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Review article

Mobile and wearable technology for monitoring depressive symptoms in children and adolescents: A scoping review

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ABSTRACT

Background: There has been rapid growth of mobile and wearable tools that may help to overcome challenges in the diagnosis and prediction of Major Depressive Disorder in children and adolescents, tasks that rely on clinical reporting that is inherently based on retrospective recall of symptoms and associated features. This article reviews more objective ways of measuring and monitoring mood within this population.
Methods: A scoping review of peer-reviewed studies examined published research that employs mobile and wearable tools to characterize depression in children and/or adolescents. Our search strategy included the following terms: (1) monitoring or prediction (2) depression (3) mobile apps or wearables and (4) children and youth (including adolescents), and was applied to five databases.
Results: Our search produced 829 citations (2008- Feb 2019), of which 30 (journal articles, conference papers and abstracts) were included in the analysis, and 2 reviews included in our discussion. The majority of the evidence involved smartphone apps, with very few studies using actigraphy. Mobile and wearables captured a variety of data including unobtrusive passive analytics, movement and light data, plus physical and mental health data, including depressive symptom monitoring. Most studies also examined feasibility.
Limitations: This review was limited to published research in the English language. The review criteria excluded any apps that were mainly treatment focused, therefore there was not much of a focus on clinical outcomes.
Conclusions: This scoping review yielded a variety of studies with heterogeneous populations, research methods and study objectives, which limited our ability to address our research objectives cohesively. Certain mobile technologies, however, have demonstrated feasibility for tracking depression that could inform models for predicting relapse.

1. Introduction

Mental health problems are common in young people, with approximately 75% of mental disorders having an onset in adolescence (Kessler et al., 2005). One of the more prevalent mental disorders is Major Depressive Disorder (MDD), which in the United States affects an estimated 3.1 million adolescents aged 12 to 17, or 12.8% of that population (NIMH, 2018). Major Depressive Disorder in children and adolescents (MDD-CA) manifests with altered mood; episodes are characterized by disturbances in sleep, appetite, psychomotor changes, which in turn affect individual, family and school functioning (Belmaker and Agam, 2008; Birmaher et al., 2002, 1996). Despite its high prevalence, evidence shows that 60% of adolescents with a major depressive episode do not receive treatment (Carlson, 2000; NIMH, 2018).

MDD-CA is challenging to diagnose and may often go undetected. Differences in phenomenology, comorbidity with anxiety, behavior, eating and substance use and eating disorders are all factors that affect this complexity in diagnosing MDD-CA (Birmaher et al., 2002, 1996; Carlson, 2000). There are difficulties in characterizing and

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discriminating clinical depression differently from emotional distress (Kramer et al., 2015). Similar to adult MDD, longitudinal studies of epidemiological and clinical samples have shown that depressive episodes tend to recur in children and adolescents. The probability of recurrence in depressed children and adolescents has previously been estimated at 40% by 2 years and 70% by 5 years in clinical populations (Fleisher and Katz, 2001; Rao and Chen, 2009). Studies of community samples have shown a 5% relapse rate within 6 months, 12% within 12 months and 33% within 4 years (Lewinsohn et al., 1994). Much like the diagnosis of MDD-CA, predicting recurrence is also difficult (Kurdyak and Cairney, 2011). Data from adult population studies have demonstrated that indicators such as history of depression and a low level of mastery (a psychological concept that describes a sense of control over one's life and experiences) were significant predictors of future relapse (Colman et al., 2011). However, the intervals of assessment in such large-scale population surveys did not correspond well with the recurrence of depressive episodes. Respondents relied heavily on recall which may have biased the results. Similar concerns impinge on clinical samples, where researchers often use retrospective self-report questionnaires, which have certain limitations such as recall bias (Asselbergs et al., 2016; Moradi et al., 2000; Patten, 2003).

Given the scale and significance of MDD noted above, and its impact on disability, impairment and suicide, there is an urgent need to improve both the monitoring of symptoms during a current depressive episode, as well as the prediction of relapse to future episodes. For the purposes of this review, monitoring refers to tracking of signs/symptoms over time, and prediction refers to estimating when signs/symptoms will re-emerge in the future (Moons et al., 2009).

To reduce the measurement error associated with questionnaires, a method of data collection known as ecological momentary assessment (EMA) has been used to collect data from individuals in their natural environment. This method includes self-reported, real time, repeated measures of an individual's mood, experiences and behaviours within their regular environment (Shiffman et al., 2008). EMA is appropriately suited for studying positive and negative affect, emotion reactivity (Armey et al., 2015; Lamers et al., 2018) in addition to dynamic behavioral variables such as activity level (Olive et al., 2016) and sleep quality and profile (Breslau et al., 1996). Each of these factors are associated with depression. Early EMA studies used random sampling technology to notify participants through instruments such as pagers to complete paper-based questionnaires and written diaries (Biddle et al., 2009), progressing to telephone-based questionnaires as technology advanced (Aldinger et al., 2014; Forbes et al., 2009; Primack et al., 2011).

Gathering EMA data has become more feasible and more intrinsically ecological with the advent of smartphones and mobile applications (apps). Additionally, more objective measurements such as location data (GPS traces) and motion data (via acceleration sensors) can also be captured through smart phones, and can provide valuable insights into the change of state for patients with mental illness (Gravenhorst et al., 2015; Gruenerbl et al., 2014). Other important data points to gather comprehensive current state monitoring for patients with depression include voice data, contextual data (e.g. number of phone calls, screen time) and environmental (e.g. weather conditions) information, all easily gathered through smartphones. Such supplementary information can provide additional context for variables collected through EMA: an example could be interpreting activity levels with the weather, given that activity could be more restricted on rainy versus sunny days (Dogan et al., 2017), or inter-relationships of emotional states and motor activity (Merikangas et al., 2018).

