Cross-platform Availability of Smartphone Sensors for Depression Indication Systems. Mixed-methods umbrella review.

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Abstract

Background: A popular trend in depression forecasting research is the development of machine learning (ML) models trained with various types of smartphone sensor data and periodic self-ratings to derive early indications of changes in depression severity. While most works focus on model performance, there is little concern about the universal usability and reliable operation of such systems across smartphone platforms. This review is a part of the MENTBEST subproject MENTINA trial exploring smartphone-based health self-management for depression. The usability and reliability of mobile applications for depression is commonly perceived through the lens of the approaches and interventions offered rather than the reliability of the built-in mobile phone functions to support effortless and exact delivery of intended interventions.

Objective: This work aimed to provide an overview of cross-platform-available smartphone data streams for the strong design and operation of digital depression indication systems that rely on objective data patterns related to depression severity changes.

Methods: To identify the already used hard- and software sensors and their purposes in mental health monitoring, an umbrella literature review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines. Three electronic databases including PubMed, Web of Science Core Collection, and Scopus were searched using smartphone, sensor data, and depression keyword combination to retrieve relevant literature reviews published within the past five years (2019-2024). Once the initial search was completed, the extracted hardware sensors were checked for availability on Android and iOS smartphones by analyzing device specifications in the PhoneDB over the past ten years.

Results: The resulting data streams observed across studies include sixteen hardware and three software data streams. Hardware data streams include accelerometer, barometer, battery level, Bluetooth, camera, cell, GPS, gyroscope, humidity, light, magnetometer, proximity, sound, step count, temperature, and Wi-Fi. Software data streams include app usage, call and message logs, and screen status. Hardware component availability on Android and iOS systems shows the changes in component trends from 2014 to 2024 as of September 2024 with the accelerometer, battery, camera, and GPS being consistent on Android and iOS while components such as gyroscope, step counter, and barometer where gradually increasing over the years, particularly on Android.

Conclusions: Multiple data streams observed across literature reviews have been consistently growing in availability across time, allowing better utilization of such outputs for depression forecasting and training machine learning models with a variety of smartphone data including smartphone sensor data. For more precise and reliable data to be utilized in the mental health field, particularly in critical areas such as tracking and predicting changes in depression severity further research is required to streamline smartphone data across varying mobile hardware and software configurations to provide reliable output for digital

mental health purposes.

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Review

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Multiple data streams observed across literature reviews have been consistently growing in availability across time, allowing better utilization of such outputs for depression forecasting and training machine learning models with a variety of smartphone data including smartphone sensor data. For more precise and reliable data to be utilized in the mental health field, particularly in critical areas such as tracking and predicting changes in depression severity further research is required to streamline smartphone data across varying mobile hardware and software configurations to provide reliable output for digital mental health purposes.

Keywords: umbrella review; mobile phone; smartphone; sensor data; digital health; depression; cross-platform; data availability

Introduction

Background

The vast variety of personally generated data can provide useful insights that empower individuals with depression to better manage experienced symptoms. Smartphone apps allow to easily collect personalized data over long time periods and enable the use of powerful machine learning (ML) models that can potentially identify individual data patterns related to the severity of depression or predict changes in symptoms and the probability of relapse or remission. Periodic self-ratings concerning depression related symptoms and life events are mostly collected actively via questionnaires, whereas data from hard- and software components are mostly recorded passively to derive biomarkers, behavior patterns (e.g., phone/app usage) and external moderating factors (e.g., environmental conditions).
Several promising works are already using smartphone data to train supervised ML models for mental health monitoring ([1–6]), but only a few are based on continual data from studies lasting longer than 30 days. The existing studies show insufficient consideration on the reliability and practicability of the chosen algorithms in real-world scenarios. Once models are deployed and operated, the performance of model prediction results may vary depending on the algorithm's capability to handle missing and erroneous data due to reasons such as varying smartphone platforms or data availability. Moreover, the variety of installed hardware and software components and the steadily evolving technology in this field makes it even more challenging to build failsafe applications that work across various environments in the present and future.

