CONTRIBUTED PAPER

Digital Phenotyping and Feature Extraction on Smartphone Data for Depression Detection

This article provides a comparative overview of relevant studies on depression detection using smartphones, with a focus on the behavioral phenotype and feature extraction algorithm of major depressive disorder on smartphone data.

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ABSTRACT | Smartphones are widely used as portable data collectors for wearable and healthcare sensors that can passively collect data streams related to the environment, health status, and behaviors. Recent research shows that the collected data can be used to monitor not only the physical states but also the mental health of individuals. However, extracting the features of digital phenotypes that characterize major depressive disorder (MDD) is technically challenging and may raise significant privacy concerns. Addressing such challenges has become the focus of many researchers. This article provides a comprehensive analysis of several key issues related to ubiquitous sensing to aid in detecting MDD. Specifically, this article analyzes existing methodologies and feature extraction algorithms used to detect possible MDD through digital phenotyping from smartphone data. In particular, five types of features are summarized and explained, namely, location, movement, rhythm, sleep, and social and device usage. Finally, related limitations and challenges are discussed to provide paths for further research and engineering.

KEYWORDS | Depression detection; digital phenotyping; feature extraction; sensors; smartphone.

I. INTRODUCTION

Major depressive disorder (MDD) is foreseen by the World Health Organization (WHO) to be the leading cause of the increasing global burden of disease by 2030 [1]. Approximately, 350 million people worldwide have been affected by depression [2]. The lifetime risk of MDD is 15%–18%, and the worst outcome is that many people finally choose to end their lives, which adds up to 850 000 suicides reported every year [3], [4], [5]. Individuals suffering from MDD often exhibit symptoms such as persistent low or depressed mood, anhedonia or decreased interest in pleasurable activities, feelings of guilt or worthlessness,

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lack of energy, poor concentration, appetite changes, psychomotor retardation or agitation, sleep disturbances, and suicidal thoughts. Despite much effort being devoted to depression detection and intervention, new data suggest that the prevalence of MDD is on the rise, particularly in young people. Currently, MDD diagnosis relies mainly on questionnaires to deduce the severity of depression symptoms reported by patients [6] or clinical personnel, for which there is a risk of subjective bias [7]. To address this risk, an objective and quantifiable healthcare system can be leveraged for support. Compared to research methods that rely on specialized and fixed devices for data collection, such as text [8], [9], audiovisual [10], [11], body posture [12], [13], and physiological data [14], [15], the widespread and anytime accessibility of smartphones presents significant potential for healthcare, offering extensive data support and innovative solutions to help doctors quickly and accurately diagnose the risk of depression.

Smartphones have been widely used in healthcare for various applications, such as real-time physiological monitoring, chronic disease management, mental health assessment, and early detection of conditions such as cardiovascular disease, diabetes, and sleep disorders [16]. Smartphones can not only work as the data collection node and sensor gateway [17], but also contain abundant sensors that could infer the physical and mental condition and environmental context of their users [18]. In 2020, 5.5 billion mobile devices were connected to the mobile Internet, of which 75% were smartphones [19]. The wide use of smart devices offers an opportunity to passively collect daily behaviors related to long-term mental health and well-being. Insel [20] believes that objective and ecological measurements of smartphone sensors can capture early signs of mania or depression. Forchuk et al. [21] discuss the feasibility and acceptability of mobile technology to track depressive symptoms using various sensor devices embedded in smartphones [22], [23], [24] to monitor people's behavior, the surrounding environment, and relevant data on mental state. Therefore, researchers can leverage the various sensors and data collection capabilities of smartphones to quickly and extensively gather users' behavioral, psychological, and physiological data, aiding in the identification of depression symptoms and severity. This assessment method enables real-time monitoring of patients' emotional and behavioral changes without disrupting their normal daily activities.

While existing surveys emphasize the importance of feature engineering, they often lack detailed discussions on the technical and mathematical aspects, which are crucial for detecting depression. For example, global positioning system (GPS) sensors can be used to extract a variety of location-based features related to daily activities, such as maximum travel distance, location variance, and dwell time [25], [26], [27]. These features are significantly correlated with patient health questionnaire (PHQ) scores, indicating that individuals with depression tend to exhibit lower levels of physical activity. Furthermore, integrating multiple data sources, such as Wi-Fi and GPS, can enhance data completeness and predictive capabilities regarding depression, facilitating the identification of social activities of users and their effects on psychological states [28]. Additionally, movement characteristics, such as step count and activity patterns, not only reflect users' dynamic conditions but are also closely linked to mental health, serving as predictors for behaviors associated with social isolation and depression. Sensors embedded in smartphones, such as accelerometers, can monitor circadian rhythm instability, allowing analysis of the relationship between lifestyle rhythms and emotional states [29], [30]. In addition, accelerometers and light sensors can be used to assess sleep quality, establishing connections with symptoms of mental disorders. A reduction in social activities is closely associated with depressive symptoms [29], [31]; using Wi-Fi and Bluetooth sensors, users' social relationships can be inferred, while the frequency of calls and text messages further reveals the intensity of social interactions. Although smartphone sensor data hold the potential for extracting digital phenotypes of depression, issues such as multimodal data fusion, privacy concerns, and others have garnered significant attention. Therefore, this article focuses on the manifestation of behavioral phenotypes in feature extraction algorithms based on smartphone sensor data, highlighting weaknesses in privacy protection, as well as identifying open questions and engineering challenges.

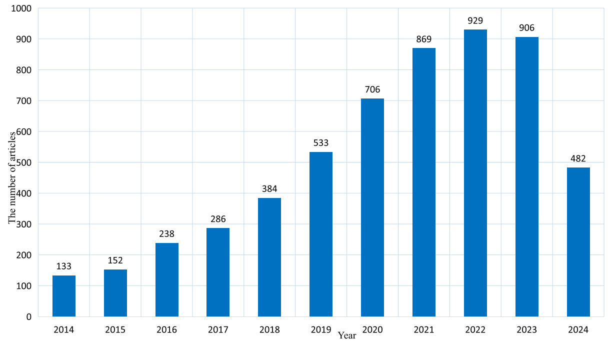

Fig. 1. ***Number of literature queried from databases.***

This article is limited to feature extraction methods used in depression detection research utilizing smartphone data. By searching the literature on electronic databases such as IEEE Xplore, Web of Science, PubMed, Medline, PsycInfo, ACM DL, Scopus, and Google Scholar, the following search terms were used: (depression or bipolar disorder (BD) or dysthymia) and (smartphone or mobile phone or cellphone). We observed the articles about smartphones detecting depression in the past ten years. Excluding duplicates, non-English language, reviews, and those without relevant search terms in abstracts from the 5618 (Fig. 1) pieces of the literature yielded 358 (Fig. 2) relevant pieces of the literature in the recent ten years. Excluding studies such as questionnaires, online surveys, smartphone

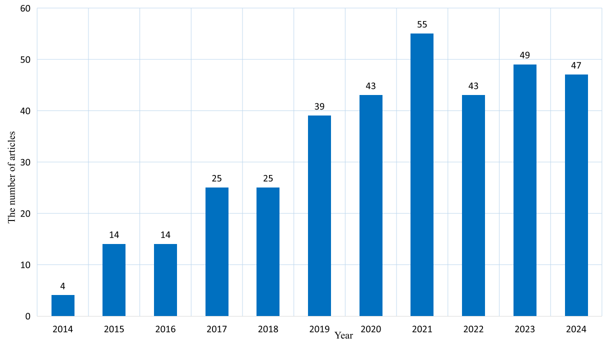

Fig. 2. ***Number of relevant literature in the recent ten years.***

program interventions, scale surveys, self-reporting, mindfulness training, and nonhumans, 45 articles and reports were finally selected for our review analysis from 2014 to September 2024. Although the related research is not sufficient as a whole, the number of articles shows an unambiguous growing trend. It is obvious that this topic has attracted more and more attention.

Contributions: This article provides a comparative summary presentation of relevant studies on depression detection based on smartphones, with a particular focus on the behavioral phenotype and feature extraction algorithm of MDD on smartphone data. Specifically, the main contributions of this article are as follows: 1) summarizes several important aspects of ubiquitous sensing for depression detection using smartphones; 2) conducts in-depth research on feature extraction algorithms and digital phenotyping based on smartphone data; and 3) discusses open issues and challenges for achieving future practical applications.

The rest of this article is organized as follows. Section II briefly summarizes the methods and analysis. Section III mainly analyzes and compares different feature extraction algorithms based on smartphone sensor data. Section IV discusses the open issues and challenges. Finally, Section V concludes this article.

II. OVERVIEW OF DEPRESSION DETECTION WITH SMARTPHONE

Earlier researchers found that behavioral components and motivation states are observations that can be monitored through mobile phone sensors [32]. When the smartphone came out, due to its rich sensors, flexible computing interface, and larger communication bandwidth, smartphone sensors were used to mark the location information of the subjects, the mobile trajectory, and sleep quality, as well as the number of places visited, distance from home, the number of locks or unlocking the screen, and other features to record or predict activities of the subjects [33]. These activities are highly correlated with the behavioral characteristics described in [34] and are widely used in objective quantitative evaluation of depression [35]. In addition, smartphone-based depression detection and intervention have been reviewed. With the ability of ubiquitous sensing, sensor data were used to acquire physical and emotional conditions based on some specific context processing and context reasoning mechanisms [36]. This would facilitate subsequent research or application based on context awareness with smartphones. Thieme et al. [37] presented a systematic review of current machine learning approaches in the computer and Healthy Communities Initiative literature on psychosocial-based mental health conditions. Seppälä et al. [38] observed that sensor data are related to symptoms of mental disorders, such as depression and bipolar, systematically reviewing the original studies of sensor-based mHealth applications. Nevertheless, their usability in clinical practice needs further validation. Wu et al. [35] conducted a systematic review of the literature and meta-analysis of smartphone apps for depression and anxiety disorders to assess the impact of persuasive design and behavioral economic techniques on clinical outcomes. Cornet and Holden [39] explored the literature on smartphone-based passive sensing for health and well-being in depression, stress, geriatrics, and general mental health. Mohr et al. [23] conducted a critical review of personal perception research related to mental health, focusing primarily on smartphones but also including research on wearables, social media, and computers, which provided a landscape of relationships between sensor data, features, and behavioral markers related to mental disorders. However, it is evident that there is still a lack of a systematic review summarizing the detailed methodologies for detecting depression using smartphones (such as feature extraction methods) and the challenges of clinical application. Therefore, this section summarizes several important aspects of ubiquitous sensing of depression detection using smartphones based on a comprehensive search strategy for investigation.

A. Depression Detection With Ubiquitous Smartphone Sensing

Compared to other wearable devices, smartphones are carry-on and frequently used, making ubiquitous awareness prolonged and low-costing to be conducted, e.g., where the subject is, what the user is doing, how the surroundings are, how long the condition lasts, etc. [40], [41]. Those activities and their context information made flourishing investigations of research domains such as human activity recognition (HAR) [42], [43], emotion awareness [44], and healthcare. Nowadays, smartphones have many built-in sensors, such as proximity sensor, ambient light sensor, complementary metal–oxide–semiconductor (CMOS) image sensor, microphone, GPS sensor, accelerometer, humidity sensors, temperature sensors, pressure sensor, fingerprint sensor, magnetometer, gyroscope, and touch sensor. These sensors can actively or passively sense physiological or behavioral data related to physical or mental health conditions [45].

