of Science represents a cross-domain database. The search query was the same for these three platforms. Query: "digital phenotyping" OR "passive sensing" AND (stress OR anxiety OR ((mild OR moderate) AND depression)).

Results

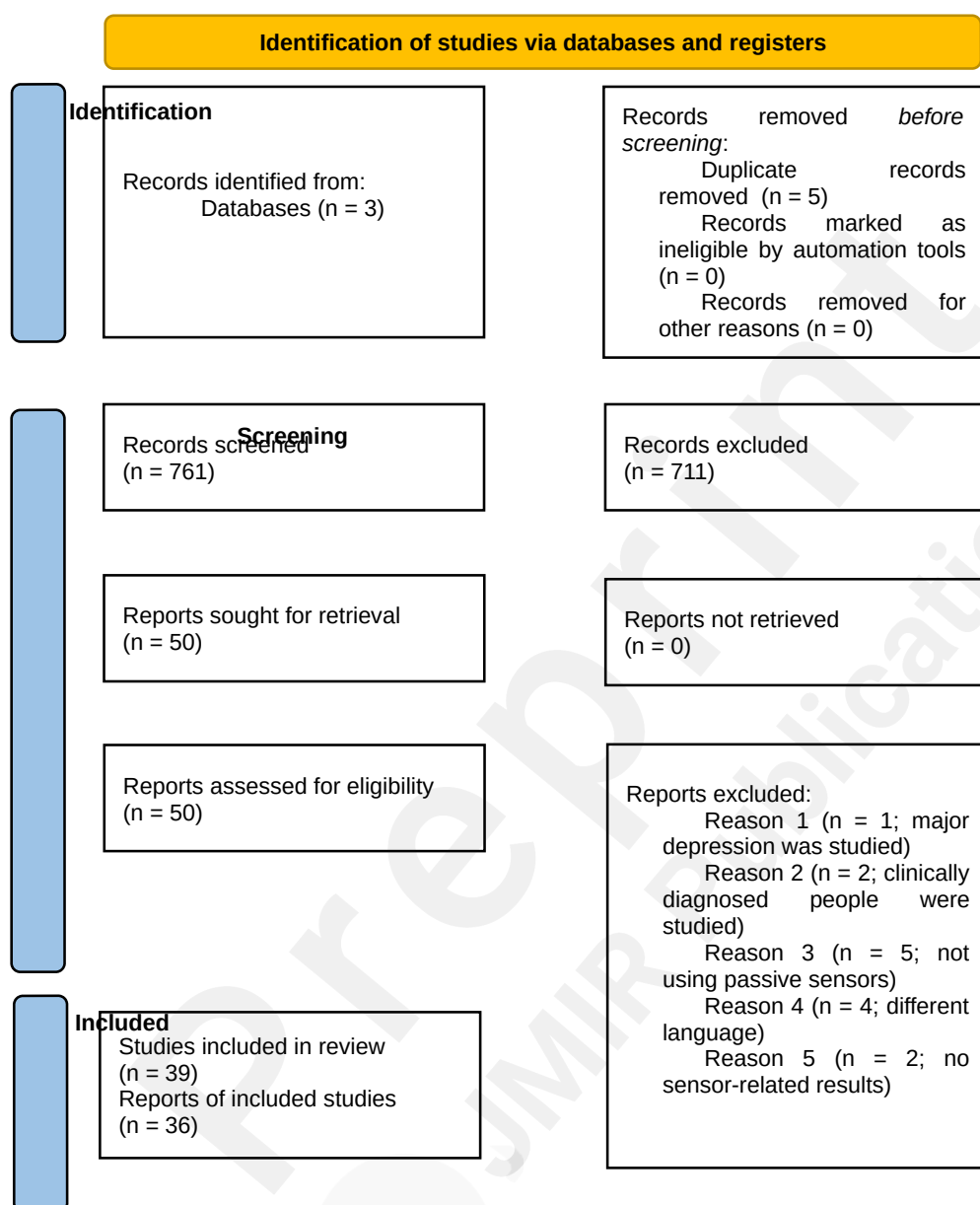


Figure 1: Systematic literature reviewing process and search results with PRISMA diagram

Duration

The study length varied from one week [18] to 3 years [26]. In studies done with the students, a semester or spring/winter term was a common duration. Studies with general adult non-clinical populations were typically longer compared to those with students.