Recent literature lists plenty of passively collected smartphone data streams mostly used in transformed manner for mental health monitoring. While hardware components like accelerometers, ambient light sensors, Bluetooth, camera, Global Positioning System (GPS), gyroscopes, microphones, and Wi-Fi are among the most used smartphone data sources [7–15] hardware components like barometers [8] and temperature [13] sensors are named only a few times in relevant works, but can also play an important role in the context of mental health monitoring. Most sensors are not directly used for depression modeling, but rather serve as a proxy for key figures that are correlated with depression symptoms. Typical key figures derived from smartphone hardware components data are estimates on physical activity, sleep duration, sociability, mobility, circadian rhythms, stress, and the environment recognition [7–15]. Besides hardware components, smartphone operating systems also provide valuable information for mental health monitoring. Software sensors measuring smartphone and application usage offer key figures on sociability, distractedness, stress, and mood estimates in case of access permissions to application, phone-call, and text-message logs [7–15]. Although several systematic reviews already provide a good overview, a complete collection of all smartphone data sources already used for mental health monitoring is missing to the best of our knowledge.

We aim at closing the gap of current work and results can give a guideline for the informed decisions related to recruitment and data collection setup prior to commencement of clinical studies applying mental health monitoring via smartphones. In particular the results of this work can serve as a comprehensive path for the setting up of the MENTINA trial. The subproject MENTINA trial is part of the EU-funded research project MENTBEST [16] aiming to investigate the value of data-driven interventions in the context of management of depression severity. Participants of the trial will use an app for one year that collects data from smartphone sensors passively while requiring the users to periodically give feedback on personal well-being via self-reports. Besides bi-weekly feedback with Patient Health Questionnaires 9 (PHQ-9), participants will be also asked to daily rate their mental health condition by answering PHQ-2 questionnaires throughout the trial. The app will be available on Android and iOS smartphones and is based on the Monsenso app [17,18], developed by the Danish digital health solution provider [19].

Objective

In alignment with the preparation of the MENTINA trial, the following research questions should be answered in the course of this work:
(1) Which data streams provided by smartphones have been used in literature to build models for depression monitoring?
(2) Which smartphone data streams are available across smartphone vendors and operating systems to build reliable platform-independent software systems for depression monitoring?
(3) Which proxies have been constructed from raw smartphone data streams to build key figures for depression models?

Methods

Umbrella Review

Protocol and Registration

The umbrella review has been registered in the PROSPERO database (registration number: CRD42024581256) and was conducted in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines.

Information Source and Search Strategy

During the preparation phase of the MENTINA trial in September 2024 the umbrella review has been performed by querying the scientific databases PubMed, Web of Science Core Collection, and Scopus to get a comprehensive overview of the existing reviews in the field.
The search strategy included querying the scientific databases with the search term *smartphone sensor data depression* to find reviews related to clinical depression or dealing with depression symptoms. In alignment with the fact that people tend to have smartphones not longer than five years [20], filters have been added to only receive review papers from the past five years (2019-2024) to focus on currently used smartphone sensors for depression modelling.

Eligibility Criteria

The reviews have been considered only when the screening of title and abstract confirmed that the review (1) has been written in English and/or German, (2) has been published in journals indexed in Scopus database, (3) focused not only on one, but multiple smartphone sensors to (4) build digital phenotypes of individual's mental health. Given the great amount and redundancy of works in this field, articles with insufficient information on the eligibility criteria were not considered.