With the great success of computer vision, CMOS image sensors have been widely used in ubiquitous awareness

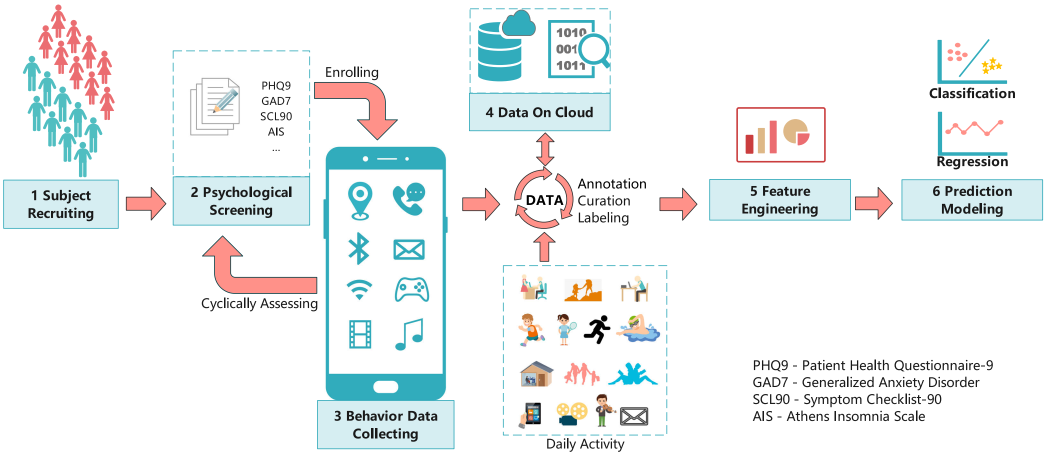

Fig. 3. ***Overview of mental disorder assessment lifecycle.***

and healthcare. Combining inertial sensors with biographic, ambient, object, and visual sensors can provide sufficient information and high accuracy for activity detection [46], [47]. Furthermore, the motion recognized by the sensors reveals human emotions [48]. Proximity sensor, GPS sensor, ambient light sensor, microphone, humidity sensor, temperature sensor, and magnetometer reflect the physical aspects and surroundings, which provides much general context information of what we are doing. In addition to sensors, Bluetooth connections, app usage, short message service (SMS), call logs, and other smartphone usage patterns can provide long-term information on cognitive, emotional, and social activities. Some of these directly reflect typical characteristics of depressed patients, such as lack of social interaction [49]. The awareness of behavioral patterns from smartphone raw sensors data could map to high-level behavior markers of depression [22], [23], [50], which are typical symptoms in the current diagnosis criterion [34]. Active sensing always recovers the patterns of daily life, such as sleep and living rhythm. Passive data are objectively recorded by the phone [51], including duration of voice communication, social activity, such as incoming and outgoing calls and SMS, mobility measured with an accelerometer, and the phone identifier of the smartphone connection. It is common to use different modalities of sensors to monitor people's emotional states. More and more researchers are using multimodal fusion for health monitoring, identification of stress and mental loads, and people's interaction with ambient, location, chronic disease management, and so on. The comprehensive ubiquitous awareness ability paves the way to recover the potential digital phenotype of depression in daily life with smartphones. In addition, according to the timeline, we outline the research of smartphone-based behavioral data on mental disorder assessment in the past ten years. Table 1 listed the following data for each study: first author (publication year), participant group and sample size, technology used, study time, and purpose of the study. Based on this, we outline the general framework for the mental disorder assessment lifecycle.

Activities recognized based on smartphone sensing applications discussed above relate to specific mental states, such as depression, bipolar, and anxiety. The mental disorder assessment lifecycle with smartphones always involves six steps, as shown in Fig. 3, including subject recruitment, psychological screening, data collection, data processing, feature engineering, and prediction modeling. Behavioral data were used as objective quantitative evaluation data, while the screening scores of mental state assessment scales were often used as labels for classification or regression learning. With the popularity and convenience of smartphones, many pieces of research tried to use numerous built-in smartphone sensors to predict emotions [52]. Furthermore, to meet the research needs of respective teams and real-time monitoring, researchers also began to develop relevant mobile applications of multimodal mobile sensing systems to effectively collect behavioral patterns and evaluate mental states. Abdullah and Choudhury [53] reviewed the use of sensing technologies to diagnose and monitor multiple severe psychiatric illnesses in patients. In the whole lifecycle, three processes of mobile sensing and computing are critical for depression detection, i.e., mobile sensing, data collection, and feature extraction.

1) *Mobile sensing:* In general, a mobile sensing framework consists of hardware and software sensors. The first one refers to embedded sensors, such as GPS and accelerometers in mobile devices, while the second one counts the user-generated data from the Internet. Sensing tasks can work continuously (continuous sensing) or in an event-triggered sensing manner. For the prior one, in a sensing task, the relevant sensors work continuously under the parameter settings, such as sampling rate and duration. However, some sensing tasks are only meaningful in certain sampling contexts. Thus, the researchers defined triggers to capture data in a context-aware manner.

2) *Data collection:* The scale of data contribution in mobile sensing can range from small to large, encompassing individual, group, and community levels. Furthermore, incentives for subjects using mobile sensing involve considerations such as ethics, privacy protection, and entertainment, among others.
3) *Feature extraction:* In this stage, the data collected from relevant sensors can be uploaded to the cloud for data processing. Besides, relevant features can be extracted. Based on different algorithms, we can analyze the data to extract relevant information and assess the subjects' mental states. Finally, feedback could be given based on the evaluation results.

B. Data Multimodality and Experimental Duration in Smartphone Applications

Data for depression detection based on smartphone digital phenotyping typically comes from applications (Apps) (either preinstalled or specially developed), and these data are of multiple types. These applications can provide continuous or intermittent user data according to the experimental design requirements. Therefore, this section first introduces common data collection applications, summarizes the duration of existing research studies, and finally describes the multimodal aspects of digital phenotyping studies.

Smartphone applications are frequently developed to collect data on user activities. From Table 1, we can see that many studies have used their smartphone apps to monitor and track depressive symptoms among adults, children, and the elderly. The feasibility of smartphones for data collection means that the detection of depression mainly focuses on active and passive data streams. Active data collection uses a mobile phone through simple ecological momentary assessment (EMA) from a mobile sensing system to collect subjective data. The patient enters items on a daily basis, including mood, sleep, level of activity, and medication. Some items are customizable to accommodate patient differences, while others consistently provide aggregated data for statistical analysis. A daily alarm reminds the patient to fill out the form. Passive data collection uses smartphone sensors to collect objective data to monitor the level of daily activities (based on GPS, gyroscopes, Wi-Fi, and accelerometer data) and the number of social activities (based on phone calls, screen events, and text messages). These datasets are abstracted for analysis to protect user privacy, while still supporting the use of objective data for EMA. Specifically, the smartphone apps used include: AWARE [29], mindLAMP [54], Behavidence [55], Passive Data Kit [56], The Carat app [57], Delphi [58], MovisensXS [59], Callistics and StayFree [60], DataCollector [61], Jouw Leefomgeving [62], Studentlife [63], Moment [64], Purple Robot [65], iHOPE [66], LifeRhythm [67], MoodTraces [25], and Fine [68]. Use of wearable devices is included: Fitbit Charge 2 [69], ActivePERS/PAMSys [70], Wristband sensors [59], and Silmee W20 [71].

In addition, the experimental period is one of the important factors in depression assessment because depressive symptoms can change over time. The diagnostic criteria of MDD in DSM-5 include counting the number of symptoms presented during a two-week period. PHQ-9 [72] uses a two-week assessment cycle, and self-rating depression scale (SDS) [73] adapts the period less than one week. The longer the time, the more accurate the assessment of the depression state, but the long-term behavioral data might reflect inconsistency in the behavioral patterns due to the change of the core symptoms of depression, which will eventually affect classification modeling.

At the same time, since the application that collects data often runs continuously in the background, frequently reading, storing, and uploading high frame rate sensor data will bring much power consumption. This affects the user experience to some extent and leads to difficulties in recruiting participants. These constraints require the researcher to determine a reasonable duration of the experiment. Longer experiments would be more valuable if subjects could provide multiple times of valid scale assessments during the experiment, such as once every two weeks. The reliability and validity are to be confirmed when the self-reporting scales are repeated many times. Doctor's follow-up would provide more precise labels, but this may limit the number of subjects.

The unimodal data generated by each sensor captured by smartphone apps have limitations in reflecting user behavior and emotional states. For example, GPS can provide coarse-grained location information about subjects visited, but due to its low sampling rate, it is difficult to predict movement patterns. Additionally, its positioning accuracy is significantly reduced in indoor environments, making semantic correspondence with activity locations challenging. Therefore, multimodal sensing provides complementary information for each other [97], which would achieve a more robust and precise prediction model in the learning task of activity recognition, emotion awareness, etc. The high frame rate inertial sensor is a good complement to GPS to improve the ability to describe specific actions; thus, conducting multimodal fusion of GPS, accelerometer, and gyroscope data can integrally mark the motion trajectory and emotion status. The combination of GPS and Wi-Fi can realize the automatic labeling of visited places. In addition, Bluetooth could be used to monitor sleep quality and social interaction, and body movement information could be monitored by combining actigraphy. To provide a more intuitive understanding of the functions of different sensors for more efficient implementation of multimodal fusion studies, Table 2 summarizes the potential applications, advantages, and disadvantages of some frequently used combinations of smartphone sensors. The combinations of sensors are not limited to those listed in Table 2. While considering a feature-level or decision-level fusion, there are more possible fusion strategies. Supervised or unsupervised learning subprocesses would be good in the preprocessing stage or feature engineering.