EMA can be combined with mobile interventions, which are advantageous in that they can make treatment cheaper and more accessible to a wider range of individuals (Myin-Germeys et al., 2016), while also allowing monitoring of adherence to pharmacological and psychological treatments. Finally, EMA assessments allow for much more individually tailored interventions, and can provide treatment at moments of high risk or high symptom intensity (Myin-Germeys et al., 2016).

A previous letter to the editor of a leading child psychiatry journal highlights the gap in research on the utility of smartphones to improve care for child and adolescent depression (Wu et al., 2016). Sensor-based monitoring and predictive algorithms supported by mobile devices can augment intervention (Chan et al., 2014) and longitudinal digital phenotyping for research (Torous et al., 2017). Furthermore, patients are interested in mobile monitoring of their mental health (Torous et al., 2014). In light of the growth in mobile and wearable monitoring research over the past decade, we used the present scoping review to address the question: How are mobile and wearable devices being used to characterize child and adolescent depression?

Specifically, we aim to (1) evaluate apps and wearable technologies that have been used to monitor depression (including the kinds of data they capture, feasibility) and (2) identify any models to predict recurrence based on data collected from mobile apps or wearables.

2. Method

Scoping reviews are used to rapidly map concepts within a research area, and to identify the extent, range and nature of the evidence available on a particular subject (Davis et al., 2009). This review used the 20 item Preferred reporting items for systematic reviews and meta-analysis extension for Scoping Reviews (PRISMA- ScR) (Tricco et al., 2018) to ensure appropriate rigor, and is organized according to the following 5 steps, as per Arksey and O'Malley's (2005) conceptualization:

Step 1. Identifying research question

What is the extent of the literature on monitoring depression in children and youth (including adolescents) through mobile and wearable technologies?

We sought to gather information on the following research objectives: (1) evaluate if mobile and wearable tools capture the dynamic nature of depressive symptoms in child and adolescents by (i) detailing the types of apps and wearable technologies that have been used to monitor depression in this population, (ii) identify the kinds of data they capture, (iv) to review the feasibility of these technologies, and (2) to identify if these new technologies can predict recurrence.

Step 2. Identifying relevant studies

A detailed search strategy was developed through consultation with a certified medical librarian (see Fig. 1). Four search concepts were explored: i) monitoring or predicting, ii) depression, iii) mobile health technologies (including mobile apps or wearables) and iv) children/adolescents/youth. The search was conducted in July 2018 and updated in February 2019. The databases used to complete the search included MEDLINE, PsychINFO, EMBASE, LISTA, and CINAHL. Title, abstract and subject headers were searched, along with Medical Subject Headings (MeSH) where available. The search was limited to articles written in the English language (or those with English translation).

Step 3. Study selection

Articles were deemed “potentially relevant” and screened for full-text if they: (1) studied monitoring or prediction, (2) were focused on depression (MDD) or depressive mood, (3) used mobile apps (any platform) or wearable technology (e.g. electronic watches, bracelets), and (4) were focused on a population of children and youth (including adolescents). Children include those younger than 10, adolescents are those within the 10–19 age group, with ‘youth’ being those in the 15–24 age range, according to the WHO (2019). Articles were excluded from the final review if: studies used mobile apps solely for providing

1. Sensitivity and Specificity"/
2. "predictive value of tests"/ or roc curve/
3. false negative reactions/ or false positive reactions/ or observer variation/
4. scor*.ti,ab,kf.
5. obser*.ti.ab.kf.
6. or/1-5 [predictive concept[
7. (monitor* or track* or chart* or experience sampl* or ambulatory assessment* or real-time emotionality assessments* or ecological momentary assessment* or self-surveillance).ti,ab,kf.
8. ecological momentary assessment/
9. or/7-8 [monitoring concept]
10. mood disorders/ or exp depressive disorder/
11. (mood disorder* or affective disorder* or depress*).ti,ab,kf.
12. or/10-11 [depression concept]
13. Telemedicine/ or Cell Phone/
14. Text Messaging/
15. (mhealth or m-health or telehealth or tele-health or telemedicine or tele-medicine or telepsychiatry or tele-psychiatry or digital* or phone* or smartphone* or smart-phone* or mobile* or app or apps or applications or ipad* or handheld* or wearable*).ti,ab,kf.
16. 13 or 14 or 15 [mhealth concept]
17. 6 or 9 [predicting or monitoring concept]
18. 12 and 16 and 17 [depression + mhealth + predicting or monitoring + youth]
19. adolescent/ or child/
20. (adolescen* or child* or youth*).ti,ab,kf.
21. or/19-20 [youth concept]
22. 18 and 21 [depression + mhealth + predicting or monitoring + youth]

limit 22 to yr="2008-Current"

Fig. 1. Search Strategy in MEDLINE.

treatment, focused on other types of depression (such as bipolar or postpartum depression), or if they were non-empirical papers such as study protocols or conceptual papers. Only articles published from January 2008 onward were included. The year 2008 was selected as a cut-off since we were especially interested in smartphone applications being used for this purpose, and there was a large upsurge of mHealth literature published after this time (Donker et al., 2013; Fiordelli et al., 2013). Since this is a scoping review, conference proceedings were included in the final list if they met the inclusion criteria, and all types of study methodologies (i.e. quantitative, qualitative, mixed methods, systematic reviews) were included. Manual review ("hand combing") of included publications' references was conducted.

Step 4. Search procedure

The search procedure was divided into two phases: (1) title and abstract review and (2) full-text article review. For the first phase, two independent raters (SP, LS) screened the articles and rated as "include" or "exclude". Any discrepancies were resolved by a third rater (JS). Full-text article review was then performed by one reviewer (LS), and at this point, any additional articles that did not meet the inclusion criteria were excluded and discussed with the remainder of the team.