Selection of Studies

The full text versions were obtained and the contents of potentially relevant papers were analyzed to select items matching the following criteria: (1) review papers only, (2) reviews already summarizing the use of raw smartphone sensors over multiple other works, (3) reviews showing the sensor purposes in terms of depression recognition and (4) reviews that have passed *A MeaSurement Tool to Assess systematic Reviews* (AMSTAR) [21] evaluation. For the AMSTAR evaluation reviews have been chosen only if particular items could be answered with "Yes". The items of relevance were:

1. Item 2 ("Was there duplicate study selection and data extraction?")
2. Item 3 ("Was a comprehensive literature search performed?")
3. Item 6 ("Were characteristics of the included studies provided?")
4. Item 11 ("Were potential conflicts of interest included?").

Narrative Synthesis

To synthesize the literature contents relevant for this work, the smartphone sensors referenced in the retrieved reviews were extracted and separated into two collections for hardware and software data streams. The collections were additionally enriched with its purposes in terms of depression recognition across all works. The two collections were sorted alphanumerically and inserted into tables to allow a condensed overview of already used smartphone data streams for depression recognition in literature. The hardware sensor collection served as foundation for the investigation on cross-platform sensor availability.

Cross-platform Sensor Availability

Smartphone Operating System (OS) Market Analysis

To assess the prevalence of commonly used mobile operating systems, market share data from the past two years was analyzed using statistics from the portal Statista. To highlight the global significance of Android and iOS, worldwide market share data was extracted. Additionally, regional analyses focused on Europe, with a particular emphasis on Denmark, Germany, and Spain, to provide insights into the operating system market landscape in these countries, where the MENTINA trial will be conducted.

Phone Specifications Database

PhoneDB maintains the "world's largest" [22] database for mobile device specifications providing technical details for smartphones, tablets, smart watches and several other types of handheld devices. While PhoneDB is not a complete collection, it gives a comprehensive overview of smartphone releases the past 20 years [23]. PhoneDB was used in a couple of other scientific works [23,24] and serves as valuable data source for deriving trends for technical specification trends. Besides information on the operating system the devices are running, the database provides more than 290 parameters per device, including information on the presence of installed hardware sensors. PhoneDB offers licensed database dumps or free limited access to the database via pre-configured database queries using PhoneDB's web-based "Detailed Parametric Search Tool". The search tool allows to query device specifications based on built-in sensors, which has been used for this work.

Data Queries

PhoneDB was queried multiple times to retrieve the number of devices matching the search criteria. The search criteria included filters on the device category, release date, operating system and installed hardware including whether the devices are equipped with built-in hardware components. To identify operating-system-dependent trends in hardware component availability, the database has been queried for annual Android and iOS smartphone specifications with corresponding components installed from 2014 to 2024. To get a baseline, queries without any hardware component filter were executed to get the annual total number of Android and iOS releases for the respective years.

Data Analysis

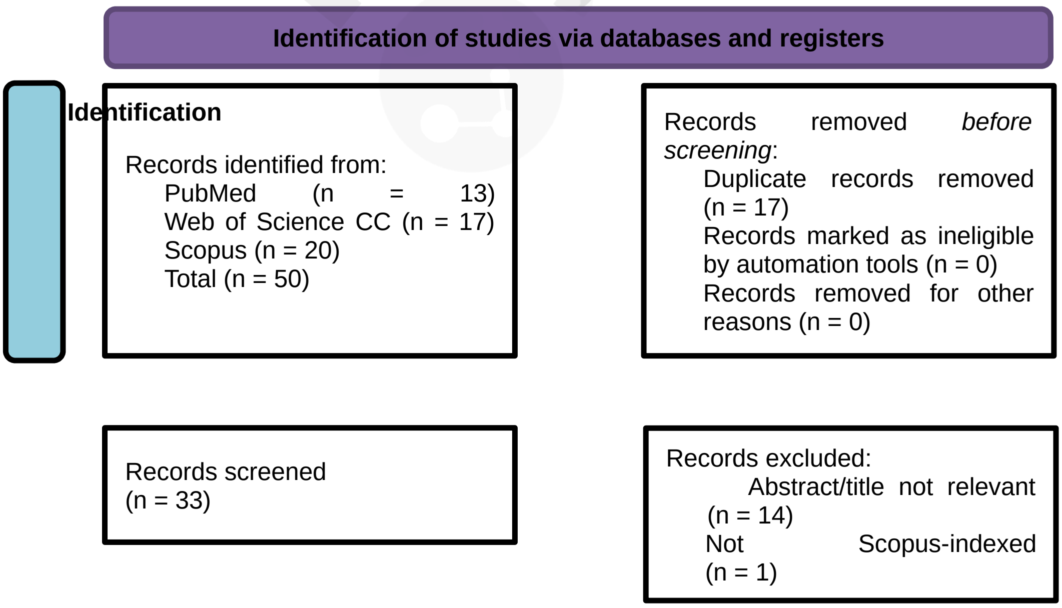
The PhoneDB query results were saved in one file for iOS and one file for Android. Each file consisted of a data table with hardware components as rows and years as columns. The table cells represented the number of device releases in the particular year that had the corresponding hardware component installed. For the baseline, a row consisting of the total number of device releases over the considered years was added to each file. Based on the Android and iOS data tables, the hardware component availability in percent was calculated by dividing the number of device releases with the corresponding hardware component installed, and the total number of device releases in the respective year, multiplied by hundred.