Table 1 Meta Comparison of Research on Depression Detection From 2013, Where BD and MDD Are Indicated for Bipolar Disorder and Major Depressive Disorder

No./Ref.	Authors (Year)	Sample (Size)	Technology	Period	Research purposes
1 [29]	Balliu, B. et al.(2024)	Depression (n=183)	Smartphone App (AWARE)	3 years	Validating the feasibility of longitudinal mood assessment in a clinical population and predicting symptom severity weeks in advance using digital data
2 [31]	Lee, J. K. et al.(2024)	Late-life depression (n=685)	Smartphone App	Larger than 2 years	Development of an algorithm to predict depression in old age by constructing longitudinal data
3 [54]	Langholm, C. et al.(2023)	BD, MDD (n=116)	Smartphone Apps (mindLAMP)	12 weeks	Demonstrating the potential of numerical phenotyping methods for clustering depression, BD, and healthy controls
4 [74]	Faurholt-Jepsen, M. et al.(2023)	BD (n=150)	Smartphone Apps	6 months	For the first time, the effect of additional smartphone-based treatment on mood instability in patients with BD was investigated
5 [75]	Sun S. et al.(2023)	Recurrent MDD (n=623)	Smartphones, Wearables	14 days	The relationship between mobile health-derived characteristics and depression symptom severity
6 [55]	Choudhary et al.(2022)	Android users (n=558)	Smartphone App (Behavidence)	average of 10.7 days	Using personal non-invasive sensors to help detect and monitor depression in a continuous and passive manner
7 [76]	Sewall et al.(2022)	Participants (n=384)	Smartphone App	about 4 months	Investigate the relationship between smartphone use duration and frequency, social media use duration, and depression, anxiety, and social isolation
8 [77]	Zhang et al.(2021)	Participants (n=316)	Smartphone App	variant	Exploring the value of NBDC data from the PHQ-8 in predicting depressive symptom severity
9 [69]	Rykov et al.(2021)	Adults (n=290)	Fitbit Charge 2	least 14 days	Study of features extracted from wearable device sensor data to detect depression risk in the population
10 [56]	Meyerhoff et al.(2021)	Android users (n=282)	Smartphone App (Passive Data Kit)	over 16 weeks	To assess the relationship between changes in behavioral characteristics induced by cell phones and subsequent changes in mental health symptoms
11 [78]	Di Matteo et al.(2021)	Adults (n=112)	Smartphone App	2 weeks	Using smartphone data to predict generalized anxiety disorder, social anxiety disorder, and depression
12 [57]	Asare et al.(2021)	Participants (n=629)	Smartphone App (The Carat)	average of 22.1 days	To assess the use of smartphone data on human behavior in predicting depression and identifying behaviors that influence it
13 [70]	Mishra et al.(2021)	Elders (n=10)	Wearable pendant sensor	12 months	To assess the negative impact of social isolation on the health of older adults during COVID-19
14 [79]	Di Matteo et al.(2021)	Adults (n=112)	Smartphone App	2 weeks	To determine whether language attributes can be used to detect the severity of social anxiety disorder, generalized anxiety disorder, depression, etc.
15 [58]	Moshe et al.(2021)	Adults (n=60)	Smartphone App (Delphi) and wearables	30 days	Exploring the predictive effects of using data from smartphones and wearable devices for depression and anxiety disorders
16 [80]	Nguyen et al.(2021)	Students (n=60)	Smartphone phone sensing	over 10 weeks	Depression detection using data from the phone's built-in sensors
17 [81]	Kim et al.(2021)	Students (n=48)	Smartphone phone sensing	over 10 weeks	Proposed method to diagnose user depression via smartphone
18 [59]	Pedrelli et al.(2020)	MDD (n=31)	Smartphone App and wristband sensors	8 weeks	Explore the feasibility of assessing depressive symptom severity using characteristics of data obtained from wristbands and smartphone sensors
19 [82]	Di Matteo et al.(2020)	Adults (n=112)	Smartphone App	2 weeks	Using passively acquired audio from smartphones to identify anxiety and depression
20 [83]	Busk et al.(2020)	BD (n=84)	Smartphone App	1 week	Examining the feasibility of predicting BD scores based on daily smartphone self-assessment
21 [84]	Rozgonjuk et al. (2020)	Participants (n=454)	Smartphone App	least 1 week	Investigating whether the frequency of Instagram use is associated with psychopathological variables
22 [60]	Razavi et al. (2020)	Participants (n=412)	Mobile App (Callistics, StayFree)	variant	Exploring the potential of patients' cell phone use patterns to consistently screen for depressive symptoms
23 [61]	Masud et al. (2020)	Participants (n=33)	Smartphone App (DataCollector)	11 weeks	A method to assess depression levels through smartphone monitoring of daily activities

Table 1 *(Continued.)* Meta Comparison of Research on Depression Detection From 2013, Where BD and MDD Are Indicated for Bipolar Disorder and Major Depressive Disorder

24 [71]	Tazawa et al. (2020)	Depressed vs. controls (n=86)	Wearable devices (Silmee W20)	variant	Develop a machine learning algorithm to screen for depression and assess severity based on data from wearable devices
25 [85]	Moukaddam et al. (2019)	MDD (n=22)	Smartphone App	variant	Investigate whether daily mood self-reports via cell phones can monitor and classify clinically depressed individuals
26 [62]	Helbich et al. (2019)	The Dutch (n=45000)	Smartphone App (Jouw Leefomgeving)	variant	Examining how environmental exposures in people's daily activities and residential histories affect depression and suicide rates in the Netherlands
27 [86]	Cho et al. (2019)	Mood disorders (n=55)	Smartphone App and wearable tracker	2 years	Assessing emotional state by passively acquiring various log data
28 [63]	Huckins et al. (2019)	Students (n=257)	Smartphone App (Studentlife)	variant	Mobile sensing data shows promise for mental health diagnosis and neuroscience
29 [87]	Sarda et al. (2019)	Diabetes (n=47)	Smartphone-sensing App	20 weeks	Analyzing the association of smartphone sensing parameters with depressive symptoms and proposing a method to assess the risk of diabetic patients
30 [88]	Huang et al. (2019)	Speakers (n=887)	Smartphone-sensing App	variant	New features extracted from smartphone audio recordings were used to detect depression
31 [64]	Elhai et al. (2018)	Students (n=68)	Smartphone App (Moment)	variant	To explore the correlation between smartphone use and psychopathology
32 [89]	Rozgonjuk et al.(2018)	Students (n=101)	Smartphone App	variant	Exploring the relationship between depression and anxiety severity and minutes of screen time
33 [90]	McGinnis et al. (2018)	Children (n=63)	Available wearable sensor	variant	A new method for diagnosing anxiety and depression in young children is proposed
34 [91]	Renn et al. (2018)	Depression (n=353)	Smartphone App	variant	To address the challenge of collecting smartphone-based physical activity data
35 [49]	Wang et al. (2018)	Students (n=83)	Smartphone Apps, Wearable Sensor	18 weeks	Address mental health assessments using mobile sensing
36 [92]	Place et al. (2017)	Participants (n=73)	Mobile app	12 weeks	A report on models of clinical symptoms for post-traumatic stress disorder and depression derived from a scalable mobile sensing platform
37 [65]	Saeb et al. (2017)	Participants (n=208)	Smartphone App (Purple Robot)	6 weeks	Explore the relationship between semantic location access patterns estimated by cell phone sensors and depression and anxiety disorders
38 [66]	Hung et al. (2016)	Depression (n=59)	Smartphone App (iHOPE)	8 weeks	Study the effectiveness of smartphone-based EMA for Chinese patients with depression
39 [93]	Beiwinkel et al. (2016)	BD (n=13)	Smartphone application	12 months	Investigating whether smartphone measurements can predict clinical symptom levels
40 [94]	Elhai et al. (2016)	Participants (n=308)	Smartphone App	variant	Levels of smartphone use and behavioral mechanisms of poor mental health
41 [67]	Farhan et al. (2016)	Students (n=79)	Smartphone App (LifeRhythm)	8 months	The possibility of using data collected by smartphone sensors for depression screening is discussed
42 [68]	Dang et al. (2016)	MDD (n=4)	Smartphone App(Fine)	1 week	It is important to design objective and validated screening techniques for depression
43 [95]	Farhan et al. (2016)	Students (n=60)	Smartphone phone sensing	10 weeks	Analysis of smartphone sensing data and extraction of different behavioral traits associated with depression
44 [25]	Canzian et al. (2015)	Adults (n=46)	Smartphone App (MoodTraces)	10 months	Analysis of GPS-tracked movement patterns in individuals with depressive disorders
45 [96]	Roh et al. (2014)	Depressives (n=23)	Wearable Sensors	variant	Designing a wearable depression monitoring system for depression identification

C. Depression Behavioral Phenotype in Smartphones

Digital phenotyping in the context of depression detection involves analyzing patterns in smartphone data to identify changes in behavior and mood that may be indicative of depression. For example, changes in smartphone usage patterns, such as increased social media scrolling or decreased texting, may suggest a decrease in motivation or interest in social interaction, which are common symptoms of depression. The behavioral phenotype reflected by smartphone sensors can effectively identify mental disorders after feature engineering [23]. The researchers found that mobility and social activity are related to

Table 2 Sensor Modalities, Applications, Advantages, and Disadvantages

Sensors: GPS	Accelerometer	Wi-Fi	Gyroscopes	Microphone	Smartphone usage	Bluetooth	Actigraphy	Physiological signal	Applications	Advantages	Disadvantages
√		√							Mark location information	Improve features extraction of physical activities	Unable to capture activity trajectory in real-time
√	√		√						Mark location information, mobile trajectory and extract clustering numbers, distance information to predict activity ability	Capture speed information and reduce the effects of noise, offer efficient data information of physical activities for emotion recognition	Unable to capture specific activities in real-time and relationship between activities and motion
				√	√	√			Monitor sleep equality by capturing information of voice and interaction events	Capture screen lock and unlock events, calls and messages numbers related to emotion recognition	Unable to locate location information, such as home stay
	√		√						Differentiate similar behavior patterns, recognize different activities	Reduce the effects of noise, offer efficient data information of physical activities for emotion recognition	Unable to capture specific activities in real-time and relationship between activities and motion, unable to record the change of activity speed
√	√		√	√	√				Monitor location, sleep equality and social interaction	Capture location, voice information, physical activities, screen lock and unlock events, calls and messages numbers related to emotion recognition	Lack of temporal dynamics and hierarchical activities representation. That may exit location dependency
				√			√		Monitor the information of body movement and sleep state	Capture physical movement and audio information to recognize the change of emotion state	Unable to obtain efficient information of physical activities and specific locations
	√							√	Recognize human activity and monitor emotion state	Provide functional means during extra exercise to estimate strength, track health management issues	Disable to achieve monitor of subjects' activities in real-time

("√" if the protocol satisfies the property)

the severity of depressive symptoms [49], [98]. Subjects with more severe depression tend to show worse social activities and less social communication. Depressive subjects also prefer to stay home and suffer more restless sleep. In addition, the use of the smartphone itself can also reflect the current mental state of the subjects [26], [99], [100], [101], [102], [103], [104], [105], [106]; for example, behavioral markers including abnormal phone unlock patterns, irregular usage times (e.g., late-night phone use), and increased engagement in certain apps (e.g., social media or browsing) are related to depression.

In 1999, researchers first found a significant correlation between passive perception data (e.g., telephone recording) from mobile phones in depression and behavioral patterns [72], [107]. In the following studies, mobile phone usage records that contain the frequency of smartphone usage, screen lock or unlock, the number of SMS received or rejected, and the number of connected or outgoing calls were extracted for investigating people's sleep status [26], [68], [108], [109]. It found that the "display unlock" event in the middle of the night may indicate that the person is not sleeping. Multiple "show unlock" events in the middle of the night indicate that the person is not sleeping well and is likely to suffer from insomnia.

Furthermore, smartphones have been explored to provide unobtrusive monitoring by analyzing the activity patterns of individuals suffering from depressive disorders. According to [110] and [111], researchers developed a set of extended mobility features and considered the user's mobile trajectory (e.g., from GPS readings) as a series of stagnation and movements. The measurements considered include the total distance moved in a study period, the maximum length away from home, the radius of gyration, etc. Several related studies [25], [49], [67], [68], [108], [110], [112], [113], [114], [115], [116], [117] were conducted to capture depression-related behavioral patterns, in particular on reduced mobility. For example, a lack of exercise due to a person staying at home for a few days due to depression could be captured [118], [119].