Step 5. Charting the data

Study data was abstracted individually by one researcher (LS). The following information was extracted: sample characteristics (size, type of population), the type of research design, primary study objectives, type of technology of mobile app used, outcome measures, study results, significant predictors of depression, study limitations, and impact on mental health outcomes.

3. Results

The initial search resulted in 829 articles after deduplication. Of these articles, 791 were excluded after title and abstract screening, due to non-eligibility leaving 38 articles that were retained for full-text review (Cohen's κ = 0.79; 8 articles were discussed amongst the screeners and with a senior researcher). Further exclusions included articles that used phone call-administered EMA instead of mobile apps, or articles published prior to 2008. After exclusion of such articles, and the addition of 2 articles through manually checking references, 30 articles were left for inclusion within the review (see Fig. 2 for PRISMA flow diagram, see Table 1 for a synthesis of study details).

3.1. Introductory information

Studies were published from 2009–2019 clustered in North-America, Western Europe and Australia (see Fig. 3), with a large

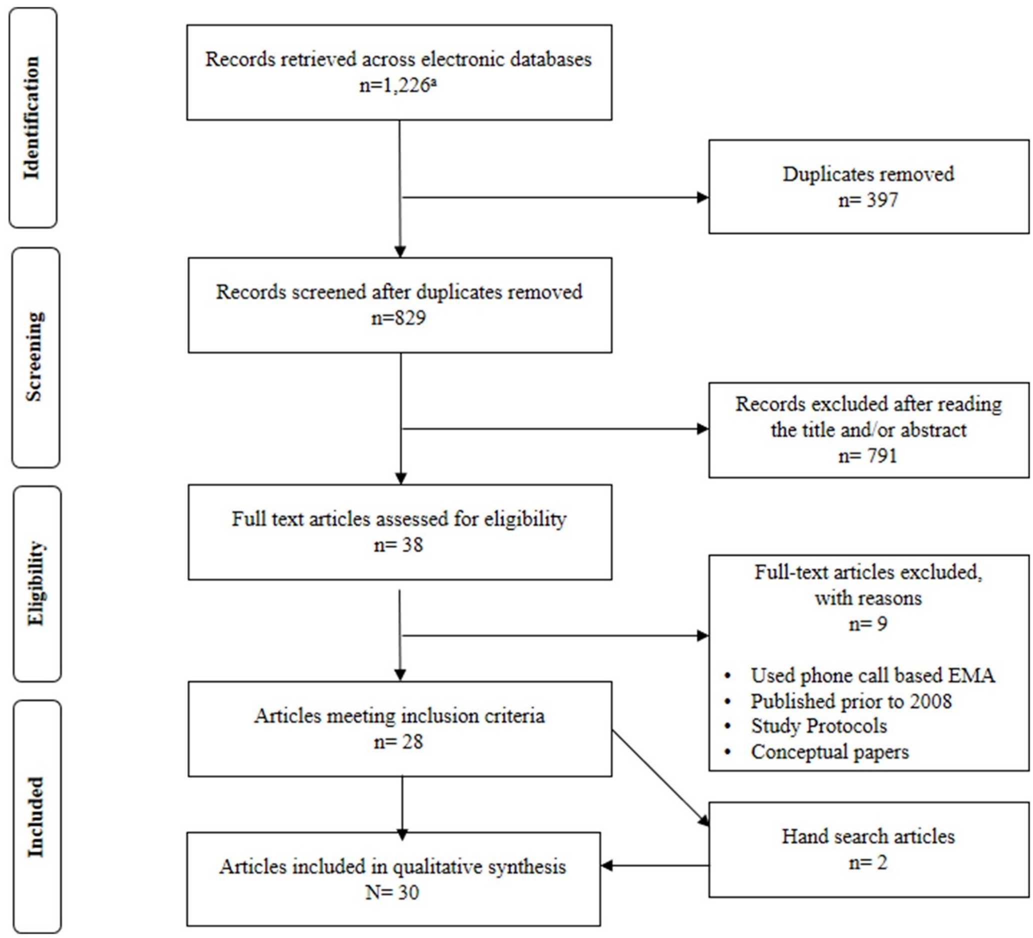

Fig. 2. Flow diagram of search history. Note: [a]PsychInfo:153; Medline:328; EMBASE: 570; CINAHL:161; LISTA: 14.

increase within the last year, indicating a steep pace of growth in the literature (see Fig. 4). Studies were carried out on a range of populations, with populations as young as 3–7 year olds (McGinnis et al., 2019) up until young people of age 25 (Hetrick et al., 2018). Certain studies had a conference paper/ abstract along with the complementary journal articles. Given below is a narrative synthesis of the major themes found from our 30 studies.

Themes related to research aim 1: To evaluate if mobile and wearable tools capture the dynamic nature of depressive symptoms in child and adolescents

3.2. Mobile interventions to monitor mood

A majority of studies (n = 25) used smartphones to track or monitor depressive symptoms among children and youth. Smartphone applications (apps) used included: Acer Liquid Z-200 (Kirchner et al., 2017), Mobiletype (Kauer et al., 2011, 2012; Reid et al., 2011), CopeSmart (Kenny et al., 2016), PETE (Cushing et al., 2017), SOLVD (Truong et al., 2017), eMate (Asselbergs et al., 2016), iYouVU (Asselbergs et al., 2016), daybuilder (Løventoft et al., 2012), and Studentlife (Ben-Zeev et al., 2015).

A few studies used early mobile devices including handheld computers (Adams et al., 2009; Hickie et al., 2015) for data capture. Yet another study used a combination of text message reminders and web-based surveys to collect information (Connolly and Alloy, 2017). Data captured from these technologies were also similar to those captured by smartphones, including questionnaires such as Children's Depression Inventory (CDI), Children's Hassles Scale (CHS) (Adams et al., 2009), Stress-Reactive Rumination Scale (SRRS), Beck Depression Inventory (BDI-II) (Connolly and Alloy, 2017), and activity, mood states and sleep data (Hickie et al., 2015).