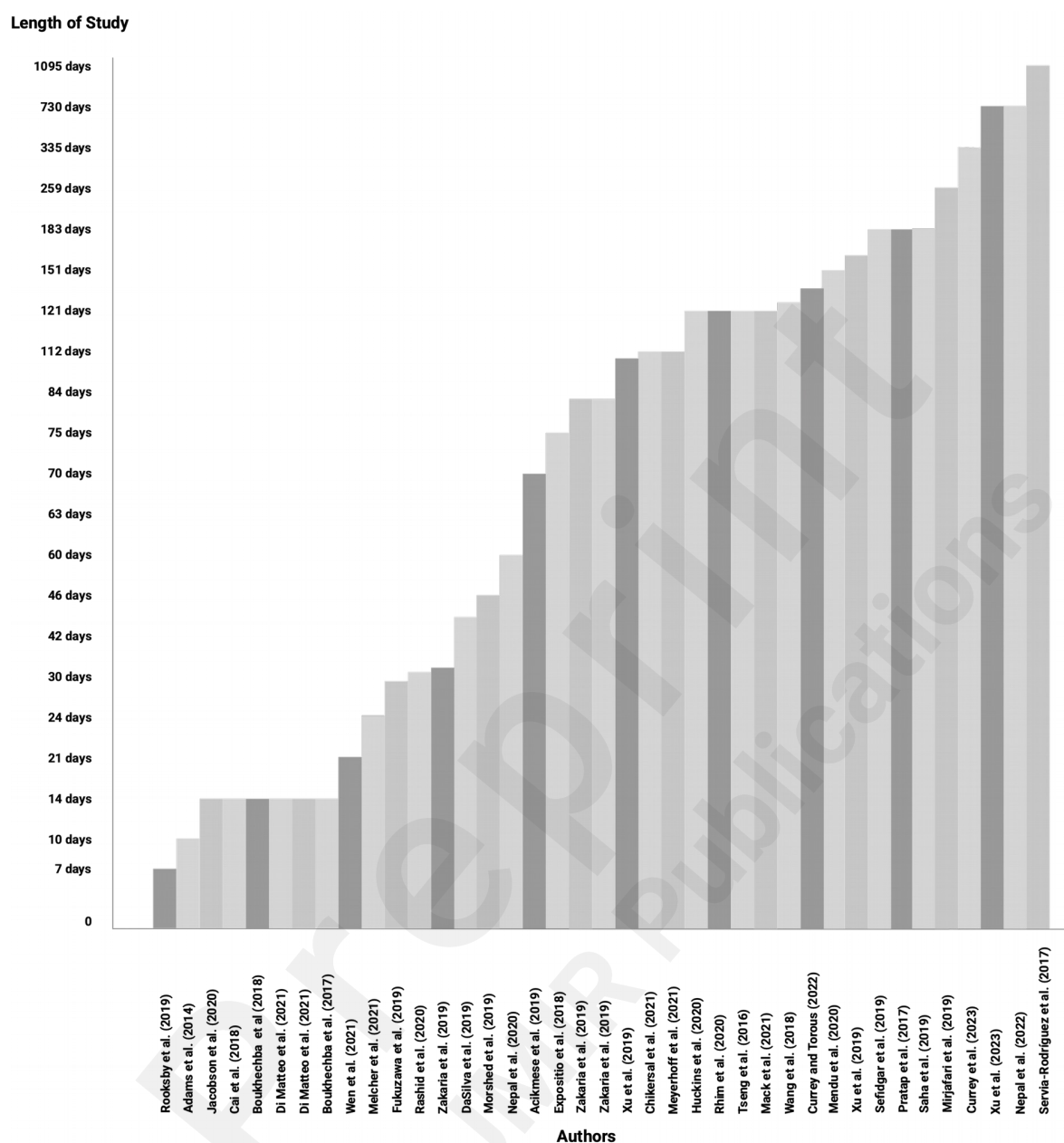


Figure 2: Duration length of the reviewed studies

Number of Participants

The number of participants varied with a minimum of seven adults [27] to 18000 [22]. Apart from the 3-year longitudinal study with 18000 participants [22], the average number of participants was 146.8. We observed a pattern of attrition, where the number of participants that completed the study was lower than the number recruited. The number of participants reported in this review is the final sample size. For example, one study [28] recruited 112 participants with 84 participants who completed the study. In study [29], there was a drastic drop from 1180 participants enrolled to only 359 of them completing the study. Another significant drop [30] was seen where 750 participants were interested in the research while only 141 of them completed the study. Similarly [27] initially had 11 participants and 6 of them dropped out. Another study [31] had the same issue where 86 participants started and 76 of them completed the study.

Publication Years of the Studies

While the query started with the year 2010, the earliest publication was from 2014 [27] extending to articles published as of March 2023 [32]. Over the years, the interest in detecting and predicting stress, anxiety, and mild depression within the non-clinical population has increased (Figure 3).

Number of Publication

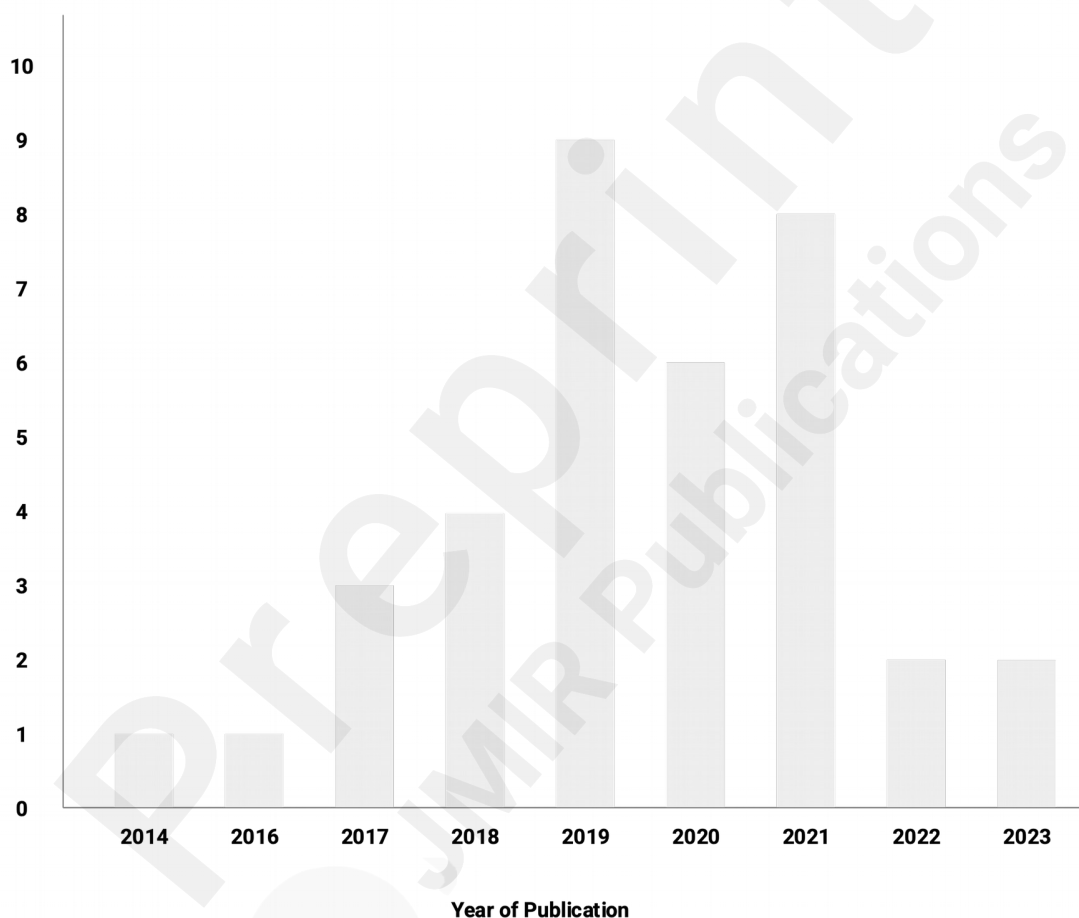


Figure 3: Publication years of the reviewed reports by year

Studies with iOS and Android Operating System

The Android operating system was more common than iOS. Only four studies were compatible with only iOS [33,34,35]. Some studies were available for both iOS and Android [18,27,29,30,36, ,Error: Reference source not found,38,39-52]. Some studies were for only Android users [26,28,31,53-60]. The reasons identified for the use of the Android operating system was that it has more freedom to capture more modalities such as keyboard typing and usage of apps and because Android devices enable applications to run more easily in the background [31].