Table 3 Features of Data Collection and Extraction

Section	Label	Features Category	Data Source	Main Features	References
III-A	Location-based Features	**Mobility** • GPS tracking • Clustering of locati-ons (etc. home stay) • Transition time	• GPS	***Mobility metrics***: position variance, position number (clustering number), total distance, average moving speed and time spent in moving, entropy, and stay-home time, time spent in a state	[29] [75] [74] [54] [69] [56] [78] [58] [80] [61] [91] [67] [95] [25] [93]
III-B	Dynamic Movement-based Features	**Activities** • Movement • Step count	• GPS • Accelerometer • Gyroscope • pedometer	***Movement metrics***: total distance, the maximum value of the distance between two different locations, $g(t_1, t_2)$, σ_{dis}, the maximum distance away from home, the number of different places visited, the number of different important places visited, $r(t_1, t_2)$, steps	[29] [31] [54] [55] [69] [56] [58] [80] [62] [63] [91] [92] [67] [95] [25] [93]
III-C	Rhythm-based Features	**Circadian rhythm** • Voice • GPS • Smartphone usages	• Accelerometer • Microphone	***Time-domain Features***: Magnitude, SMA, RMS, varSum(n), avgNLE, CL ***Frequency-domain Features***: FFT energy, Peak power, Discrete Fourier Transform (DFT) Peak Power, Peak frequency, Entropy	[29] [69] [56] [78] [57] [80] [82] [61] [92] [95] [86]
III-D	Sleep-based Features	**Sleep state** • Voice • Sleep • Environment • Actigraphy	• Accelerometer • Microphone • Light intensity • Screen events	***Sleep Features***: statistical features. For example, the sum, average, maximum, and minimum length of cycles during which participants are awake, restless, or asleep, and the start and stop times of the shortest and longest cycles, the number of sleeping samples, restless samples, awake samples, and weak sleep efficiency.	[29] [31] [75] [74] [54] [55] [69] [78] [70] [127] [58] [81] [59] [82] [49] [66] [86]
III-E	Social Interaction-based Features	**Social behavior** • Phone calls • Messages • Social network • App usage • Screen events	• Bluetooth • Usage patterns	***Features***: Sad duration, communication frequency, number of Bluetooth devices surrounding, lock/unlock statistics.	[29] [31] [75] [74] [55] [57] [58] [80] [59] [84] [60] [61] [62] [89] [49] [92] [93] [94] [77]

To further study the relationship between the severity of depression symptoms and mobile tracking, Saeb et al. [110] started to collect the trajectory data from people who suffered from different depression levels by ready-made multimodal systems such as “Purple” mentioned above [120]. A series of activity sites was marked as an activity sequence using GPS and Wi-Fi data. The number of interactions between sequences can capture the behavior patterns related to depression symptoms, such as the decreased activity level of participants. The circadian rhythm, acceleration, and location sensors were also used [101], [106], [121], [122], [123], [124] to extract the hours of outdoor activities, access of different locations, average hourly activity levels, and daily patterns. Accelerometer readings are used for activity recognition [125], such as stationary, walking, or running [51], [116]. Finally, the data and the analytical results from the smartphones are compared with the diagnostic ground-truth values. The above experimental studies concluded that depression patients move less in the geographical space, have a slower circadian rhythm such as moving irregularly between different locations, and use smartphones for a long time and more frequently [68], [110], [120].

III. DIGITAL PHENOTYPING AND FEATURE EXTRACTION ALGORITHMS

Digital phenotyping is a rapidly growing field that uses digital data to monitor and assess an individual’s health and well-being in real time, which is a promising approach for detecting depression using smartphone data. By analyzing patterns in digital data, such as changes in sleep, physical activity, or social interaction, researchers and healthcare professionals can gain insight into an individual’s mental and physical health status. In the context of digital phenotyping, feature extraction refers to the process of identifying and quantifying behavioral or physiological features from digital data, such as smartphone usage patterns, social media activity, or wearable sensor data. These features can then be used to create a digital phenotype, a profile of an individual’s behavior and health status based on their digital data, with better interpretability to enhance the transparency and trust of the detection results. Emotion sensing [126] depends on the effective features, which can reflect the behavioral markers of mental disorders [23]. Feature extraction also plays a critical role in prediction modeling based on traditional machine learning algorithms. Therefore, to provide a reference for researchers in related fields, this section investigates and summarizes the feature extraction methods and possible digital phenotyping of mental disorder assessment based on smartphones.

According to the characteristics of the data in the digital phenotyping, this section summarized and explained the existing feature extraction methods of the raw sensor data from the five aspects listed in Table 3, namely, location, movement, rhythm, sleep, and social-based features. Table 3 consists of six columns, including section, label, features category, data source, main features, and references. The content of this section is organized as follows.

1) In terms of location-based features, we take into account the features that describe mobility, including GPS tracking, location clustering, and transition time.

2) Regarding dynamic movement-based features, we consider features that describe participants' activities, including movement and step count information.
3) Regarding rhythm- and sleep-based features, we take into account features that describe subjects' physical states and environment features collected from the physical surroundings of the user.
4) Regarding social interaction-based features, we consider features that describe social behavior, including events related to phone calls, messages, and social-related data collected from Bluetooth.

We also take into account the features that describe the usage of smartphones, including the usage of applications and screen events of lock and unlock. Furthermore, research often extracts the characteristics of time windows from different channels, such as passive sensors, active behavior, and the corresponding behavior changes are investigated by analyzing the features extracted [27], [108], [112].

A. Location

Previous research has proposed location features [25], [29], [54], [74], [93], [110], [111], with researchers hypothesizing that individuals with depression tend to travel less and exhibit more irregular location patterns. Based on this hypothesis, GPS sensor data representations have been extracted to assess participants' location changes and infer potential depression. Table 4 presents various combinations of location-based features used for predictive modeling. Among these features, home stay, position variance, entropy, and total distance are the most frequently used. Home stay and total distance measure the intensity of daily activity or social isolation, while location variance and entropy reflect the diversity of users' daily lives. We divided numerous features extracted from the location data captured by smartphones into two categories, i.e., original GPS data and location clusters.

The GPS sensor provides users with continuous location information, and the raw GPS data outline the places users have visited, their trajectories, and movement patterns. Extracting mobility-related features from GPS information serves as an intrinsic metric for daily activities or exercise intensity. These features [25] include maximum distance, radius, location variance, total distance, and position coordinates. Studies have shown that GPS characteristics can predict the severity of depression symptoms. Additionally, a comparison with the PHQ scale for diagnosing depression revealed a strong correlation between the maximum travel distance and PHQ scores across the two locations, indicating that individuals with depression exhibit lower activity levels. Furthermore, pauses can be represented geographically, reflecting the locations where users spend a certain amount of time. The pause location is defined as a tuple: $\mathrm{PI} = \langle \mathrm{ID}, t^a, t^d, C \rangle$, where ID is an identifier, t^a is the arrival time, t^d is the departure time, and C is the longitude–latitude pair. To capture the diversity of activity locations, statistical analysis is conducted by introducing spatial–temporal properties such as location variance to identify behavior patterns associated with depression [25]. For a specific user, the moving track $\mathrm{MT}(t_1, t_2)$ of the time interval $[t_1, t_2]$ is defined as the sequence of locations visited by the user in the time interval: $\mathrm{MT}(t_1, t_2) = (\mathrm{PI}_1, \mathrm{PI}_2, \ldots, \mathrm{PI}_{N(t_1,t_2)})$, where $N(t_1, t_2)$ is the total number of locations visited in the interval $[t_1, t_2]$. Based on that formalized definition, researchers can obtain a richer representation of the location-based behavioral patterns listed. Similarly, studies have shown that the level of social isolation depends on the amount of time participants spend at home compared to other locations [26], [27]. Different stays at home situations have been studied in a previous study using GPS data [110]. Staying home is a significant indicator of depression and social anxiety. The higher the level of social anxiety, the longer the subject stays at home in a fixed time window.

Compared to existing questionnaire-based methods, metrics derived from smartphone-based digital phenotyping can capture behavioral characteristics specific to individual users and time periods, allowing for moment-by-moment quantification of user motivation indicators. The radius of gyration is commonly used to quantify coverage, defined as the deviation of visited locations from a central location over a specified time interval. However, GPS data may be incomplete, resulting in discontinuities in the dataset. Yue et al. [28] fused location data by combining GPS data collected from smartphones with Wi-Fi association records to obtain more comprehensive data, thereby improving the representation of depression characteristics in digital phenotyping. The Wi-Fi association records refer to the logs of smartphones that connect to the wireless access point (AP). Additionally, since smartphones must connect to nearby APs, the locations of these APs can be used to approximate the user's position.

Individual behaviors and locations exhibit significant differences [115]. Detecting user movement patterns is crucial, typically achieved through clustering methods to characterize the frequency of appearances in high-activity areas, the transition counts between different regions, the radius of rotation [25], the time spent at frequently visited locations, and the most common activities. Saeb et al. [110] used the *Lomb–Scargle* method [113] to extract the motion law from the position pattern following a 24-h cycle. The moving speed and time between the two samples are calculated. Samples with a speed >1 km/h are marked as moving, otherwise as static. The samples marked as static are clustered by density-based spatial clustering of applications with noise (*DBSCAN*) [49], [114]. The frequent locations visited by participants are searched by a density-based clustering algorithm and marked as global or local clusters. In addition, by calculating relevant statistical data on the dwell times of the clusters, such as the minimum, maximum, standard deviation, and mean deviation for both local and global clusters [67], [110],

Table 4 Extracting Depression-Related Features From GPS Data

Year	Author	Description	Features								
			Position variance	Clustering number	Entropy	Standard entropy	Homestay	Circadian rhythm	Transition time	Total distance	No. of places
2015	Saeb et al. [128]	The Relationship between Clinical, Momentary, and Sensor-based Assessment of Depression.	√	√	√	√	√	√	√	√	×
2015	Canzian et al. [25]	Consider the user's movement trajectory as a series of stops and motions.	×	×	×	×	√	×	√	√	√
2016	Farhan et al. [95]	Extraction of behavioral features associated with depression in smartphone sensing data.	√	×	√	√	√	×	×	√	×
2016	Farhan et al. [67]	The potential for depression screening from data collected from smartphone sensors.	√	×	×	×	√	×	×	√	×
2017	Chow et al. [27]	Using mobile sensing to test clinical models of depression.	√	√	√	√	√	√	×	√	×
2017	Place et al. [92]	Modeling clinical symptom recognition of PTSD and depression from smartphone sensing data.	×	√	×	×	×	√	×	×	√
2018	Yue et al. [28]	Depression features were extracted from the data obtained from GPS and Wi-Fi records.	√	√	√	√	√	×	√	√	×
2018	Wang et al. [49]	Used "StudentLife" [98] to prove that social and sleep behavior features are significantly related to the severity of depression.	×	×	×	×	×	×	×	×	√
2020	Masud et al. [61]	A method to assess the level of depression in people using smartphones by monitoring personal daily activities.	×	√	√	×	×	×	×	×	×
2021	Nguyen et al. [80]	Depression detection using data from the smartphone's built-in sensors.	√	×	√	√	√	×	×	×	×
2021	Moshe et al. [58]	Explore GPS, screen, sleep and other data from smartphones and wearables.	√	×	√	√	√	×	×	√	×
2021	Matteo et al. [78]	Using smartphone sensors to collect data on adults' daily lives.	×	√	×	×	×	×	×	×	×
2023	Sun S. et al. [75]	Extracting home isolation duration and maximum distance traveled from home characteristics.	×	√	×	×	√	×	×	×	×
2024	Balliu et al. [29]	Determine information such as where participants spend their time.	×	√	√	×	√	×	×	×	√

("√" if the protocol satisfies the property, "×" if not)

[112], we can capture different depressive behaviors within a time slice. This analysis also includes the positional entropy and normalized positional entropy of local and global clusters, which relate to the overall location model (global) and the user location model (local).