3.3. Wearable devices to monitor sleep and diagnosis

Six articles discussed the use of actigraphy, which are wristwatch-like devices that measure acceleration, to provide an estimate of the individual's movement, activity and sleep/wake cycles. Actigraphy has been frequently used in pediatric sleep research, with common reported sleep variables including sleep duration, sleep efficiency and bedtime/ sleep onset (Meltzer et al., 2012). Sensitivities varied (ranging from 0.68 to 0.99), while specificities to detect waking after sleep onset were poorer, when actigraphy was tested against polysomnography and direct observation. There were two studies (McGinnis et al., 2018, 2019) that used a belt-like actigraphy device to determine the feasibility of analyzing data from a 90-second task to aid with clinical diagnosis.

3.4. Data types captured by mobiles and wearables

Data captured by devices varied, consisting of the following categories:

i Mobile phones:
  a passive analytics: including measures such as call logs for incoming and outgoing calls (i.e. call time/date, duration, and contact/ relationship to participant), text message events (i.e. time/date and contact), screen time (i.e. length of on/off, time/ date), app use (i.e. name of app launched, when, and for how long), and mobile phone camera use

Table 1
Summary of Studies on Mobile and Wearable Technology for Monitoring Depressive Symptoms in Youth.

	Authors (Year)	Location	Sample (size)	Study Duration	Technology used	Study Purpose
Systematic reviews						
1	Baltasar-Tello et al. (2018)	Madrid, Spain	various	various	Mobile apps (and web-based)	To systematically examine published data regarding ecological momentary assessment (EMA) in children and adolescents with mood disorders
2	Dubad et al. (2018)	Coventry, UK	various	various	Smartphone apps	To examine psychometric properties, usability and clinical impacts of mood-monitoring apps in young populations
Journal articles						
3	Adams et al. (2009)	Montreal, Canada	Children, aged 7 to 14, of parents with a history of MDD ($n = 49$)	6 weeks	HP Jornada 720 handheld computers	To test the theory that individuals who possess high levels of self-criticism and/or dependency are vulnerable to developing depression following negative events
4	Asselbergs et al. (2016)	Amsterdam, Netherlands	Student population ($n = 33$)	6 weeks	Smartphone apps (eMate, iYouVU)	To explore mobile phone based unobtrusive EMA as proxy measures of clinically relevant user states and contexts
5	Ben-Zeev et al. (2015)	Lebanon, USA	Young adults, aged 19 to 30 ($n = 47$)	10 weeks	Smartphone apps (Studentlife)	To examine whether information captured with multi-modal smartphone sensors can serve as behavioral markers for one's mental health
6	Connolly and Alloy (2017)	Philadelphia, USA	Undergraduates ($n = 121$)	1 week	Smartphone web based survey	To examine momentary ruminative self-focus and stress-reactive rumination as predictors of depressive symptoms utilizing a smartphone EMA
7	Cousins et al. (2010)	Pittsburgh, USA	Youth with and without Affective Disorder diagnosis ($n = 128$)	5 weeks	Cellphone interviews and actigraphy	To examine relationships between affect and sleep in youth with affective disorders using EMA
8	Cousins et al. (2011)	Pittsburgh, USA	Youth ($n = 94$)	8 weeks	Cellphone interviews and actigraphy	To examine relationships between affect and sleep in youth with affective disorders using EMA
9	Cushing et al. (2017)	Lawrence, KS, USA	Adolescents, aged 13 to 18 ($n = 20$)	20 days	Smartphone app (PETE)	To conduct an exploratory latent profile analysis of EMA data to demonstrate an empirical method of identifying invalid responses, and to provide a preliminary investigation of mood profiles
10	Forchuk et al. (2015)	London, Canada	Youth with mood or psychotic disorder ($n = 394$)	12 to 18 months	Smartphone app (Electronic personal health record app)	To investigate the perceptions of clients using information technologies such as websites, mobile phone applications, and virtual reality programs
11	Forchuk et al. (2016)	London, Canada	Patients receiving outpatient mental health services, aged 16 to 21 ($n = 41$)	6 months	Smartphone app (Electronic personal health record app)	To explore the use of a electronic personal health record to support youth in managing their mental health
12	Geyer et al. (2018)	Virginia, USA	Undergraduates ($n = 60$)	14 days	Smartphone app	To examine how affect ratings during social interactions predict later perceptions of those interactions, and whether this differs by social anxiety and depression severity
13	Hetrick et al. (2018)	Melbourne, Australia	Young people who experienced depression or suicidal ideation, aged 18 to 25 ($n = 8$)	4 workshops	Smartphone app (in development)	To address the gap between guidelines about monitoring and real-world practice by codesigning an app with young people
14	Kauer et al. (2012)	Melbourne, Australia	Patients with mild or severe mental health outcomes ($n = 114$)	6 weeks	Smartphone app (Mobiletype)	To investigate whether people who monitored their mood, stress, and coping strategies would have increased emotional self-awareness (ESA) compared with an attention comparison group, and to determine if an increase in ESA would predict a decrease in depressive symptoms
15	Kenny et al. (2016)	Dublin, Ireland	Youth, aged 15 to 18 ($n = 208$)	28 days	Smartphone app (CopeSmart)	To explore the utility of a mobile phone app as a means of collecting EMA data pertaining to mood, problems, and coping efficacy
16	Kirchner et al. (2017)	Barcelona, Spain	High-school students ($n = 90$)	1 week	Smartphone app (Acer Liquid Z-200)	To examine community adolescents' perceptions regarding both the intensity of and variability in their daily sadness/depression, anxiety, and somatic problem
17	Magallón-Neri et al., 2016	Barcelona, Spain	Adolescents ($n = 110$)	1 week	Smartphone app (Android based mobile app)	To explore the viability of Ecological Momentary Assessment for measuring the mental states associated with psychopathological problems in adolescents
18	McGinnis et al. (2019)	Burlington, USA	Young children, aged 3 to 8 years old ($n = 63$)	90 s task	Actigraphy (belt-worn IMU)	To detail a new approach for identifying children with internalizing disorders using an instrumented 90-second mood induction task
19	Nguyen-Feng et al., 2019	Minnesota, USA	Undergraduate students ($n = 382$)	14 days	Smartphone app	To explore the feasibility and efficacy of an Ecological Momentary Intervention (EMI) for reducing psychological distress for individuals with and without an emotional abuse history