Studies with Students

Table 1. Summary of the reviewed studies with student participants

Study	Aim	Data Collected	Operating System	Behavioural Patterns	Predictive Modelling	Verification	Sample Size
Huckins et al. (2020) [39]	Detect depression, anxiety, and stress	GPS, Accelerometer, Lock/Unlock, Light sensor	iOS & Android	Depressed students tended to visit fewer locations. Time spent with phone was higher for depressed students.	Linear regressor was used to inspect how behavioural changes are affected by COVID-19 news reports	PHQ-4	217 students
Melcher et al. (2021) [43]	Detect stress and depression level	GPS, Accelerometer, Call logs, Phone usage	iOS & Android	Sleep variance is correlated with depression and stress.	n/a	PHQ-9, DASS, GAD-7, PQ, PSS, PSQI	100 students
Jacobson et al. (2020) [53]	Predict social anxiety severity, depression, stress, and positive and negative state	Accelerometer, Call logs, SMS	Android	The SMS/call response time from students with social anxiety depends on the sender relationship.	XGBoost was used to predict social anxiety disorder	SIAS, DASS-21, PANAS	59 students
DaSilva et al. (2019) [41]	Predict stress	GPS, Accelerometer, Lock/Unlock, Microphone, Light sensor	iOS & Android	Stressed students are more likely to spend less time in campus food locations and more time in schoolwork locations. Stressed students have more frequent conversations during the day compared to evenings.	n/a	MPSM	94 students
Acikmese et al. (2019) [60]	Predict stress level	Accelerometer, Microphone, Bluetooth, Light sensor, Lock/Unlock, Phone charge, App usage (GPS and WIFI collected but not used)	Android	Students were successfully categorised as stressed/non-stressed using the measured sensors	LSTM was used to classify stress achieving	Self-reported stress	48 students
Rooksby et al. (2019) [18]	Understanding students' perspectives about digital phenotyping	GPS, Lock/Unlock, Phone charge, App usage	iOS & Android	Students have privacy concerns about: app usage, Bluetooth, call logs, camera, keyboard, microphone; but not with: battery charging, light or SMS count.	n/a	PHQ-9, GAD-7, WEMWBS	15 students
Chikersal et al. (2021) [Error: Reference source not found]	Detect end of semester depression symptoms	GPS, Bluetooth, WIFI, Lock/Unlock, Call logs	iOS & Android	Depressed students are less social, visit fewer locations but more campus locations, and have higher phone usage. Bluetooth, campus map and phone usage had the most detection accuracy.	Trained an ensemble classifier with the outputs from 1-feature set models with different setting combinations	BDII-II	138 students
Morshed et al. (2021) [58]	Predict mood, stress, anxiety, and depression	Accelerometer, Microphone, Bluetooth, Light sensor, WIFI, GPS, Lock/Unlock, Phone charge	Android	Mood was negatively correlated to: duration of sleep, number of conversations, amount of activity and outdoor mobility.	Ridge regression with regularisation was used to infer mood instability score	PAM, PANAS	48 students
Zakaria et al. (2019) [44]	Detect depression and stress	WIFI	iOS & Android	Stressed students spent less time on campus and attended fewer activities on campus.	The random forest stress model with domain-specific features achieved best result with feature sets changed every 6 days	PSS-4, PHQ-8	62 students
Zakaria et al. (2019) [44]	Detect depression and stress	WIFI	iOS & Android	Stressed students spent less time on campus and attended fewer activities on campus.	The random forest model that excluded domain-specific features achieved best result	PSS-4, PHQ-8	11 students

					with feature sets changed every 6 days		
Zakaria et al. (2019) [44]	Detect depression and stress	WIFI	iOS & Android	Stressed students spent less time on campus and attended fewer activities on campus.	The random forest model with neuroticism score of big-5 feature added achieved best result with feature sets changed every 15 days	PSS-4, PHQ-8	35 students
Wang et al. (2018) [45]	Predict depression	Light sensor, GPS, Accelerometer, Microphone, Lock/Unlock	iOS & Android	Depressed students used their phones more often in campus schoolwork locations, visited fewer locations, and had fewer conversations.	Lasso regression was used to predict pre and post survey PHQ-9 score	PHQ-4, PHQ-8	83 students
Exposito et al. (2018) [33]	Detect stress	Keyboard 3D Touch	iOS	Students' typing pressure increased under stress.	n/a	Self-reported stress	11 students
Rhim et al. (2020) [31]	Detect subjective wellbeing and stress	Accelerometer, GPS, Screen on/off, App usage, Notifications	Android	Lower subjective wellbeing was associated to more time spent on campus.	Hierarchical regression models were used to predict subjective well-being	COMOS WB	78 students
Sefidgar et al. (2019) [42]	Detect stress, anxiety, and gender discrimination	Accelerometer, GPS, Lock/Unlock, Screen on/off, Call logs	iOS & Android	Students who experienced discrimination became more physically active, their phone usage increased in the morning, they had more calls in the evenings, and spend more time in bed on the day of the discrimination.	Linear regression was used to predict long-term changes in mental health states; hierarchical linear modelling was used for short-term prediction	UCLA Loneliness, PSS, CES-D, STAI, Self-reported affect and fairness of treatment	176 students
Cai et al. (2018) [37]	Detect state affect, stress, anxiety, and depression	Accelerometer, GPS, Call logs, SMS	iOS & Android	Negative emotion was related to university locations. There were less negative emotion associated to leisure locations such as cinemas. On Fridays and Saturdays, students reported less negative states.	Compared support vector machine, random forest and XGboost with leave-one-subject-out cross validation and leave-one-observation-out cross validation to predict negative affect. The model is support vector machine with leave-one-observation-out validation	SIAS, Self-reported affect	220 students
Boukhechba et al. (2018) [54]	Measure response latency to EMA in different locations	GPS, Call logs, Accelerometer, SMS	Android	No results relating sensors to symptoms of depression or anxiety.	Used random forest, support vector machine and a multilayer perceptron of one hidden layer with leave-one-participant-out cross validation to predict compliance rate of EMA responses	Self-reported affect	65 students
Xu et al. (2019) [34]	Detect depression	Accelerometer, Batter/charge, Bluetooth, Call logs, Screen, Location, Lock/unlocks	iOS	Multimodal features in sensor data can improve detection accuracy. Behavioural rules generated by the model can represent the difference between classes	AdaBoost with decision-tree based components achieved best performance when features were hybrid (contextually filtered + unimodal)	BDII-II	169 students
Xu et al. (2019) [34]	Detect depression	Accelerometer, Batter/charge, Bluetooth, Call logs, Screen, Location, Lock/unlocks	iOS	Multimodal features in sensor data can improve detection accuracy. Behavioural rules generated by the model	AdaBoost with decision-tree based components achieved a similar result as majority-	BDII-II	138 students