Lesson 1: Location-based features, which contain GPS tracking, location clustering, and transition time, are widely used in smartphone-based sensing systems to detect the location shift of subjects and further investigate their daily activity. Experiments showed that mental state and positional information had a significant correlation. Most of the existing studies obtained the position information through GPS. However, Wi-Fi or inertial sensors would be good complements for more accurate sensing. Positional features mentioned above are effective in detecting one's position variation and places visited, in which researchers used clustering algorithms to filter the stationary sample data and cluster the location data points [110], [129]. Some clustering algorithms, such as DBSCAN and K-means, have the limitation that the result is heavily dependent on the entry parameters, so algorithms such as OPTICS [130] or its variants, which have flexible clustering granularity, would be more suitable for extracting position-based features with spatial–temporal attributions.

B. Movement

Unlike location-based features, movement-based features can characterize dynamic movement states of subjects [29], [31], [54] in digital phenotyping research, rather than static location information. In this section, we categorize the characteristics based on dynamic movement into two parts: movement and step count, drawing on previous research, as shown in the features category section of Table 3. Movement analysis reveals daily activity patterns of users, which can indicate fluctuations in mood and changes in social interactions, thereby providing early signs of depression. The step count, as an easily obtainable metric, reflects an individual's activity level; lower step counts may be associated with worsening depressive symptoms, aiding in the identification of potential mental health issues.

Research findings indicate that regular physical activity is associated with chronic diseases and may even reduce the risk of developing chronic conditions such as cardiovascular disease [131] and obesity [132]. This also applies to mental health disorders, as numerous studies have shown that physical activity interventions can positively impact both psychological and physical health in patients with BD [93]. Therefore, assessing daily movement is an important aspect of understanding the development of depression. Vancampfort et al. [133] systematically evaluated quantitative studies on the correlation of physical activity in patients with BD. Additionally, Mata et al. [134] found that participants with depression who engaged in self-initiated daily physical activities experienced significant increases in positive affect with longer durations and/or higher exercise intensities.

Motion tracking is understood as a series of pauses and movement sequences by the user, that utilize GPS to mark movement trajectories and frequencies to determine the activity levels of the subjects. Continuous tracking of locations would form discrete time series with the spatial–temporal attribute. Canzian and Musolesi [25] used the mobility patterns from GPS traces to unobtrusively monitor subjects affected by depressive mood disorders by defining some metrics on movement, i.e., visited places, important places, and the routine index. Visited places denote the number of different places visited, important places denote the number of different significant places visited, and the routine index quantifies how different the places visited by the user compared in the same time interval on other days. Additionally, by analyzing the places visited and mobility patterns, we can infer a person's daily behavioral activities and trajectories to predict their psychological state [25]. Fig. 4 shows a demonstration trajectory collected from GPS and other sensors. Mobility, behavioral, and movement patterns, based on features of digital phenotyping from smartphones, can be semantically described in this diagram in relation to depression-related activity patterns, such as social isolation and cocooning. In addition, the compass and gyroscope can represent an extension of location, providing smartphones with enhanced spatial awareness in relation to the physical world (i.e., orientation and direction), thereby improving location accuracy. The mean and variance of instantaneous velocity can also be used to describe the mobility of subjects, which holds intuitive and significant implications for predicting the severity of depression. Combining location-based and trajectory-based features can roughly describe the living conditions of subjects in physical space.

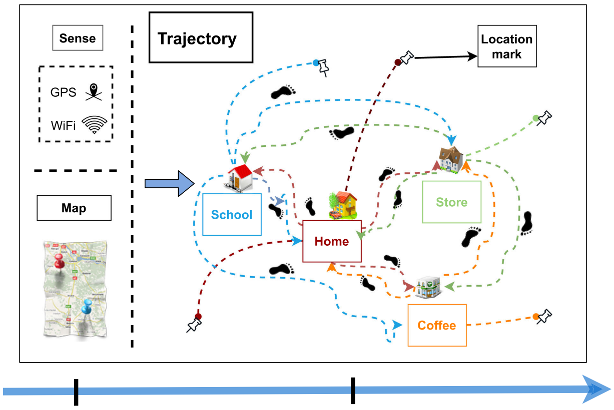

Fig. 4. ***Trajectory demonstration of daily life.***

The step count can also reflect the psychological state and emotional changes of the user, as shown in Table 3. Doryab et al. [108] extracted additional activity and movement-related features from step data collected via the application programming interface (API), such as the total and maximum step count over a fixed period. Other features are derived from the "bouts" [108], and a "bout" is a continuous period during which a certain characteristic is displayed. The "bouts" are called sedentary if the number of steps a user takes in an interval is less than the predefined threshold; otherwise, it would be an active bout. Examples of step counter-based features include the total number of times of exercise or sedentary [117], the minimum, maximum, and average duration of activity and sedentary. They also calculated the minimum, maximum, and average steps over all active bouts. In addition, Gruenerbl et al. [116] also studied inertial sensors and GPS tracks. Unlike the above experiments, this experiment used position sensors to extract hours of outdoor activities, access to different locations, the average value of outdoor activities per hour, and the variance of outdoor activity time. The precondition is that researchers considered that the most visited place is their home. Based on these features, the location features such as travel distance and 24-h in and out time percentage are extracted. It is believed that most people have their travel patterns and often go to certain places at a specific time. These patterns change in both depression and mania, for example, becoming less frequent or more unstable. In addition, individuals with depression may travel and go out less frequently, and

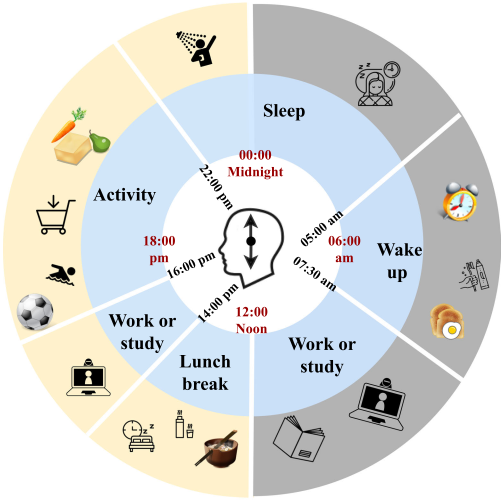

Fig. 5. ***Circadian rhythm of people. In the work stage, GPS can be used to monitor people's location, and their working status can be captured by the information on smartphone usage. In the activity stage, the location sensors can be used to capture the duration of outdoor activities and count the access to different locations.***

experiments have shown that location features outperform accelerated and fused multimodal recognition.

Lesson 2: Comparing the location-based features, the dynamic movement-based features focus on describing the activity information of subjects between different physical spaces, in which the significant correlation between mobility and depression can be observed (see Fig. 4). In addition, contextual tags of movement information can be used to investigate the correlation between interaction mobility and depression levels. Combining these features, the living patterns of the subjects in the physical space can be roughly described. In addition, features such as step counts and movement could be observed as a specific digital marker that can establish a correlation with depression symptoms to automatically monitor people's mental state.

C. Rhythm

The instability of circadian rhythms is associated with an increased risk of depression and other mental disorders, which can be predicted through smartphone-based digital phenotyping of an individual's mental state [29], [30]. Fig. 5 illustrates the circadian rhythms of an average person in their daily life. Extracting rhythm patterns underlying daily activities requires abstract representation and pattern recognition. Although there is currently no definitive evidence linking the regularity of lifestyle rhythms to depression, circadian rhythm abnormalities have been shown to relate to core clinical features of depression, such as daytime fatigue, sleep disturbances, and low physical activity levels [135]. Unlike specific sensor applications, such as proximity sensors and environmental light sensors, accelerometers can capture subtle behaviors at a relatively high sampling rate. Data collected via GPS can typically be used to assess individuals' circadian movement characteristics [86], [110], capturing temporal location information. Additionally, proximity sensors can detect when the user is on a call, while environmental light sensors can monitor sleep rhythms. Similarly, accelerometers record high-resolution and high-sensitivity movement sequences. These features measure the extent to which participants' location sequences adhere to circadian rhythms or specific lifestyle patterns.

Multimodal sensors integrated into smartphones can accurately perceive users' daily activities. Some studies have combined accelerometers with sensors like GPS to capture both local activity rhythms and long-term activity patterns. Other research has focused on extracting time–frequency features from raw accelerometer signals [106] to differentiate between patients with depression and those with BD [101], [106], [123]. To reduce the impact of peak value and noise, statistical measures such as the variance, mean value, and standard deviation of three axes are measured. We summarized the existing features into two categories, i.e., time domain (TD) and frequency domain. The TD primarily consists of signal magnitude area (SMA), root mean square (RMS), support vector machine (SVM), nonlinear energy, and curve length (CL). Among them, SMA is used to identify the active period during the call. The rms of acceleration during the conversation is an indicator of the time-average power in the signal. It represents a sequence of discrete values for a signal, and the rms results show the difference in mobile activities in the telephone conversation. The lower the rms, the lower the motor response of depression patients, and the higher the motor response of manic patients. The SVM feature is used to measure the activity intensity and speed of the smartphone during the call. To capture the mutation of phone activity during a call, characteristic average nonlinear energy and CL are used.

The frequency domain includes features such as the fast Fourier transform (FFT) and its variants. FFT is widely used to extract frequency-domain features from high sampling rate acceleration data. Similar to TD [106], the time window is also applied to perform FFT. Each sample window produces the corresponding components. If we want to investigate the activity features, the energy features can be used to assess movement intensity. The total energy of the acceleration signal can be calculated by the normalized sum of the square of its spectrum coefficient – the sum of the square of the discrete FFT component size of the signal and the window length. These features could be used to assess the activity intensity. Combining the FFT energy average, FFT energy standard deviation, FFT energy, discrete Fourier transform (DFT), and frequency size, the entropy helps to distinguish activities from different complexity. Additionally, these features are used to assist in identifying signals with similar energy values in different motion models [106]. Garcia-Ceja et al. [123] extracted the features of the signal in the time–frequency domain from the original data collected by the accelerometer. By drawing the entropy and the estimated density function image, from the median vertical line of the three lines drawn, we can see that the entropy feature is a useful candidate feature independent of other features to distinguish the high- and low-pressure levels and the medium- and low-pressure levels. To see if there are significant differences between each pair of pressure levels, Mann Whitney U [124] test was used and corrected with Bonferroni P-value. Statistical test results showed that for most features and participants, there was a significant difference between each pair of pressure levels (except for the peak amplitude feature). And the average accuracy of recognizing two-phase emotional states using only accelerometer features can reach more than 80%, with slightly better performance for frequency-domain features [106].