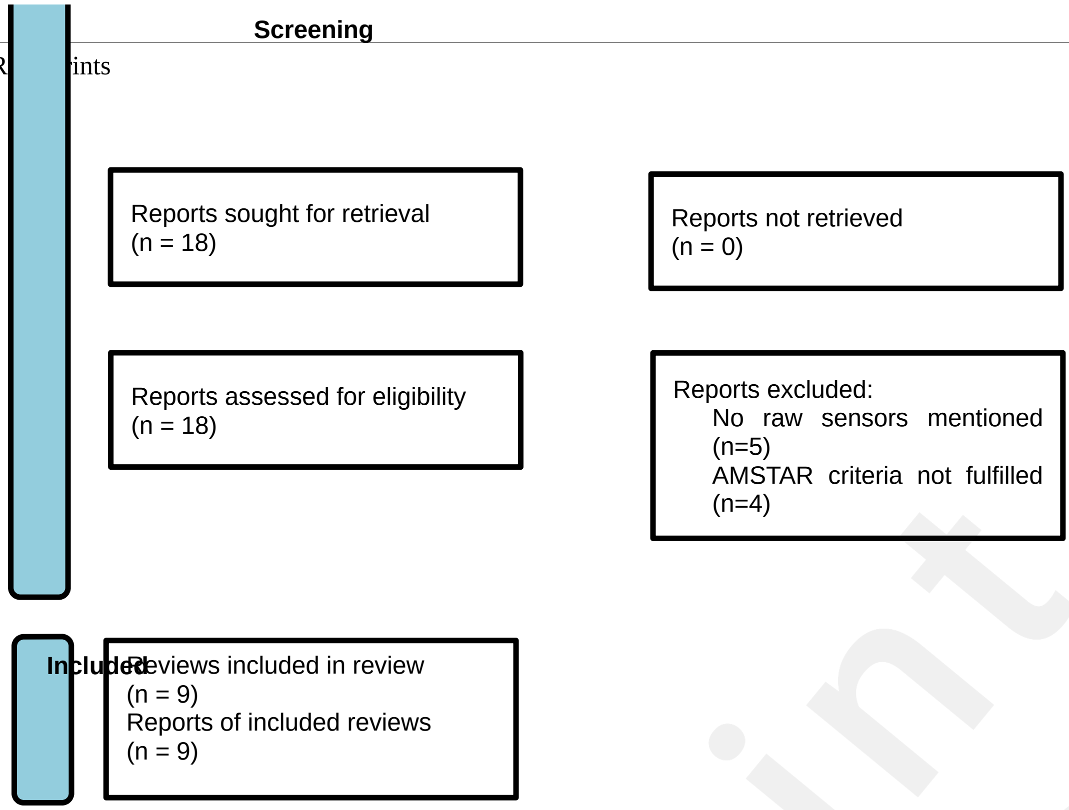
Results

Umbrella Review

A PRISMA flow chart (see Figure 1) has been created to illustrate the information flow of the umbrella review. Aligned with the search strategy, 50 records were found in total across the three queried scientific databases (PubMed, n=13; Web of Science Core Collection (CC), n=17; Scopus, n=20). After removing duplicates (n=17), 15 records were removed due to non-relevant abstract and title (n=14) or not being indexed at Scopus (n=1). For the remaining 18 records, full text reports were requested and screened to meet the eligibility criteria. Five more records were removed for not mentioning the use of raw sensors in the report (n=5). Four more articles were excluded due to not meeting the AMSTAR criteria [21]. Finally, nine reviews were selected for data extraction and synthesis.

Figure 1. PRISMA flow chart based on the PRISMA flow chart template [25].





The studies included in the umbrella review are listed at Table 1. For transparency reasons, please see the list of excluded records and exclusion reasons at Multimedia Appendix .

Table 1. Included articles of the umbrella review.

Ref.	Title	Author	Year
[7]	Use of smartphone sensor data in detecting and predicting depression and anxiety in young people (12–25 years): A scoping review	Beames *et al.*	2024
[8]	Passive Sensing of Health Outcomes Through Smartphones: Systematic Review of Current Solutions and Possible Limitations	Trifan *et al.*	2019
[9]	Digital Phenotyping for Stress, Anxiety, and Mild Depression: Systematic Literature Review	Choi *et al.*	2024
[10]	Loneliness and Social Isolation Detection Using Passive Sensing Techniques: Scoping Review	Qirtas *et al.*	2022