				can represent the difference between classes	based baseline predictors		
Boukhechba et al. (2017) [56]	Predict social anxiety	Call Logs, GPS/Location, SMS/Email	Android	High socially anxious students may be more likely to buy food so they can eat at home, and they tend to visit fewer different places and have a narrower range of activities	Decision tree was used to predict social anxiety score	SIAS	54 students
Rashid et al. (2020) [47]	Predict social and evaluate effectiveness of imputation methods to handle missing data	GPS, Pedometer, Accelerometer, Activity, Call, Text/Messages	iOS & Android	No results relating sensors to symptoms of depression or anxiety; subjective measures exhibit different levels of variability across both measures and participants	Evaluated 7 predictive models: linear regression, decision tree, XGBoost, lightGBM, random forest, MERF and CatBoost	SIAS, self-reported dimensions of social anxiety	80 students
Mendu et al. (2020) [48]	Explore the relationships between private social media messages, personality traits and symptoms of mental illness	Facebook private messages	iOS & Android	Late night communication is highly predictive of both loneliness and anxiety	Used random forest classifier to select features; used support vector machine with leave-one-subject-out cross validation to predict each psychological measure binarily	STAI, UCLA Loneliness Scale, Ten-Item Personality Inventory	103 students
Tseng et al. (2016) [49]	Detect stress and its relationship with academic performance	Location, Activity, Step Count, Audio, Accelerometer, Device Usage, Charging Event, Battery, Light, SMS, Call, Currently running apps	iOS & Android	Students slept less during exam periods and slept more during breaks; they felt more stressed during the breaks and exam period; sensor data are able to capture different routines during weekdays, weekends and breaks	n/a	PSQI, ESS, MCTQ, PROMIS-10, BHM-20, CD-10, Flourishing Scale, Perceived Stress Scale, BFI, PHQ-8, UCLA Loneliness Scale	22 students
Mack et al. (2021) [50]	Understand the behavioural and mental health associated with the COVID-19 pandemic	GPS, Accelerometer, Lock/Unlock, Light sensor	iOS & Android	Differences in phone use, sleep, sedentary time and number of locations visited were found to associate with the COVID-19 pandemic; these behaviours along with anxiety and depression were strongly associated with increased interest in COVID fatigue	n/a	PHQ-4	217 students
Xu et al. (2023) [50]	Evaluate the cross-dataset generalisability of depression detection	GPS, Accelerometer, Locks/Unlocks, Bluetooth, WIFI, Call logs, Microphone, Gyroscope, Light sensor	iOS & Android	Deep learning based domain generalisation algorithms do not perform well in depression detection on longitudinal data. Cross-year from the same institution generalises slightly better than cross-institutions	A multi-task learning model with the 1D-CNN based embedding, fully connected layers for reordering and classification	Weekly surveys on self-reported depression symptoms and affect; BDI-II; PHQ-4	534 students
Nepal et al. (2022) [52]	Explore the association between students' COVID-19 concerns and behavioural and mental health	GPS, Accelerometer, Lock/Unlock, Light sensor, Phone Usage	iOS & Android	Heightened COVID-19 concerns correlates with increased depression, anxiety and stress	Evaluated different deep learning models to classify COVID-19 concerns: CNN, InceptionTime, MCDCNN, ResNet, MLP, TWIESN, LSTM, FCNN. FCNN performed best with an AUROC	Self-reported affect, PHQ-4	180 students

Currey and Torous (2022) [35]	Explore the possibility of predicting survey results on mental health from passive sensors	GPS, Accelerometer, Screen time	iOS	GPS was the most predictive feature, Screen time metrics and Bluetooth were not predictive. The choice of passive sensors needs to be tailored to specific survey being predicted.	score of 0.7 Logistic regression was used to predict survey scores.	PHQ-9, GAD-7, PSS, UCLA Loneliness, PQ-16, PSQI	147 students
Currey et al. (2023) [32]	Explore the cross-dataset generalisability of symptom survey improvement	GPS, Accelerometer, Screen time	iOS & Android	Logistic regression was able to predict change in mood across two datasets of student participants. Students across two cohorts had similar sensor results	Logistic regression was used to predict weekly score improvement from both active and passive features	PHQ-9, GAD-7, PSS, UCLA Loneliness, PSQI, Prodroma ; Questionair-16, DWAI	698 students

Table 1 review studies that have been conducted with student populations. The average length of the studies with students was 132.5 days. The average number of participants was 137.2. There were significantly more studies with students compared to employees or general adults. Studies with students had similar size of samples compared to studies with adults but smaller than studies with employees. In the studies with students, various passive sensors were used and some were found to be effective for detection/prediction.

22 out of 28 studies (78.6%) used machine learning models for prediction. 10 studies (35.7%) [34,37,44,47,48,54,56] used decision-tree based methods; 8 studies (28.6%) [31,32,35,39,42,45,47,58] used regression-based methods. Three studies in recent years (10.7%) [50,52,60] used deep neural networks due to their enhanced ability to discern underlying patterns in large unstructured datasets. The three studies have an average sample size of 148.3 exceeding the average of 137.2 observed among student populations. Tree-based methods have the best performance in structured data which the reported studies mostly trained on. In studies over the last three years [32,34,50], researchers addressed the generalisability of their proposed detection method, and verified its applicability across students from various years, classes, and institutions. Four studies (14.3%) [39,50,58,60] in Table 1 used the StudentLife dataset [61]. One of them also used the Tesseract dataset [62]. Each study contributed substantial original analyses including different patterns of use and is considered a “study” in this systematic review. Entries that have 'n/a' values in the predictive modeling column indicate that the study did not involve any attempts to predict future occurrences. However, these studies may still contain statistical analyses as part of their research approach. Overall, students who experienced depression and stress visited fewer locations, became less social, and accrued increased screen time.