(*continued on next page*)

Table 1 (*continued*)

	Authors (Year)	Location	Sample (size)	Study Duration	Technology used	Study Purpose
20	Reid et al. (2011)	Melbourne, Australia	Youth, aged 14 to 24 (n = 114)	2–4 weeks	Smartphone app (mobiletype)	To examine the mental health benefits of a mobile phone application which monitors mood, stress, coping strategies, activities, eating, sleeping, exercise patterns, and alcohol and cannabis use
21	Shrier et al. (2017)	Boston, USA	Depressed young women, aged 15–23 (n = 16)	4 weeks	Smartphone app (in development)	To explore the perspectives of depressed high-risk young women on using a smartphone ecological momentary intervention for sexual risk reduction
Conference papers						
22	Løventoft et al. (2012)	Copenhagen, Denmark	Youth with depression (n = 6)	3–4 weeks	Smartphone app (daybulider)	To field test a prototype of a smartphone app intended to support people with depression
23	McGinnis et al. (2018)	Burlington, USA	Young children, aged 3 to 7 years old (n = 59)	90 s task	Actigraphy	To test the use of a 90-second fear induction task during which participants' motion is monitored using a sensor in diagnosing anxiety and depression
Conference abstracts						
24	Bickham et al. (2019)	Boston, USA	Adolescents, aged 14–19 who scored at least 5 on PHQ-9 (n = 55)	7 days	Smartphone app	To examine whether adolescents suffering from at least mild depression were experiencing different levels of positive affect, negative affect, and sadness when engaging in different types of social interactions
25	Hickie et al. (2015)	Bethesda, USA	Clinical sample of youth with emerging mood disorders (n = 1000)	2 weeks	Palm Micro-computers	To explore mobile monitoring of activity, mood states and sleep to examine the specificity of patterns associated with different subgroups of mood and anxiety disorders in diverse samples
26	Kauer et al. (2011)	Melbourne, Australia	Young people identified by GP as being at risk of depression, aged 14 to 24 (n = 110)	6 weeks	Smartphone app (Mobiletype)	To investigate whether self-monitoring increases young people's awareness of their moods and reduces depressive symptoms and whether emotional self-awareness mediates the relationship between self-monitoring and depressive symptoms
27	Schreuder et al. (2018)	Groningen, Netherlands	Adolescents twins (n = 166–192)	1 year	Text + web-based survey via smartphone	To examine whether Early Warning Signs (EWS) predict the symptom cluster (e.g. depression, psychosis, etc.) that will develop.
28	Truong et al. (2017)	Houston, USA	Youth with MDD, aged 12 to 17, and their parents (n = 13)	8 weeks	Smartphone app (SOLVD)	To evaluate whether a smartphone application can be useful in monitoring and classifying depression symptoms in a clinically depressed adolescent population compared to standard clinician psychometric instruments
29	Venz et al., 2016	Dresden, Germany	Community sample of adolescents and young adults, aged 14–21 (n = 81)	4 days	Smartphone app + actigraphy	To explore the short-term interplay between mood measures, assessing which pairwise connections of items are most strongly correlated
30	Wichers et al. (2018)	Groningen, Netherlands	Adolescent participants (n = 239)	4 months	Text + web-based survey via smartphone	To replicate their previous study that revealed empirical support for Early Warning Signals, and second, to further translate this idea to personalized models