[11]	The utility of smartphone-based, ecological momentary assessment for depressive symptoms	Yim *et al.*	2020
[12]	From smartphone data to clinically relevant predictions: A systematic review of digital phenotyping methods in depression	Leaning *et al.*	2024
[13]	Mobile and wearable sensors for data-driven health monitoring system: State-of-the-art and future prospect	Virginia Anikwe *et al.*	2022
[14]	Using digital phenotyping to understand health-related outcomes: A scoping review	Lee *et al.*	2023
[15]	Mobile phone enabled mental health monitoring to enhance diagnosis for severity assessment of behaviours: a review	Gopalakrishnan *et al.*	2022

Each included review was screened for smartphone data streams that have been already used for mental health monitoring in the past. The data streams were divided into *hard-* and *software* data streams to distinguish data derived from installed hardware components and data provided by the operating system. For each found data stream it was assessed how the data was used to derive insights for mental health. Table 2 depicts the results of the data extraction and synthesis by listing the found smartphone data streams in rows over the relevant studies as columns. The table cells indicate whether a smartphone data stream has been mentioned in the respective article regarding mental health monitoring. In case a data stream has been mentioned, but it was not clear how it has been used for mental health, the respective table cell was filled with “listed”. To improve the readability of the table, clusters have been built for similar terms. A list of mapped original terms to umbrella terms is shown in Table 3.

Table 2. Extracted smartphone hard- and software data streams and respective use regarding mental health monitoring at relevant articles.