Studies with Adults

Table 2. Summary of the reviewed studies with adult participants

Study	Aim	Data Collected	Operating System	Behavioural Patterns	Predictive Modelling	Verification	Sample Size
Di Matteo et al. (2021) [55]	Detect anxiety and depression	Microphone	Android	Generalised anxiety and depression are correlated to reward-related words. Social anxiety is correlated to vision related words.	n/a	LSAS, GAD-7, PHQ-8, Sheehan Disability Scale	86 Canadian adults
Di Matteo et al. (2021) [28]	Predict general anxiety disorder,	GPS, Microphone,	Android	Depressed individuals did not avoid specific	Three logistic regression	LSAS, GAD-7,	84 Canadian adults

	social anxiety disorder, depression	Screen on/off, Light sensor		situations and social interactions, while anxious individuals did. Depressed individuals spent more time at home while anxious individuals left home but avoided locations that might require social interaction.	models were used to predict social anxiety disorder and generalised anxiety disorder with repeated k-fold cross validation	PHQ-8, Sheehan Disability Scale	
Wen et al. (2021) [40]	Detect impulsive behaviour, positivity, stress	Call logs, Lock/Unlock, Phone charging	iOS & Android	Impulsivity is highly correlated with phone usage and screen checking	Used lasso regularisation to first select features and trained a linear regression model to estimate trait impulsivity scores	BIS-15, UPPS, PAM, Self-reported feelings	26 adults
Fukuzawa et al. (2019) [57]	Predict anxiety levels and stress	Light sensor, Gyroscope, Accelerometer, App usage	Android	Anxiety is higher during weekdays compared to Fridays and Saturdays. Mobility decreases when stress and anxiety increase. During mild exercise, anxiety is reduced. Sleep is negatively correlated with stress.	Used linear classifier by Lasso and XGBoost to classify change of anxiety	STAI	20 adults
Pratap et al. (2017) [29]	Detect depression	GPS, Call logs, SMS	iOS & Android	Daily and weekly mood ratings were poorly associated with sensor data.	n/a	PHQ-2 & 9	359 Hispanic/Latino adults
Adams et al. (2014) [27]	Detect stress level	Microphone	iOS & Android	Stress can be recognised from speaking speed, energy, and absence of speed in the laboratory environment.	n/a	PANAS, PSS-14, MAAS, Self-reported affect	7 adults
Meyerhoff et al. (2021) [59]	Detect anxiety and depression	GPS, Call logs, App usage, SMS	Android	Location is associated to depression and anxiety. Lower exercise correlated with depression.	n/a	GAD-7, PHQ-8, SPIN	282 adults
Servia-Rodríguez et al. (2017) [26]	Predict mood	Location/GPS, Accelerometer, Microphone, Text/message, Calls,	Android	Strong correlation between daily routines and users' personality, well-being perception, and other psychological variables; females send/receive more text messages per day than males, though their call patterns are similar; the most emotional stable participants tend to be more active and stay in more noisy places and text less than unstable participants	Used stacked Restricted Boltzmann Machines (RBMs) to classify moods	Big-five personality test, Self-reported mood, Self-reports of locations	18000 adults mainly

Table 2 reviews studies conducted with the general adult population. Apart from the three-year longitudinal study [26], the average duration was 71.2 days. The average number of participants was 138.8. Two studies [28,55] were conducted on the same set of participants. 4 out of 8 studies used predictive modelling with regression-based being the most common models [28,40,57]. Overall, this research shows that GPS, ambient audio, and illuminance related to individuals' emotional state. Depressed adults were less likely to leave home and

were less physically active whereas socially anxious adults were more active and left their home more often but avoided going to places where they needed to socially interact.

Studies with Employees

Table 3. Summary of the reviewed students with employee participants

Study	Aim	Data Collected	Operating System	Behavioural Patterns	Predictive Modelling	Verification	Sample Size
Mirjafari et al. (2019) [38]	Predict stress and job performance	Accelerometer, GPS, Lock/Unlock, Light sensor	iOS & Android	Higher performers unlock their phone less during evenings, have less physical activity and visit fewer locations weekday evenings, and were more mobile and visited more locations during weekends.	Evaluted logistic regression, support vector machine, random forest and XGBoost for employee performance classification. XGBoost is the best model with 5-fold cross validation	ITP, IRB, OCB, CWB	554 employees
Nepal et al. (2020) [30]	Detect stress, wellbeing, and mood	GPS, Lock/Unlock, Accelerometer, Bluetooth, Phone usage	iOS & Android	Promoted employees spent more time on their phones early morning and late evenings and had more unlocks during night time compared to non-promoted employees. Women's mobility increased after promotion while men's decreased.	Evaluated logistic regression, support vector machine, gaussian naïve bayes, random forest and k nearest neighbour to classify promoted or non-promoted period. The best model is logistic regression trained on ROCKET based features		141 employees
Saha et al. (2019) [46]	Predict stress and workplace performance	Light sensor, GPS, Accelerometer, Microphone, Lock/Unlock	iOS & Android	Stress was higher with increased role ambiguity.	Linear regression was used to predict a wellbeing score	IRB, ITP, OCB	257 employees

Table 3 reviews studies done with employees. One study used the Tesseract dataset [61] and the other two studies recruited participants. Compared to students and adults, the employee population was the least studied with the fewest articles. However, the studies with employees had the largest number of participants with mean of 317.3. All the three studies used predictive modelling and two of them [30,38] evaluated a variety of models with logistic regression, support vector machine and random forest being the most common methods. Detecting and predicting employees' stress in workplaces was examined in tandem with employees' work performance. The research goal for these studies is to understand underlining reasons for lowered work-related productivity. In contrast to the other two populations (students and adults), less mobility was seen as positive for employees because less mobility in workplaces was associated with more positivity and higher performance.