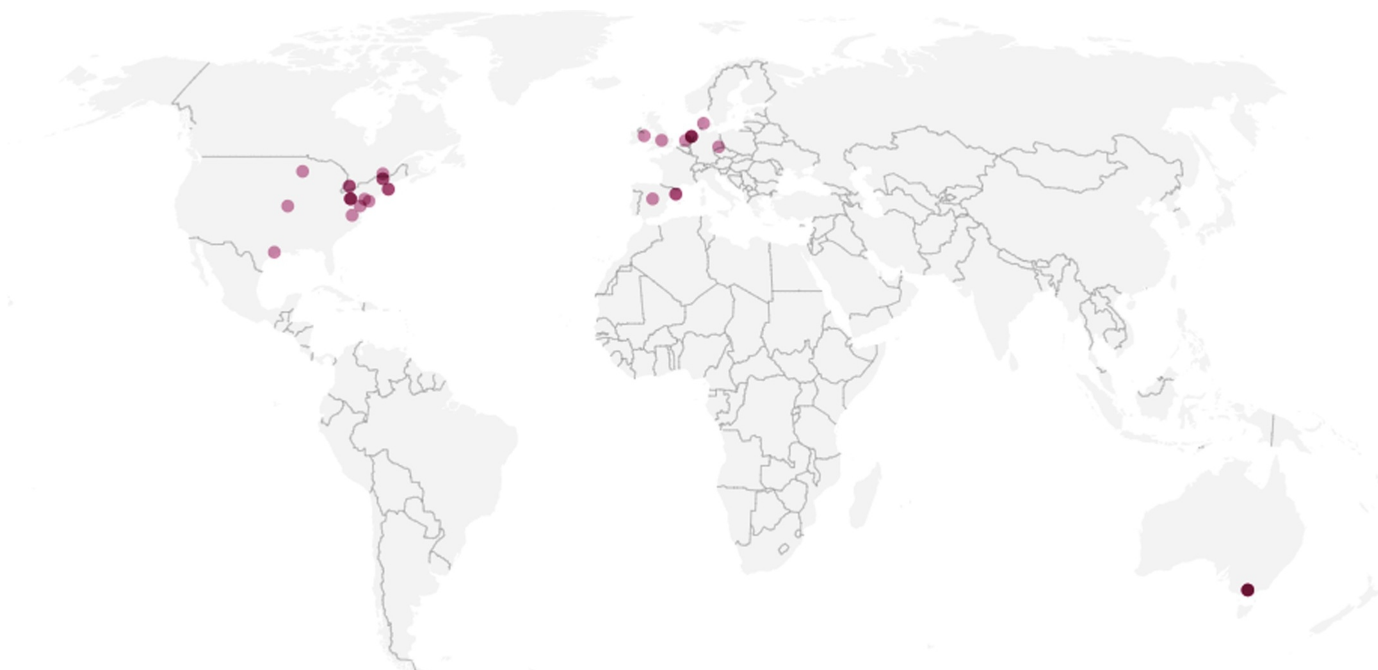

Fig. 3. Geographic location of where studies have been conducted(DatawrapperGmbH, 2018).

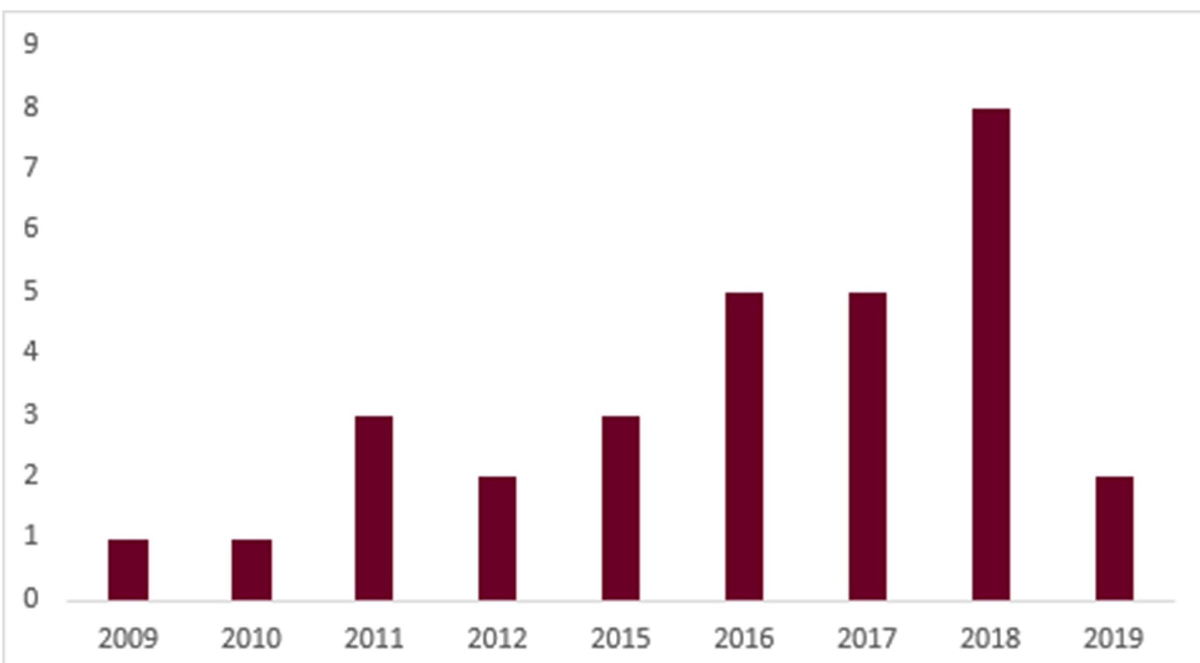

Fig. 4. Number of studies published until date (2008- February 2019).

b physical health: including energy, alcohol use, cannabis use, quality and quantity of sleep, diet, quantity and type of exercise

c mental health: measuring include affect (I-PANAS-SF), mood, clinical mood domains, stress, recent stressful events, responses to stressful events, formal help seeking, informal help seeking, depression, anxiety, mental state, and coping strategies

ii Mobile phones + wearables:

a movement and light: including measures such as an individual's current activities and location

3.4.1. Feasibility of mobile and wearables technology amongst youth and adolescent population

Two papers arising from the Youth-Mental Health Engagement Network study explored the important aspect of feasibility and acceptability of mobile technologies for tracking depressive symptoms (Forchuk et al., 2016, 2015). Using qualitative focus groups, the researchers evaluated a smartphone-based personal health record (PHR) for youth, and found that the patient-healthcare provider therapeutic relationship was strengthened by the means of youth being able to keep track of their behaviour, sleep, mood and medications, leading to more open conversations (Forchuk et al., 2015). Moreover, symptom tracking was the most commonly used feature of the PHR, which demonstrates the feasibility of EMA-like data collection via a smartphone (Forchuk et al., 2016) in youth. Another benefit as reported by participants in this study are an increased self-awareness and autonomy with the use of mobile mood tracking tools. In contrast, participants were interviewed about the design of an app, and expressed frustration when usability problems and software crashes were evident (Løventoft et al., 2012) – detriments which would decrease use. In studies that reported on the development of mobile apps for self-monitoring, feasible features included well-being trackers, brief personalized interventions triggered by back-end algorithms (Hetrick et al., 2018), receiving prompts to complete self-reports as well as receiving messages of support (Shrier and Spalding, 2017).