Reference	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]
Hardware data streams (X/9)[c]	**Mental health monitoring**								
accelero-meter (9/9)	physical activity	physical activity, sleep, well-being	physical activity	physical activity	circadian rhythm	physical activity	physical activity, stress	mobility, physical activity, sleep	physical activity, social activity
barometer (1/9)	-	physical activity	-	-	-	-	-	-	-
battery level (4/9)	-	sleep, well-being, circadian rhythm	sleep	-	-	listed	-	social activity	-
Bluetooth (8/9)	social activity	circadian rhythm, sleep, social activity, well-being	mobility, social activity	social activity	social activity	environ-ment	-	mobility, social activity	mobility, social activity
camera (4/9)	-	well-being	listed	-	listed	-	-	-	social activity
cell (3/9)	-	listed	-	-	-	mobility	-	-	listed
GPS (9/9)	mobility	circadian rhythm, physical activity, sleep, well-being	mobility, physical activity	mobility, physical activity, social activity	circadian rhythm	circadian rhythm, environ-ment, mobility, physical activity	circadian rhythm	mobility	mobility, physical activity, social activity
gyroscope (7/9)	listed	circadian rhythm, physical activity, social activity, well-being	physical activity, sleep	-	-	mobility	circadian rhythm	physical activity	physical activity
humidity (1/9)	-	-	-	-	-	-	well-being	-	-
light (9/9)	sleep	listed	sleep	listed	listed	environ-ment, sleep	listed	sleep	sleep, social activity
magneto-meter (2/9)	-	physical activity, well-being	-	-	-	-	circadian rhythm	-	-
proximity[a] (1/9)	-	-	-	-	-	-	circadian rhythm	-	-
sound (8/9)	social activity	circadian rhythm, physical activity, sleep, social activity, well-being	sleep, social activity	sleep, social activity	listed	-	circadian rhythm	social activity, sleep	environ-ment, sleep, speech

step count[b] (6/9)	physical activity	physical activity	physical activity	-	-	physical activity	physical activity	physical activity	-
temperature (2/9)	-	-	-	-	-	-	physical activity	-	environment
Wi-Fi (8/9)	mobility	circadian rhythm, physical activity, sleep, social activity, well-being	mobility	social activity	listed	mobility	-	mobility	mobility, physical activity, social activity
Software data streams (X/9)[c]									
app usage (8/9)	listed	circadian rhythm, sleep, social activity, well-being	social activity	social activity	mood	circadian rhythm mood, social activity	-	social activity	social activity, stress
call and message logs (9/9)	social activity	circadian rhythm, sleep, social activity, well-being	social activity	social activity	mood	social activity	circadian rhythm	social activity, stress	social activity, stress
screen (8/9)	listed	listed	stress, well-being	listed	listed	social activity	-	social activity, sleep	sleep

[a]Step counts are usually derived by sensor fusion of multiple other (hardware) sensors. Modern smartphones are equipped with dedicated motion coprocessors to do this task in energy-efficient manner [26].

[b]Proximity sensors are usually realized with an emitting infrared LED and a detecting photodiode [27].

[c](X (=times occurred in included studies) / total number of included studies).

Table 3. Mapping table of umbrella terms and assigned terms found across literature.

Umbrella term	Original terms in literature
data stream	
app usage	app usage, application usage, browser usage, in-phone activity
light	light, ambient light
screen	screen status, lock/unlock status, screen time, screen events
sound	sound, microphone, audio, voice, speech
purpose	
circadian rhythm	circadian rhythm, daily-life behavior, behavioral marker
environment	environment, surrounding, workplace conditions
mobility	mobility, location, homestay
physical activity	physical activity, motion, human activity, movement
sleep	sleep, bedtime, sleep disturbance
social activity	social activity, loneliness, social avoidance, social rhythm, social function, social habits, social interaction, sociability, social anxiety
stress	stress, distractedness

As the results at Table 2 show, the most mentioned hardware data streams include

1. Accelerometers
2. Light sensors

3. GPS

While accelerometers are mostly used to derive a proxy measure for physical activity, light sensors are broadly used to gather insights about the sleep behavior of individuals.

GPS serves various purposes to build proxy measures for mental health. The most prominent application of GPS in terms of mental health monitoring is to derive information about individual's mobility, which includes for instance the number of location changes, or the time spent at home. Similar information could be also retrieved from the current position of a smartphone in cellular networks, which has been also mentioned in one study. In contrast to cell information, GPS was also broadly used to track physical activity and helped to determine one's circadian rhythm, gathering for instance markers for daily-life behavior. Only a few studies mentioned GPS in context of measuring social activity, but according to the included studies, social activity is often approximated by identifying the number of closely located devices in one's environment using Bluetooth.