Passive Sensors

Table 4. Sensor summary of reviewed studies

Sensor	Behaviour	Evidence for Effectiveness	No Evidence
GPS	Location and physical activity	[18,26-28,30-35,38,39,41-43,45-47,49-52, 58,59]	[Error: Reference source not found,54]
Microphone	Voice recognition, ambient sound, sleep	[26-28,41,45,49,51,55,58-59]	[46]
Light sensor	Time spent in darkness and sleep	[28,39,49,50-52,57,60]	[58,59]

Accelerometer	Movement and physical activity	[26,30-32,34,37-39,41-43,45-47,49-52,57-59,60]	[53,54]
Lock/Unlock	Phone usage	[18,30,34,37-40,42,45,49-52,60]	[35,41,46,58]
Call logs	Social interaction, incoming and outgoing calls	[26,34,40,42,47,49,51,53,56]	[36,37,43,54,59]
Bluetooth	Social interaction	[30,34,37,51,58,59,60]	[35]
WiFi	Indoor location	[37,44,51,58]	
Keyboard	Typing patterns and muscle activity	[18,33]	
SMS/Email	Social interaction, incoming and outgoing messages	[26,47,49,53,55,56]	[29,36,54,59]
App Usage	Phone usage, social media	[18,30,39,43,52,57,59]	
Screen On/Off	Phone usage	[28,31,34,42,49]	[35]
Gyroscope	Orientation of smartphone	[51,57]	

Table 4 provides an overview on the range of sensors used to detect patterns related to mild mental health symptoms and summarises the evidence of effectiveness of various sensors. The second column lists the sensor and the third column lists how the data from that sensor is interpreted, in other words, the human activity that the sensor data is intended to represent. The fourth column indicates which articles found significant associations between the specific sensor and stress, anxiety or mild depression. Next we discuss the types of activities detected by sensors.

Social Interaction - Call & Text logs, Audio, Microphone, Bluetooth

The social interaction of an individual is reflective of their current mood and mental state [56,63-65]. We may expect depressed and stressed individuals to decrease their social interaction. This is measured through frequency of receiving texts and calls, how fast individuals respond, and frequency of being around others. 13 studies (33.3%) [26,34,36,37,40,42,43,47,49,51,53,56,59] looked at call logs to understand social interaction patterns: mainly the number of the calls, incoming and outgoing calls, the number of missed calls, and the duration of the calls. One study [53] stated that people who are experiencing social anxiety are likely to be avoiding the interaction during the day and are expected to have more missed calls. It stated that the time to get back to someone's missed call might be longer for the people who have anxiety. Similarly, those with mild depression may have a lower call rate [42]. Late night communications is also found to be highly predictive of loneliness and anxiety [48]. Meta data about text messages was examined in studies [29,53] including the frequency of receiving text messages and the average time of responses. Socially anxious people might take different times to respond; some might be faster, while others are slower in response duration. In one study [53], call text decreased when people experiencing social anxiety. In study [43], bluetooth data was utilised to understand social interaction, tracking the individual's mobility and location. It stated that individuals who are experiencing more negative mental states would avoid locations requiring social interaction. Adults who are experiencing anxiety would avoid leaving the house to not interact [28]. Stressed students were found to speak and socially interact less than non-stressed students, and to stay in quieter places and have most of their conversations between 9 am to 6 pm [41].

Location – GPS, Bluetooth & Wi-Fi

Location data can give insights into individuals' mental health state in terms of the normal or abnormal variety and frequency of locations visited [66]. As Table 4 has shown location has been one of the most commonly used passive sensors for stress, anxiety, and mild depression research. The research [28] found that location data positively correlates with

symptoms in depressed and anxious individuals. One study [59] found that location data is highly inversely correlated with mild depression severity. The main way that this is measured is by the frequency of exiting a house, and by the variety of the locations visited, and mobility. The frequency of exiting a house is less frequent for the individuals who are depressed, and there is less variety in the visiting locations for socially anxious individuals. Individuals who are feeling depressed often experience being less energetic [67,68]. The duration of visitation to a location has not significantly impacted by depression severity. However, the duration of visitation to a location might have more impact on the individuals who have experienced social anxiety if it requires social interaction [28]. One study [41] found that the more time students spent in the study environments around campus, the more stressed they were. This study also found that stressed students spend less time in the campus food locations in the university campus [41]. During the evening, stressed students spent less time around noisy locations and often did not leave their house after 6 pm [41].

Voice Recognition – Audio

The microphone is used to measure audio data. One study [27] examined how stressed people speak by analysing their voice including speed of speech, how energetic their vocality is, and the pitch. One caveat is that study [27] used audio captured within lab environments. In variable environments, it will be harder to recognize the changing voice patterns. The absence of speech is another way of understanding the mental state [55]. One study [28] identified that depressed people tend to speak less and use more death-related words. The general pattern identified was that anxious people tend to speak less.

Sleep - Accelerometer, Audio & Illuminance

Sleep is highly correlated with individuals' mental state [43,69,70]. One study [28] stated that sleep disturbance is detrimental to mental well-being. Yet, occasional sleep disturbance is not necessarily predictive. For example, for those with social anxiety, sleep disturbance might be positive because it suggests night-time activity and social interaction. Meta data on time spent in darkness can be indicative of sleeping patterns. Study [57] stated that anxiety levels increase when the time spent in darkness has increased. People experiencing anxiety and negative mental states tend to spend more time in the dark over longer periods. Study [28] found that individuals with symptoms related to stress and depression preferred to spend more time in darker environments. In study [57] an accelerometer was used to measure sleep and its relationship with anxiety and stress which have negative correlation. Another study [41] stated that stress changed students sleep patterns where they became less likely to move around between 6 pm and 12 am. Study [49] found students slept less during exam periods and slept more during breaks, and they felt more stressed during both breaks and exam periods. Study [39] highlighted individual differences in sleep patterns. One person with depression might sleep more while another with depression might sleep less.

Phone Usage – On and Off Screen, Lock/Unlock & App Usage

Smartphones today are used for self-regulated “distractions” such as use of social media [44]. This type of self-regulated distraction is seen to reduce stress [42]. Study [Error: Reference source not found] showed that depression can impact concentration levels, so if distraction by phone can be measured, this could be a potential predictive marker. Study [58] outlined that for post semester depression, phone usage at night is not predictive while another study [44] summarised that phone usage during the day is predictive for depression.

Physical activity & Mobility – Accelerometer

According to the Table 4, along with location, the accelerometer is one of the most widely

used passive sensors in digital phenotyping research to monitor participant's mobility, activity, and sedentary periods. Movement, anxiety and depression have been significantly correlated [42]. Physical activity has been identified as positive to reducing stress and reduced activity might indicate an increasing level of stress, anxiety, or mild depression [61]. People who spend more time at their desks at work, or who have increased working hours, have more stress [30,38]. Study [38] found that the amount of movement and physical activity was related to employee's stress level and highlighted that if the activity is regular, this should reduce stress. Different occupations require different levels of physical activity, social interaction, and mobility. For instance, developers spend most of their time at their desk and their tasks might require less social interaction and mobility at work but this does not mean they are more stressed. Project managers have more mobility during the day and this may be because they to move around to meet with the stakeholders [38].