Lesson 3: There is evidence that the circadian rhythms of depressed patients are significantly different from those of healthy people. Daily behavioral patterns and regularities may also be indirect expressions of core symptoms of depression in DSM-5. Smartphone-based digital phenotyping can capture detailed rhythmic events through various sensors, including contextual or semantic information, to achieve multimodal depression emotion detection. Combining movement features of circadian rhythm and time information of location data, daily mobility model and habits could be captured. For example, if a college student studies in the library at the same time every day, his circadian movement is considered more regular and visible. In contrast, students who move more irregularly between different locations are considered to have a lower circadian rhythm. The research on behavioral rhythm based on smartphone sensors has a broad research space. In addition to the signal processing methods that have been used, methods such as multilevel wavelet transform that can reflect the behavioral regularity index are worthy of further exploration.

D. Sleep

High-quality sleep maintains good health and is a recovery mechanism for physical and mental illnesses [136], [137]. Traditional approaches such as polysomnography (PSG) or actigraphy cannot be applied to daily life. In contrast, smartphone-based digital phenotyping leverages various types of sensors to provide new opportunities for passively monitoring sleep parameters and sleep stages in natural environments [29], [31], [54], [74], [75]. For example, people use microphones to record the noise, body movements, coughing, and snoring. Additionally, the midnight “show unlock” event may indicate that the person is not asleep [68]. Recently, Yang et al. [138] proposed the Internet of Things (IoT) enabled sleep data fusion network (SDFN) module, using a star topology Bluetooth network to fuse data of sleep-aware applications. In addition, a machine learning model was constructed to detect sleep events using audio signals. Many studies [139], [140] demonstrated the availability and feasibility of assessing sleep quality with smartphones or wearables for users with mental disorders. Several mobile applications have been published for sleep monitoring and improvement with mobile terminals [141].

Sleep events such as sleep, awake, midpoint, wakefulness, disruptions, restlessness, activity rhythms, and chronotype can be effectively measured and are utilized in digital phenotyping to assess useful characteristics of mental disorders in humans [26], [86], [108], [140]. However, due to changes in mobile usage patterns, it is challenging to effectively detect an individual’s sleep duration for each of the aforementioned features independently. Generally, when people sleep at night or wake up in the morning, they turn off or on the light in their room. Therefore, the light sensor can detect the environment around (dark or not). Then, the approximate duration of sleep can be measured. At the same time, when people go to bed, they lock the smartphone screen or stop using it. Based on the above states, different sleep features, such as light and phone usage patterns, can be fused to form a more accurate sleep model and predictor, as illustrated in the data source section of Table 3.

Based on the above events, we could calculate the sleep duration, sleep onset, restless times, weak-sleep efficiency, energetic sleep efficiency, maximum sleep duration, average sleep duration, the shortest and longest cycles, etc. Although the accuracy of smartphone-based sleep stage detection [142], [143] still requires further verification and validation, the statistical analysis of sleep stages, particularly during the rapid eye movement (REM) period, is useful for assessing mental disorders. In contrast to behavioral characteristics, to explore the relationship between passive sensing data from smartphones and symptoms of MDD, Wang et al. [49] calculated sleep duration, start time, and wake-up time to measure sleep change symptoms. The study then calculated the mean, standard deviation, and slope of each depressive symptom feature. The mean value of features describes the average level of the symptom features daily. Sleep inference is usually based on four smartphone sensors: light, screen unlock or lock, interaction with the phone, and audio amplitude [109]. The default sleep classifier in the study does not infer naps. It only calculates and infers the maximum amount duration of sleep. It estimates sleep duration using 30-min interval, which has been used in many other studies [98].

Abnormal sleep patterns are often associated with mental disorders. Therefore, unsupervised clustering or anomaly detection can be applied to the raw sleep event data as part of the feature engineering process, and it can also be utilized for exploratory data analysis. The sleep patterns would be described by a high-dimensional feature set, by performing dimensional reduction and clustering on which it is possible to obtain clusters and outliers, as

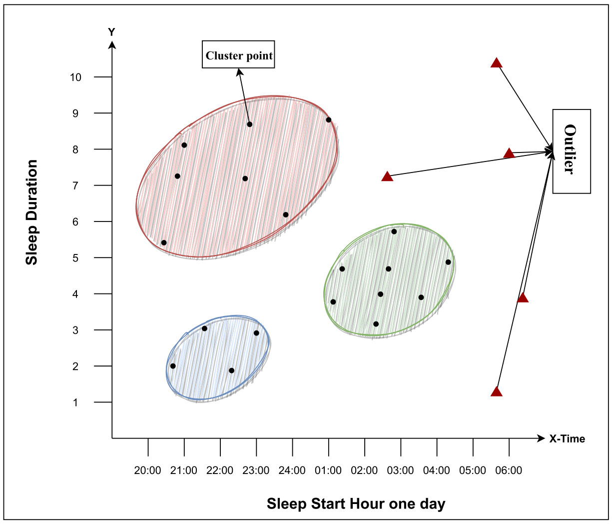

Fig. 6. ***Sleep pattern and sleep disorders recognition by clustering approaches.***

shown in Fig. 6. In Fig. 6, the cluster marked by a red triangle is seen as a deviation pattern from several normal sleep patterns; the three large clusters represent the aforementioned healthy patterns. The outliers also require more attention in the subsequent data processing. According to Section III-C, the instability of circadian rhythm is related to the risk of depression. However, sleep is one of the most important activities in daily life. Awareness of sleep events helps to gain a more fine-grained circadian rhythm.

Lesson 4: Sleep patterns and quality can be recorded by embedded sensors in smartphones, such as an accelerometer, microphone, and ambient light sensor. Smartphones also have the potential to perform sleep staging ubiquitously, overcoming the limitation of PSG or actigraphy devices. The subtle behaviors after falling asleep are important to mental disorders. However, undisturbed sleep staging remains a challenge, e.g., it is difficult to monitor and recognize activity after falling asleep due to environmental noise and sensor sensitivity. Sonar and ballistocardiography might contribute to sleep monitoring with smartphones. As a prelearning process, unsupervised methods could recognize abnormal sleep patterns and healthy sleep patterns from high-dimensional feature space. Existed sleep-based features have good performance in identifying mental disorders, but to accurately identify and assess depression, more abstract representations of features are needed. One of the feasible ideas is to perform deep learning (DL) modeling on raw sensor data rather than sleep events or sleep staging data, whereas this method requires the support of a huge sample size.

E. Social and Device Usage

Depressive symptoms can lead to decreased mood and motivation, thereby reducing an individual's willingness and ability to engage in social activities. However, smartphone usage can well reflect the level of social communication and even psychological states [29], [31], [74], [75]. Early research believes that there is a certain correlation between social isolation and depression [144]. The lack of social connections can negatively impact health and well-being [145], and can also increase the risk of depression and other mental health problems [146]. An extensive population-based smartphone dataset can provide participants' dynamic activity information about their mobility and distance from others, which can be used to measure their distance in social networks. Motion patterns and shared locations can be used to infer relationships and predict new social relationships [147], [148]. Sensors such as Wi-Fi and Bluetooth can detect the devices of the surroundings, which can be used to infer the social condition of subjects. For example, data from Bluetooth sensors can be utilized to identify relationships among members; a larger number of Bluetooth devices may indicate a denser crowd. However, individuals who spend time together during work hours are more likely to become colleagues than friends, while those who spend time together in the evenings or on weekends are more likely to become friends. Therefore, scanned addresses can be clustered into three categories [26], [108]: 1) participant's own devices; 2) related devices from families, roommates, colleagues, etc., and 3) other devices from strangers. Then, it extracted the statistics for three categories. The classification would help quantitatively estimate how many people the subjects meet daily. Besides, they can also identify a person living with others or living alone.

The intensity of social relations can be estimated by smartphone, using social networking service (SNS), contact lists, calls, and messages. Social activities with SNS might help in our context, but this article does not cover this topic due to privacy issues. Lepp et al. [103] analyzed the relationship between the use of smartphones by college students and their academic performance, anxiety, and life satisfaction. The contact field can be used to infer a relationship [149]. The time, frequency, and regularity of incoming and outgoing calls and SMS have also been used to infer relationships with high accuracy [104]. The higher the frequency, duration, and communication level of the call initiated by mobile users, the stronger the relationship [150]. In addition, research on preferences for phone calls and SMS has found that lonely participants are more likely to make calls, while anxious participants prefer to send SMS [105]. Furthermore, using smartphones for calling and texting can be utilized to monitor BD [93]. However, it is worth noting that the two parameters closely related to socialization, phone calls and SMS (in or out), are usually not controlled by smartphone users, such as fraudulent text messages and pyramid scheme calls. Therefore, Jeong et al. [151] used an algorithm to remove interference variables as much as possible to improve the accuracy of the recognition results. In addition, since people may have different patterns on weekdays and weekends, there

Table 5 Smartphone Usage Features Related to the Depressive Mental State

Group	Metric	Description
Notice	Count	total number of notifications clicked
	Unreceived Percentage	the percentage of total number of notifications clicked on total number of notifications
	Percentage Processed	the percentage of unprocessed notifications on total number of notifications
	Interaction Time	the duration of the interaction cycle between people and smartphones
	ST	average see time
	DT	average decision time for all notifications
	RT	average response time
Phone Usage	**Application:**	
	Start count	the number of times the application was started
	APP Count	the number of applications initiated
	APP Usage Time	the duration time of application initiated
	Cri APP Click Count	the number of times critical application are clicked
	Cri APP Count	the number of critical applications started
	Cri APP Usage Time	the usage time of critical application
	Non-Cri APP Count	the number of non-critical applications started
	Non-Cri APP Usage Time	the usage time of non-critical application
	Non-Cri APP Click Count	the number of times critical application are clicked
	SMS:	
	Receive Count	the number of SMSes received
	Receive Time	the time of SMSes received
	Receive Frequency	the frequency of SMSes received from people(family, friend and others)
	Sent Count	the number of SMSes sent
	Sent Time	the time of SMSes sent
	Sent Frequency	the frequency of SMSes sent to people(family, friend and others)
	Call:	
	Call-Received Count	the number of phone calls received from others
	Call-Sent Count	the number of phone calls sent to others
	Call-Received Length	the total length of calls received from others
	Call-Sent Length	the total length of calls sent to others
	Call-Received Ave Length	the average length of phone calls received from others
	Call-Sent Ave Length	the average length of phone calls sent to others
	Call-Received Std Length	the standardized length of phone calls received from others
	Call-Sent Std Length	the standardized length of phone calls sent to others
	Call Unique Numbers	the number of unique numbers

must be some errors in the statistical results. Thus, the statistical results of smartphone usage could be combined with location information with other sensors for higher accuracy.