Since quantitative measures of feasibility consisted of heterogeneous assessment metrics, comparing compiled data on feasibility is impractical. Certain studies reported on how often participants responded to alerts (i.e. 82% (Connolly and Alloy, 2017)), while others discussed how many participants provided daily mood ratings (79%(Truong et al., 2017) and 18%(Kenny et al., 2016)), yet others measured how many participants provided ratings for the full duration of the study (66% (Asselbergs et al., 2016)).

3.4.2. Ethics and privacy

Several studies commented on privacy, which is often a point of concern for mobile apps tracking or monitoring mental health. Truong et al. mentioned that their study was "well tolerated with no privacy or operability concerns", suggesting that "a well-designed app can be used to track mood and anxiety levels reliably" (Truong et al., 2017). In a study on developing an EMA intervention for young women with depression to reduce their sexual risk, participants mentioned concerns about comfort, convenience or privacy such as "As long as it isn't on the first screen where if I just left my phone around it ..", with the general being positive (Shrier and Spalding, 2017). There were also technology features discussed that could allow for increased privacy. A study capturing speech data through the mobile phone discussed a detection system that destructs raw audio in real-time while extracting and storing characteristics of speech instead of the actual conversation, in order to protect participant privacy (Ben-Zeev et al., 2015).

Although there is emerging research in the field of differential privacy, which constitutes a strong standard for balancing privacy and accuracy, none of these emerging methods have been applied to the studies listed in this review.

Themes related to research aim 2: To identify if these new technologies can predict recurrence

3.5. Correlational and predictive models derived from mobile and wearable technologies data

Several studies ($n = 11$) have developed multilevel models from the data collected from smartphones to answer a variety of research questions and outcomes. Models were built to study associations, such as the effect of individuals' self-criticism and dependency levels on their depressive symptoms using hierarchical linear modeling (Adams et al., 2009), or the association of daily problems with daily mood ratings by hierarchical regression.(Kenny et al., 2016) Sensor data were found to correlate with brief Patient Health Questionnaire (PHQ-9) scores (Truong et al., 2017), and sensor-derived sleep and geospatial activity was found correlated with daily stress levels (Ben-Zeev et al., 2015). Certain studies focused on prediction, such as predicting day-to-day variation in EMA mood ratings based on unobtrusive EMA data utilizing forward stepwise regression and naïve benchmark regression (Asselbergs et al., 2016), predicting depressive symptoms through stress-reactive rumination with hierarchical linear modeling (Connolly and Alloy, 2017), predicting wakefulness and sleep efficiency through mood during the day using repeated measures linear mixed effects models (Cousins et al., 2010, 2011), predicting diagnosis for internalizing disorders (McGinnis et al., 2018, 2019), and predicting future symptom development (e.g. depression, psychosis, etc.) (Schreuder et al., 2018; Wichers et al., 2018).

4. Discussion of scoping review findings

This scoping review surveyed digital techniques that are able to capture the dynamic nature of depressive symptoms and disorders in children and adolescents: these techniques constitute a substantially new, potentially useful element in symptom tracking and in clinical management. Digital phenotyping (or the use of computer-readable data for differentiating phenotypes) has been used to characterize and predict relapse of other mental illness such as schizophrenia (Barnett et al., 2018b) and can be particularly valuable for tracking MDD and MDD-CA given the recurrent and episodic nature of depression. Specifically, the degree of accuracy in profiling mood variability over time can be readily enhanced by mobile technologies, and compared to traditional methods for symptom tracking, data from EMA as well as unobtrusive, objective measurements including location tracking, call logs and light sensors, allow for a more thorough, digital phenotyping of MDD. Since studies varied considerably varied in their predicted outcomes, comparing and contrasting model performance in a meaningful way is not possible at present. However, the wide range of models developed from smartphone-based monitoring tools indicates a spectrum of opportunities with such data capture technologies.

Research aim 2: Digital phenotyping in correlational and predictive studies of MDD-CA

Correlating changes in circadian activity to recurrences, or physical activity with daily measures of mood, constitute the next-level targets, and illustrate digital phenotyping's potential in affective disorders research. In addition to measures found among the studies in this review, which included EMA data, passive data and actigraphy, other digital methods that have been used to classify and predict depression include speech acoustics and language (France et al., 2000; Hashim et al., 2017; Low et al., 2011), facial expression (such as eye-gaze estimation, head pose estimation, facial landmark detection) (Ringeval et al., 2017) and structured and unstructured electronic medical record data (Huang et al., 2014). After validation against standard psychometric tools, unobtrusive biosensor and mobile usage data may offer a host of possible proxy measures for clinically relevant variables and user states, and at the same time reduce measurement error in general and recall bias in particular.

A further step would include prediction models, and the potential of digital phenotyping methods for improved modeling of future relapse (Malhi et al., 2017): This is an urgent priority in MDD, and perhaps even more so in MDD-CA. Similar studies within adult MDD literature have found a unidirectional relationship of activity predicting mood the next day (Choi KW, 2019; Merikangas et al., 2018) as well as bidirectional relationships between sleep duration and activity and energy and activity (Merikangas et al., 2018).

However, due to the preliminary nature of most studies in this review, evaluating how digital phenotyping can assist predicting MDD-CA relapse appears premature. Studies reviewed here ranged in duration from 1 week to 12–18 months, with a majority (63.6%) falling within or under the 6 week range. Since clinical investigations (Fleisher and Katz, 2001; Rao and Chen, 2009) show a probability of recurrence estimated at 40% by 2 years, and 70% by 5 years in depressed children and adolescents, a minimum of observation of 24 months could represent a reasonable tradeoff between feasibility and the probability of a relapse for longitudinal digital phenotyping studies of relapse prediction. Also, most studies reviewed here focused on a small number of predictor variables, and/or were narrow in their scope (e.g. determining the effect of rumination on life stress and depression). This means that more long term studies analysing multiple variables for more protracted time of observation will be necessary to detect significant predictors for relapse of depressive episodes. Additionally, the heterogeneous study samples ranged from clinical samples of depressed children and youth to the general student population, and included children and youth with anxiety and other comorbidities, making direct comparisons difficult.