Muscle Activity - Keyboard

Stress can cause muscle tension [73,71]. One study [33] collected stressed users' data via the keyboard in a laboratory environment and found a significant association between stress and typing pressure. The typing pressure was significantly increased under stressful conditions.

Challenges

Digital phenotyping for mild mental health symptoms with non-clinical participants can present ethical challenges, limitations of the research, and technical challenges. We review the challenges that were stated in the literature.

Ethical Challenges

The studies that mentioned ethical concerns are [28,37,44,46,58]. Ten articles specifically mentioned privacy related ethical concerns [18,30,43,46,54,57,60]. A major concern for participants across several studies is whether authorities, such as employers or teachers, will have access to the data. In one study [18], students were worried that their information would be leaked to the university. Many of them were unsure if their professors or tutors would be able to see their data. For instance, a student had mentioned that they would not want their tutor to see that they were struggling with their mental health. Another student had mentioned that they would not want their professor to know that they set their alarm to 11 am. The study [30] with employees reported a similar concern where if the employees' data would be leaked to their boss and if the boss is aware of a potential mental health issue, it may impact their work performance ratings.

The methods of collecting and storing passive sensing data also present privacy concerns [18,71,74] especially when the tracked data involves sensitive topics such as mental health [74-76]. Sensors that infer individuals' social interaction provide insights into mental health status [27,28,57]. However, these kinds of data were less likely to be shared by participants due to privacy concerns. In study [43], students were not open to sharing social interaction data such as messages, call logs, and their real-time duration. In study [18], students identified the camera, microphone, call logs, and keyboard as highly unacceptable kinds of data to capture.

Location data was associated to privacy and security concerns. In study [40], participants felt uncomfortable with location tracking as it might breach their privacy and was hesitant to log their location when they move from one place to another. Some studies excluded specific sensors to protect the user's privacy. Location data was not recorded due to security concerns, even though it could provide valuable insights into mental state [Error: Reference source not found,44,57]. In study [33], the actual messages of the text messages were not captured. In

study [27], the microphone was disabled to capture calls and conversations while individuals were talking to their family members. Another ethical concern was around misuse of data. The main focus in studies of digital phenotyping with smartphones was to track participants' usual behavioural patterns and identify if they behaved unusually. There were concerns regarding secondary uses. For example, participants' leaked data could be used for advertising purposes or to create content [40,46].

Limitations of the Research

Coping mechanisms related to stress and anxiety vary between individuals [22,76]. Individual differences can make it challenging to label individuals as stressed, anxious, or depressed, particularly with non-clinical participants. Certain behavioural patterns can be generally expected, however, not all individuals will follow the same pattern. Study [39] mentioned that depressive individuals are reported to sleep longer but some participants slept less when they were depressed.

Nine studies (23.1%) mentioned that a short study duration is a limitation to generalising their conclusions [18,29-31,33,40,41,45,53]. To make generalisable and powerful analyses and to understand behavioural patterns associated to mild mental health concerns, it is recommended to study diverse groups for longer than a 2-week period. Two studies [41,53] focused on a particular demographic subset, namely, undergraduate students. Therefore, the generalisability of the studies are limited. In studies [18,33,45] limited variation in representation was seen as a major limitation. Studies [31,41,57] stressed the importance of selecting a wider age group as younger people use their smartphones proactively while older age groups' behavioural patterns might show differences when they are experiencing mild mental health symptoms. Study [30] was conducted using only American participants. The author suggested that wider population testing is required for more accurate results. Since each individual has their own unique differences, it is important to include diverse samples. We noticed that over the last three years [32,34,50], there has been increased focus on the generalisability of the machine learning models, with the goal of assessing generalisability across students from various years, classes, and institutions.

Technical Challenges

Digital phenotyping studies for mild symptoms related to mental health with non-clinical participants presented technical challenges. A main concern was the accuracy of the sensor data collected from smartphones. In study [18], the location data deemed inaccurate. Study [57] sought to understand the time spent in darkness and its effects on the relationship between stress and anxiety patterns, and sleep. However, when individuals carried the smartphone in their pockets or bags, the smartphone cannot detect the darkness of the environment. This presents a challenge because illuminance data was captured even when the phone was not used actively. Similar concerns have been raised in study [28] around time in darkness. From the data, it was impossible to distinguish if the participants were in a dark environment and sleeping or simply had the phone in a dark environment such as their pockets. The study [43] stated that captured accelerometer data may not accurately represent the daily activity as not all participants constantly carried their phones throughout the day. In study [55], environmental audio was not producing clear transcripts in louder environments. This study mentioned that transcripts were produced based on dictionaries, so language analysis of complex speech such as metaphors and sarcasm were ignored. Therefore, the entire content of the conversation might not be correctly interpreted. In study [28], similar challenges were identified as the speech data produced from smartphones was not clear. The recorded voices from the participants were masked by the people around them or even from other sources like TV or radio. Moreover, it was not possible to identify whether the death-

related words came from the participants or the people they interacted with.

Another technical challenge identified was battery life [Error: Reference source not found]. As expected, moment by moment data collection requires high power usage, which might shorten the battery life. Participants had to charge their phones more often, which was inconvenient, and altered usual behaviour because participants could not carry their phones as usual when phones were charging. Study [Error: Reference source not found] mentioned another technical limitation: the transfer rate was affected if the application stopped working randomly. During these times, the data was not transferred or collected. With the increase of 5G technology, Wi-Fi data for indoor locations may cease to be relevant. In study [44], some users were on their 5G indoors rather than Wi-Fi and this may point to a future trend of the use of 5G. We now turn to the discussion.