Excessive use of smartphones is associated with depression [102], [152]. By tracking the frequency of smartphone unlock and lock events, as well as the duration of use among students in dormitories and study areas [49], it has been found that excessive smartphone usage in learning environments or classrooms may indicate that students struggle to maintain focus on their work when their phones are in hand. Screen status was used in [49] to track the dynamics of depression in college students by the features such as the unlock times per minute, the total interaction time on the phone, the total time of screen unlock, the hours of the first opening or unlock of the screen every day, the last opening or unlocking of the screen every day, the time of opening, and the maximum, minimum, average, and standard deviation of the interaction cycle. Besides, Mehrotra et al. [153] extracted the depression-related phone usage. The result showed that the user's depression state had an absolute correlation with all indicators calculated by using the data collected over the past 14 days. There is a weak correlation between the indicators calculated with the data for the last seven days, except for the average response time. Additionally, the application utilizes screen interactions to demonstrate the relationship between depressive states and smartphone use [153]. Furthermore, Gong et al. [115] combined call behavior with accelerometer data and found that individuals with higher symptoms of social anxiety exhibited more accelerometer-tracked movements while making phone calls, particularly in unfamiliar environments. Table 5 summarizes the features based on social and smartphone usages. In addition, decreased socialization and smartphone use corresponded to increased levels of depression. Three main behavioral parameters are generated to understand how higher level behavior changes with psychological state, namely, social interaction, mobility, and smartphone usage in research [112]. These values are aggregations of related low-level properties. Social interaction is measured by a combination of calls, text and noise features, activity and location information, and phone usage.

Lesson 5: This section summarizes the relationship between smartphone data phenotypes, social interaction, and depression by introducing two types of feature: social-related features and smartphone usage features. In addition, Bluetooth characteristics and smartphone usage can reflect mobility, community, and behavioral patterns. Fig. 7 lists the 12 categories of features on a rose wind chart. The line segment drawn according to the statistical value in each direction indicates the magnitude of the average duration marked by the orange line and frequency marked by the blue line. The longer the line segment, the more

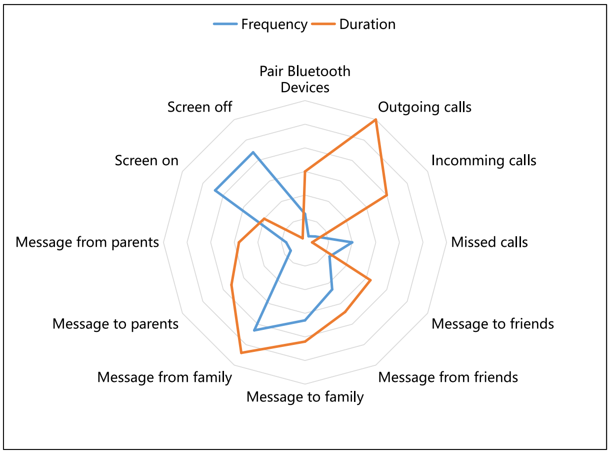

Fig. 7. ***User portrait with social and device usage attributes.***

frequent the interaction feature is. The fusion of different categories of features assuredly helps during classification modeling. However, a more detailed user portrait like Fig. 7 also makes sense. Those kinds of features can indicate the general smartphone usage tendencies of participants, for example, by reducing or increasing the use of communication applications to determine whether the subject is in a social context. These all suggest that the social-based features should be treated as highly personalized features, which would provide a potential improvement in specificity. The challenge of acquiring social data is obvious, that is, concern about privacy and access control.

IV. OPEN ISSUES AND CHALLENGES

This section will present open issues and research challenges in terms of multimodal fusion, long-term longitudinal trials, behavioral patterns, data integration-based body area network (BAN) for mental healthcare, privacy concerns of passive data, and neural aspects.

A. Depression Digital Phenotyping Is Multimodal and Should Be Investigated as Such

This article highlights how smartphones contribute to digital phenotyping for depression detection. However, the interaction between different sensor modalities is rarely addressed, with each modality typically studied in isolation. Without considering the multimodal nature of smartphone usage, our understanding of the accuracy of capturing depressive states through digital phenotyping remains limited. In particular, data fusion is the integration of data captured by different devices and sensors to improve the reliability, robustness, and generalization of identification systems. Nowadays, smartphones have abundant sensors that record different aspects of activity in time series. Combining inertial sensors with biographic, ambient, object, and visual sensors can provide sufficient information and high accuracy for activity detection systems. Emotion perception system fused different modalities, such as skeleton information [154], speech patterns [155], [156], and voice rhythm [157] to judge the emotional state of the subjects. It is assumed that the multimodal system with different channels and clues can provide more accurate recognition than the single-model method. The regularity of those activities is an indicator of one's mental state. Existing studies investigated decision-level fusion for mental disorder detection, e.g., Huckins [63] identified a positive relationship between resting-state functional connectivity (RSFC) between the subgenual cingulate cortex (sgCC) and smartphone usage patterns to better understand mental disorder.

Besides high-level correlation analysis, multimodal fusion analysis on synchronized time-series data from the sensors of smartphones provides insight into the temporal association between different modalities, which would fully reveal behavior psychological characteristics and identify the early phase of depression (see Section II-B). Heterogeneous sensors provide time series or event data with different sampling rates and forms. In order to improve the robustness of simultaneous interpretation results, several sensor fusion techniques are studied [158], [159], [160]. However, some issues need further research, such as time synchronization for data-level fusion, data incompatibility, and the curse of dimensionality [161]. Another alternative would be feature-level fusion, which has significant implications in depression detection as it allows for the integration of multiple sources of information with different data types or unsynchronized timestamps, holding great promise in improving the accuracy, efficiency, and accessibility of smartphone-based depression assessment and intervention [162]. By analyzing features such as speech patterns, physical activity, and social behavior, it is possible to develop more personalized and effective interventions for MDD.

B. Moving Research Toward Long-Term Longitudinal Trials

Depression is measured for a period according to the DSM-5 criterion, while mental state constantly changes over time. The duration of the studies in Table 1 varies from one week to two years. There are quite a few studies that use variant duration of data. We plot the fixed duration (excluding the variant duration) in Fig. 8, which shows an exponential downtrend. About 73% of studies and 92% of subjects last shorter than four months. This is because long-term data collection has technical challenges, such as energy, privacy, user experience, API constraints, and labeling work. Among these limitations, the ability to provide long-term, dynamic, and precise labels is the key to extending the number of samples and extending the experimental duration. Although some studies in the literature have explored digital phenotyping for depression detection using smartphones over specific time periods,

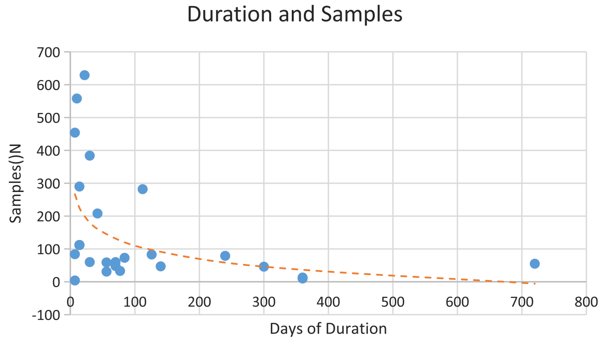

Fig. 8. ***Relation between duration and the number of subjects.***

these time frames are often limited to intermittent follow-ups. Another critical challenge, given the cyclical and episodic nature of depression, is that smartphone-based sensing technologies are particularly valuable for real-time monitoring of depressive symptoms. Specifically, mobile technology can easily improve the accuracy of describing emotions over time. Compared with traditional symptom tracking methods, unobtrusive objective measurements of data from smartphone sensors allow more comprehensive digital feature analysis of MDD.

We believe that future efforts should highlight the long-term and undisturbed way of monitoring smartphone-based behavioral data. This includes using data from pragmatic longitudinal trials and having a large sample size to determine the effectiveness of mobile technology in improving the diagnosis and recurrence prediction of depression. Although subjects in mobile applications can be easily recruited, this study requires participants to provide a lot of feedback and time [163]. Continuous long-term participation also introduces some issues: 1) high energy cost for frequent sensing on smartphones; 2) bandwidth for uploading raw data; and 3) data privacy. The built-in sensor data collection in the operating system framework might reduce power consumption. The combination of local DL and federated learning could mitigate bandwidth and privacy issues. For example, the model mentioned in [164] relieves the burden of communication bandwidth and reduces the energy consumption at the edge nodes for federated learning.

C. Digital Phenotyping Requires Richer, More Realistic Datasets

Existing studies have shown the effectiveness of depression assessment based on smartphone behavior data, which always manually mark the behavioral event corresponding to the data, or infer the behavioral scenes and semantics of the subjects based on HAR [165]. However, there are also some limitations.

1) Most studies are small scale. Compared with physiological data, behavioral data have more noise. Building a predictive model based on behavioral data requires a large number of samples to reduce the impact of noise on the model.
2) Subjects are usually college students, and the replicability of which has little evidence to support. Participants in a wider range of occupations and outpatient data need to be collected to enhance the generalization ability of the model.
3) Some patterns were discovered to recognize depression, such as social interaction, mobility, and phone usage (see Fig. 9). For example, staying at home longer has a higher risk of depression, and staying longer in other places has a lower risk of depression. However, these patterns use the semantic expression of the sensor data in terms of position stay, activity trajectory, life rhythm, and social communication. Researchers need to know when and what is going on so that the data can be understood and marked.

Digital phenotyping is termed the utilization of ubiquitous sensor data to estimate behaviors. A mental disorder also has some digital phenotyping. The depressed subject may have certain kinds of activity patterns, and those patterns might be smartphone usage patterns, mobility patterns, or activity rhythm patterns (see Fig. 9). Those patterns are called behavioral patterns [26]. The passive sensing of smartphones can detect some mental disorders by the associated behavioral patterns. Due to the need to mark the actual behavior of the original data, the modeling sample size is often limited, and some patterns that may be meaningful but difficult to describe through natural language are ignored. How to learn behavioral patterns that reflect depression in an unsupervised or semi-supervised manner deserves further research. The approach can collect a large amount of modeling data, which is suitable for the application of the Mobile Internet.