Research aim 1: Sleep phenotyping, youth perceptions

Sleep disturbances are extremely common in MDD-CA (Goodyer et al., 2017). Better understanding of MDD-CA and its heterogeneity may be derived from digital phenotyping of sleep combined with mood data; clinical intervention targeting sleep (Forbes et al., 2008), and longitudinal studies could be used to investigate related research questions on treatment and outcomes over longer periods of time.

Youth perception of mobile tracking for depression was overall positive across the reviewed studies, which is supported by previous research that found higher compliance of tasks on mobile phones than with paper. This leads to the conclusion that a mobile phones are more suitable for adolescents than other methods (Matthews et al., 2008).

However, most research in children and adolescents has focused on the *feasibility* of these technologies in modelling and/or tracking depression, with limited focus on how interventions were associated with mental health outcomes - while Kauer et al. (2012) measured the effect of mobile self-monitoring on a participant's emotional self-awareness, those studies that included more replicable mental health outcomes such as PHQ-9 scores, included these scores as a validation measure for sensor data (Truong et al., 2017), rather than a study outcome measure. With depression increasingly recognized as a major public health concern with significant sequelae in children and youth, mobile technologies for the monitoring of mood symptoms merit more rigorous investigation to determine if they can predict MDD-CA and activate early, timely interventions that can modify outcomes based on the monitoring. For example, Løventoft et al. (2012) used a detected depressive episode to activate support and relevant tasks within their study. Similar feedback loops have been added to mobile apps monitoring patients with bipolar disorder, and have shown positive results (Faurholt-Jepsen et al., 2015). One challenge that is not entirely unique to research on mobile app interventions involves continued engagement of participants throughout the study. While mobile apps allow for ease of recruitment and minimal costs in disseminating interventions, studies with active monitoring by participants require much participant feedback and time (Anguera et al., 2016), and can be challenging in certain populations, such as youth with depression.

Previous research has demonstrated that a majority of depression apps on the marketplace focus on providing therapeutic treatment and psychoeducation (65.8%), while only 3.7% are centered around mood tracking (Shen et al., 2015), which mirrors the lack of published research on tracking depression with mobile apps. Treatment-based mobile apps that focus on psychotherapy and cognitive training have had positive effects on participants with moderate levels of depression, as seen in a randomized controlled trial testing Project: EVO and iPST apps (Arean et al., 2016), however these apps serve a vastly different purpose than monitoring and tracking apps, and hence were out of scope for our review. A recently published systematic review examined mood-monitoring applications in young people across the spectrum of all mental health disorders, finding 25 articles (Dubad et al., 2018), four of which were focused on monitoring depression and thus were included this present review. Dubad and colleagues had similar conclusions that although the positive and negative impacts of apps have not yet been sufficiently investigated, there is great promise in these technologies (Dubad et al., 2018). Our paper adds to the work by Dubad et al. by broadening the scope of focus to a larger range of data collection devices (i.e. mobile apps and wearables), while also focusing in on one particular condition – depression (as compared to general mood monitoring). Statistical approaches to high volumes of longitudinal data, though not a focus of our search strategy, are integral to advancing mobile and wearable phenotyping of psychiatric disorders (Johns et al., 2019). Complexities to be addressed include longitudinal analyses of dense multivariate data, correcting for multiple tests in correlated data, lack of exchangeability of repeated measures, inclusion of appropriate confounding variables and dimensionality reduction. Confidence in future findings will hinge on rigorous data analysis; considering the above facets will facilitate the correct understanding of results both clinically and scientifically (Barnett et al., 2018a).

4.1. Limitations

Some existing depression prediction or monitoring mobile tools may have been missed due to our selection of English-language reports and of unipolar MDD rather than a broader spectrum of mood disorder phenotypes. Searching through additional databases, as well as hand combing through conference proceedings and reference lists of additional publications, would have introduced more non-indexed studies. Moreover, to emphasize prognosis and prediction, our inclusion criteria did not include any published literature on treatment studies that provided mobile intervention for MDD-CA or focused on treatment. It is also important to note that MDD manifests quite differently in children and adolescent populations (Abela and Hankin, 2008), and therefore the collective analysis of studies done on both populations can lead to overgeneralizations of each population. While we are aware of these differences, it's a necessary reality of clinicians to treat populations that span ages between childhood and adolescents, therefore we still believe that it is a relevant population grouping.

A further limitation is that conference abstracts were included via database searches, but specific conferences' proceedings were not searched. Sample heterogeneity also added a layer of complexity, making it challenging to compare and contrast outcomes, since many studies had an extremely narrow scope. As with all reviews, this review faces the limitations accompanying publication bias, wherein study outcome influences the decision to publish. We did not conduct a risk of bias assessment within each study as that is not relevant to a scoping review.

5. Final conclusions

Results from studies investigating mobile and wearable interventions suggest such technologies have the potential to aid in self-monitoring and objective data collection for monitoring and potentially predicting depressive moods in MDD-CA. However, there remains a paucity of definitive published peer reviewed literature on this topic, and given the focus on feasibility instead of clinical outcomes, it is too early to determine the effectiveness of wearable and mobile data for predicting relapse of MDD-CA – empirical inquiry is required to establish their utility for this purpose. Future efforts should highlight the development of predictive models using data from pragmatic, longitudinal experimental trials, with robust sample sizes, to determine the effect of mobile and wearable technologies on improving the diagnosis and relapse prediction of depressive illness for children and youth.

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Declaration of Competing Interest

None

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Supplementary materials

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