Discussion

This literature review examined digital phenotyping studies that detected and predicted stress, anxiety and depression in their mild states in non-clinical populations, using data from smartphones as their main data collection method. The primary objective of digital phenotyping in the context of mild mental health is similar among the three participant cohorts: students, adults and employees. However, notable distinctions emerge within these groups. Among university students, the geographical proximity and relevance of the university campus are discerned as influential factors. Moreover, academic pursuits, particularly coursework and study-related activities, assume significance within this demographic. Conversely, for employees, work aspects hold salience, accompanied by the workplace environment. The remaining studies encompass a general population cohort, delineated by undisclosed characteristics. Overall, we found that identifying behavioural abnormalities related to stress and anxiety was possible, but raised certain challenges. Generalised stress and anxiety symptoms vary largely between individuals whereas serious diagnoses like bipolar or schizophrenia have well documented behavioural changes. Sleep was a strong predictor variable yet some individuals tended to sleep more while they are stressed while others lacked sleep under stress. This may be one reason why there are fewer studies and reviews completed for stress and anxiety compared to serious conditions such as bipolar, severe depression, and schizophrenia. Another reason is that clinical psychologists and psychiatrists who are familiar with clinical populations are leading digital phenotyping research.

Studies tended to use self-report to categorise non-clinical populations as stressed, depressed, or anxious. It was not always clear whether the identified patterns the passive sensor data would effectively discriminate between groups. Most of studies used pre and post study surveys to identify participants' mental state. There were concerns raised in terms of the accuracy of the categorisation self-report surveys. For instance, study [42] stated that stressed students may not report themselves as very stressed. Melcher et al. conducted a review that found that students were concerned that about their professor learning about their data [73]. Thus, accuracy of self-report remains an issue for passive sensing studies that use self-report labels, especially when there are privacy concerns. This may be related to the high dropout rates within the studies.

Many types of data sensors were used in the reviewed studies. However, not many articles related sensors patterns to specific symptoms. For example, one study had 80% accuracy in detecting stressful days; however, it did not explain stressed individuals' behavioural patterns [44]. How the location and illuminance data interact with stress was not explained. Even when patterns are identified, they are not absolute; for example: high mobility and physical activity do not necessarily mean that the person is not stressed. In study [43], students were more mobile during exam week, despite being under high pressure and stress. In the same

study, some students were less mobile when studying for their exams which we cannot interpret necessarily as being under stress. Sensors patterns associated to depression include lack of activity and energy. Four studies [39,43,50,52] explored the effects of COVID-19 on behavioural and mental health. Additional recent investigations, which independently gathered their own datasets during the COVID-19 pandemic, have shown that quarantine measures have influenced individual behavioural patterns. For the purpose of making precise predictions in digital phenotyping, it is imperative to consider contextual and environmental factors.

Privacy and secondary data uses were the main concerns identified for digital phenotyping. Those using these systems have the right to informed consent. This means they should be made aware of how all of their data will be used, who will have access, where their data is stored and for how long, and they have the right to decline to participate. We urge researchers and medical practitioners to carefully consider the system design and requirements because data transferred to cloud and other services may fall under various service agreements. To empower end-users and to improve the quality of digital phenotyping systems, we recommend transparent algorithms and explainable artificial intelligence be combined with user-accessible and understandable displays, so that adults can engage with the process of identifying and categorising patterns related to mild mental health symptoms.

The digital phenotyping research focused on in this review may enable the design of tailored intervention programs for non-clinical participants who are showing symptoms of stress, anxiety, and mild depression. Most of the studies included in this review were conducted within a restricted timeline and limited scope of detection and prediction. Only four studies mentioned potential intervention programs upon predicting stress, anxiety, and mild depression [37,42,44,54].

Our review has limitations. We excluded studies done with clinically diagnosed people, teenagers and children. Thus we missed studies focusing on the detection and prediction of stress, anxiety and mild depression in these populations. These populations are likely to show different patterns than adults. Further, we excluded studies done with technology other than smartphones. We chose this more limited subset of technology to scope findings related to widely available technology. The availability of technology is changing rapidly and wearables like smart watches are becoming more common. As technologies become more ubiquitous, we recommend including them in future systematic reviews.

This literature review is unique in that it examines studies focused on behavioural patterns of non-clinical populations, namely stressed, anxious, and mildly depressed students, employees, and adults. We examined each type of sensor and indicated when it was significantly associated to mild mental health symptoms. We identified commonalities in the articles in terms of ethical challenges, limitations in the research, and technical challenges.

Conclusion

This systematic literature review found that digital phenotyping can be an effective way of identifying certain behavioural patterns related to stress, anxiety, and mild depression. A range of passive sensors were used in the studies such as GPS, Bluetooth, ambient audio, light sensor, accelerometer, microphone, illuminance, and WIFI. We saw that location, physical activity and social interaction data were highly related to participants' mental health and wellbeing. The surveyed literature discusses ethical and technical challenges that limit the accuracy and generalisability of results. One of the greatest challenges was the privacy concerns and these were primarily related to camera, location, SMS and call logs. Another challenge was the significant variation between individuals and their unique behaviors related to mental health. Finally technical limitations have not fully been resolved, with issues such as the sensor for illuminance still capturing data while not in use reducing the accuracy of the

collected data. It is hoped that this overview of digital phenotyping and mental health studies in the last decade, including the common privacy and technical concerns, can help move this area of research forward, ultimately improving the quality of passive sensing, and provide benefits in terms of early detection of relevant mild mental health phenomena.

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Appendix

Abbreviation	Definition
EMA	Ecological Momentary Assessment
PHQ	Patient Health Questionnaire
DASS	Depression Anxiety Stress Scales
BDI	Beck Depression Inventory
BFI	The Big Five Inventory
CWB	Counterproductive work behaviour
EDA	Electrodermal activity
ESM	The experience sampling method
GAD	Generalized Anxiety Disorder
GEE	Generalized Estimating Equations
ITP	The Psychological Type Indicator
LSAS	The Liebowitz Social Anxiety Scale
MPSM	Mobile Photographic Stress Meter
OCB	Organizational Citizenship Behavior
PAM	Patient Activation Measure
PANAS	Positive and Negative Affect Schedule
PPC	Perceived Personal Control
PSS	Perceived Stress Scale
PSQI	Pittsburgh Sleep Quality Index
PTIQ	Parent-Teacher Involvement Questionnaire
REDCap	Research Electronic Data Capture
RSE	Rosenberg Self-Esteem Scale
SAS	The Sport Anxiety Scale
SAD	Social Anxiety Disorder
SIAS	The Social Interaction Anxiety Scale
SPIN	The Social Phobia Inventory
STAI	The State-Trait Anxiety Inventory
WEMWBS	Warwick-Edinburgh Mental Well-being Scale