In addition, combining the advantages of passive data from smartphones with unified and integrated data flow between devices can reduce the pressure during data transmission or processing. Recent advances in miniature devices have fostered a dramatic growth of applications in physical health, such as medical support and healthcare monitoring. One of the main gaps identified from our review of the literature across various domains is the lack of accurate exploration of passive data in daily life to assess users' depressive states from both behavioral and physiological perspectives, particularly through the integration of smartphones and more specific devices (BAN). For instance, pacemakers can directly sense electrophysiological signals. Intracranial chip implant could record the electroencephalogram (EEG) signal. Some wearable medical sensors (WMSs) enable continuous monitoring of physiological signals in a passive and noninvasive manner [166], [167]. Smart bracelets or smartwatches can monitor health indicators such as heart rate, blood oxygen saturation, breathing, and sleep. Wearable sensors are also being used to detect stress or anxiety in everyday life [168]. Not only does the behavior data indicate a

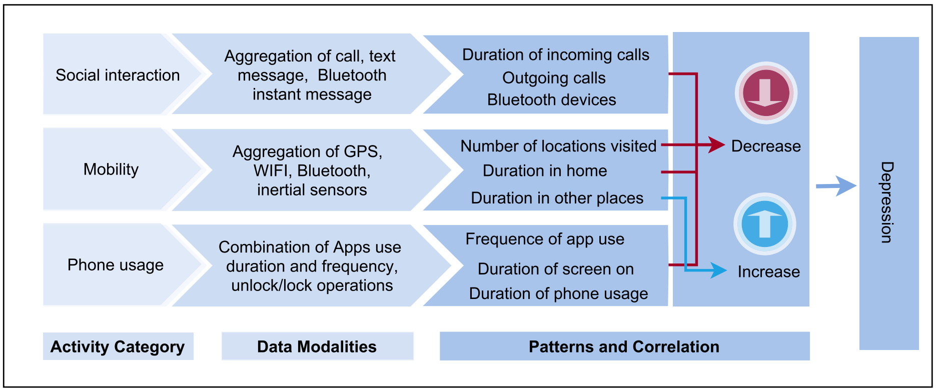

Fig. 9. ***Discovered real-world patterns for recognizing depression.***

mental disorder, but a lot of research indicates that the mental state and the features of physiological signals also have a significant correlation. Due to the capability of computation, communication, and storage, smartphones might be the center of future BAN. Sensors in the BAN organized by smartphone are embedded in the context of daily life, which aims to identify human behaviors, thoughts, feelings, and traits, which record the physiological signals. These sensors can obtain time-synchronized multimodal signals under the cooperation of the BAN, which helps to accurately reflect the physical and mental state of users. Therefore, the design of BAN and sensors should consider the needs of mental health in the future, rather than just focus on physical health.

D. Privacy in Digital Representations Should Be Given Adequate Attention

There is a lot of sensitive information about the data that is closely related to the user that does not want to be displayed, such as social data (see Section III-E). However, a gap in the literature on smartphone-based digital phenotyping for depression detection is the limited discussion of privacy concerns related to users' highly sensitive passive data. Addressing personal privacy issues in data transmission, storage, and usage is, therefore, crucial. We will also explore privacy issues concerning ethical and medical considerations.

1) Privacy Protection: Smartphones will generate a large amount of data during operation. The transmission and storage of these data will consume a lot of bandwidth and storage resources. Moreover, the data used for mental state assessment often have a certain degree of privacy. For example, consider the lack of social interaction in people with depression. According to the basic support of diagnostic criteria such as DSM-5, social data such as messages and phone calls can effectively reflect the depressive state of subjects. However, those data are highly private. Achieving efficient data transmission and processing under the premise of ensuring privacy is a challenging topic based on smartphone-based mental state assessment. Federated learning decentralizes training tasks and sends the model parameters obtained by training to the central server, which might be the solution for privacy protection [169]. Nevertheless, a malicious user can estimate the user's sensitive data by adjusting the input data to approximate the true gradient based on the difference of the federated learning gradient parameters in each round. However, how to deal with the heterogeneity between various clients such as smartphones is also a problem that needs to be solved in federated learning. Therefore, it is necessary to further improve the efficiency of data communication and protect the privacy of parameters during transmission and storage.

2) Modeling With Less Sensitive Data: Data such as microphone data, shopping records, and surfing logs could directly reflect the mental status. However, those data are too personal and sensitive that it is hard to convince smartphone users to accept a mental health application having permission to obtain those data. Less private data, such as inertial sensors, Bluetooth, and smartphone usage, should be paid more attention. Collecting less sensitive data can alleviate privacy concerns and reduce the stigma associated with mental illness. Participants may be more willing to share their data if they feel that their privacy is being protected and that their participation will not be stigmatized. Additionally, collecting data passively through mobile phones can be less burdensome for participants than traditional data collection methods, such as in-person interviews or surveys. This can lead to higher participation rates and more representative samples, which can improve the generalizability of research findings. Ciman et al. [170] try to detect the pressure through the mobile phone's "sliding," "rolling," and "text input" interaction. These features can distinguish the stress induced in the laboratory environment from the normal state. Whether such kind of behavior can provide enough data information to support anxiety or depression detection needs further investigation.

3) Ethical and Medical Issues: It is important to study the biomarkers of mental disorders revealed during the use of wearable devices and to use these biomarkers to assist doctors in diagnosis while protecting privacy and considering ethical issues.

Double-masked, randomized, and placebo-controlled feasibility trials are the accepted standard for disease assessment in clinical trials [171], [172]. Double-masked experiments are designed to eliminate subjective biases and personal preferences that may be present in the consciousness of the experimenter and the participant. Smartphone usage patterns are highly subjective and personal for different people. In depression assessment experiments, informed consent and double-masked experiments are often contradictory. Thus, the existing studies did not consider the use of double-masked experiments to avoid these impacts. Technically, today's wearable devices have more and more strict permission control on privacy, and an APP needs the explicit consent of the user for the collection of sensor and other behavioral data, which also brings difficulties to double-masked experiments. Wearable device manufacturers may have an innate advantage in data collection, but there are still challenges in addressing the ethical issues that exist, even though the leading smartphone manufacturers have embarked on the research and development of mental disorder detection functions.

The use of medication in the course of disease treatment can also cause depression [173]. Therefore, the integration of medical history and behavioral monitoring would be useful. How can smartphones be used to capture physiological indicators (e.g., plasma concentration) to help pharmacists learn more about the patient's medical history and help doctors keep track of changes in the patient's condition during medication use in an efficient and real-time manner?. This will not only relieve doctors of their workload, but also allow for more accurate and comprehensive treatment of patients. It is crucial to address ethical issues related to medical research, particularly in relation to the use of smartphones for patient monitoring. While assessing the scientific feasibility, innovation, and value of research projects, it is important to consider patients' views on the use of such devices. Some patients may not wish to be monitored in their daily lives, or they may prefer to keep their medical history private. Thus, it is essential to balance the benefits of wearable devices with patients' right to privacy and autonomy.

E. Digital Phenotyping Combined With Neural Mechanisms

Depression is one of the most common mental illnesses; however, it is often misunderstood and ignored, resulting in many people suffering without access to the necessary support and treatment. This article has shown that digital phenotypes for detecting depression based on smartphones typically extract lower level representations of depression, yet there has been insufficient exploration and explanation from a pathological perspective [174]. Recent research suggests that depression causes changes in specific regions of the brain, which are correlated to symptom severity, negative emotional rumination, as well as fear learning. Long-term monitoring of patients' smartphone usage can provide objective data for assessing the severity of symptoms and behavioral changes during treatment and recovery, highlighting another potential area that requires further attention. In addition, it can provide early warnings to alert families and medical doctors to pay additional attention to individual patients. In terms of neural research, neural factors in depression include changes in brain structure and function, as well as imbalances in neurotransmitters such as serotonin, norepinephrine, and dopamine [175]. It has also been linked to disruptions in neural networks, particularly in the regions of the brain responsible for mood regulation and emotional processing [176]. These disruptions can contribute to symptoms of depression, such as low mood, lack of energy, and difficulty sleeping. Depression medication works by altering the levels of these neurotransmitters, which can help alleviate symptoms of depression [177].

The relationship between neural and behavioral factors in depression is bidirectional. Changes in neural functioning can contribute to changes in behavior and vice versa. For example, low serotonin levels can contribute to a lack of motivation and low energy [178], which can lead to decreased engagement in social activities and exercise. In contrast, engaging in healthy behaviors such as exercise [179], social support [180], and a balanced diet [181] can improve neural functioning, help alleviate symptoms of depression, and promote long-term recovery. Smartphones cannot directly sense the state and changes of the neural system. However, smartphones can indirectly provide information about the human neural system through the use of sensors and mobile applications. The information might be the patterns of physical activity, sleep patterns, heart rate [182], voice, and facial expressions, which can indirectly reflect the neural characteristics of individuals. For long-term observation, smartphones would help us understand the developmental process and prognosis with neurological medicine therapy of MDD. Moreover, smartphones can be used to deliver interventions and treatments that can positively impact the neural system. For example, some mobile apps provide cognitive behavior therapy (CBT), mindfulness meditation [183], or stress-reducing exercises that can improve mental health and reduce symptoms of anxiety and depression. Another aspect that should be taken into consideration in the depression research based on smartphones is that the usage of smartphones and other digital devices can affect the neural system by altering sleep patterns and circadian rhythms, e.g., exposure to the blue light emitted by screens can disrupt the body's natural sleep cycle, which can have negative effects on cognitive function, mood, and overall health.

V. CONCLUSION

Digital phenotyping is a promising approach to detect depression using smartphone data. By leveraging the rich behavioral and physiological data that smartphones provide, researchers and healthcare professionals can improve early detection and intervention for individuals with depression. The approach of collecting behavior data of individuals using smartphones for depression detection has made significant progress and brought great benefits. This article provided a systematic review of the literature on smartphone sensor-based depression detection. The daily activities of subjects are a timely reflection of their mental state and can be indirectly reflected in the data collected from smartphones. We have classified the existing studies into five categories in terms of data patterns and feature extraction. Specifically, location-based features are summarized to detect one's position variation, places visited, etc. The context of the motion information can describe the activity information of subjects between different physical spaces, which is also relevant for emotional disorders. Therefore, we have refined a classification based on dynamic motion features. The above features are only partially responsive to the subjects' daily activities. Changes in circadian rhythms and sleep patterns are also related to the risk of depression; however, it requires highly sensitive sensors to monitor and collect raw data. One of the challenges of smartphone-based sleep monitoring is how to sense weaker behavior after falling asleep. In addition, online and offline social activities, including smartphone usage and communication with others, show a correlation with emotional states. Lack of social relationships increases the risk of depression and other mental health problems.

In response to the shortcomings of existing research, this article discussed the key issues and challenges in this research area from the perspectives of multimodal fusion, long-term longitudinal trials, behavioral patterns, data integration-based BAN for mental healthcare, and privacy. More specifically, data fusion can be used to integrate data collected by different devices and sensors to improve the reliability, robustness, and generalization of the recognition system. Nevertheless, fusion at the data level suffers from problems, such as time synchronization and data incompatibility. Long-term tracking, such as on smartphones, is more effective in capturing mood changes over a long period, but it also introduces issues such as energy consumption, broadband, and privacy. Wearable devices tend to be diverse and low cost, and can record daily activities at any time and from multiple angles. However, there are new challenges in efficiently and complementarily utilizing the data collected by different wearable devices. It is hoped that this article can provide a systematic and comprehensive review of key techniques for research on the identification of depression based on smartphone data and provide a valuable reference for future research. ■

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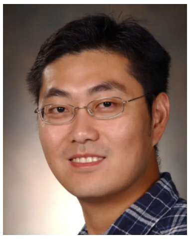

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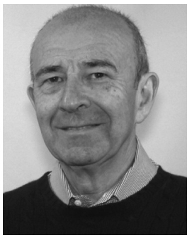

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