Similarly, some of the studies mention the use of microphones or cameras to get a means for social activity by analyzing individual's acoustic and visual environment. Several studies also mention microphones to estimate individual's circadian rhythm including sleep patterns. Those patterns are also approximated by interpreting battery levels as a few studies referenced.

A couple of other hardware data streams were additionally mentioned for estimating circadian rhythms, including data derived from proximity sensors, gyroscopes or Wi-Fi components. Furthermore, Wi-Fi and gyroscopes have been mentioned in the context of various other proxy measures for mental health monitoring, comprising mobility, social activity and physical activity.

Beyond the hardware data streams already mentioned, step counts were used plenty of times, but exclusively to derive key figures for physical activity. To complete the list of hardware data streams used for representing physical activity, temperature sensors, barometers and magnetometers were also mentioned in the literature reviews for this purpose. Finally, one relevant article stated the use of humidity sensors for approximating a person's well-being.

Table 2Furthermore, all included studies also list software data streams for the monitoring of mental health (see Table 2) along with the data from call and message logs as an insightful data source for building proxy measures for mental health. While most studies stated that call and message logs have been used to estimate individual's social activity, a few referred to using the logs for constructing the metrics on circadian rhythm. Also estimates for mood and stress were listed as a derivate of call and message logs. In principle, the same mental health characteristics were derived from using app and screen usage data across literature, while a few studies stated that the screen status was also used to approximate sleep behaviors.

Cross-Platform Sensor Availability

According to [28] the worldwide smartphone operating system market is dominated by the operating systems Android and iOS, covering 72 and 28 percent respectively as of second quarter 2024. Similarly, the smartphone operating system market in Europe is prevailed by Android and iOS [29]. Back in 2018, Android devices covered 67 percent of the European market, while iOS's market share was 32 percent. In 2023, approximately 65 percent of European smartphones were still running Android, while the remaining market was almost completely covered by iOS devices. The mobile operating system market shares in the MENTINA country Germany were similar to Europe's, consisting of 60 percent Android devices and 39 percent iOS devices in 2023 [30]. As of March

2024, the mobile operating system market in the MENTINA country Spain was dominated by Android, having a share of approximately 80 percent, while iOS covered the rest of approximately 20 percent [31]. In contrast, as of April 2024 the majority of 57 percent of mobile devices in the MENTINA country Denmark was delivered with the operating system iOS, while 42 percent of devices had Android installed [32].

Due to the worldwide market dominance of Android and iOS smartphones, PhoneDB has only been queried for hardware component availability at Android and iOS systems. Table 4 shows the fields and values of PhoneDB's search tool and corresponding combinations were used to estimate the trends of hardware component availability at Android and iOS smartphones over the past ten years.

Table 4. Used PhoneDB fields and values to meet the search criteria.

Search criteria	Field	Values
general		
year	*Release Date*	Yearly from-, to-values from 2014 to 2024, e.g. from *2020-01-01* to *2020-12-31* for year 2020
smartphone	*Device Category*	*Smartphone*
operating system	*Platform*	*Android* or *iOS / iPadOS*
data stream		
accelerometer	*Built-in accelerometer*	*Any*
barometer	*Barometer*	checked
battery	*Battery*	*Any*
Bluetooth	*Bluetooth*	*Any*
camera	*Camera Image Sensor*	*Any*
cell	*Supported Cellular Bands*	*Any*
GPS	*GPS*	checked
gyroscope	*Built-in gyroscope*	*Any*
humidity	*Humidity sensor*	checked
light	*L sensor*	checked
magnetometer	*Built-in compass*	*Any*
microphone	*Microphone(s)*	*Any*
proximity	*IR face sensor* or *LiDAR*	checked
step counter	*Step counter*	checked
temperature	*T sensor*	checked
Wi-Fi	*Wireless LAN*	*Any*

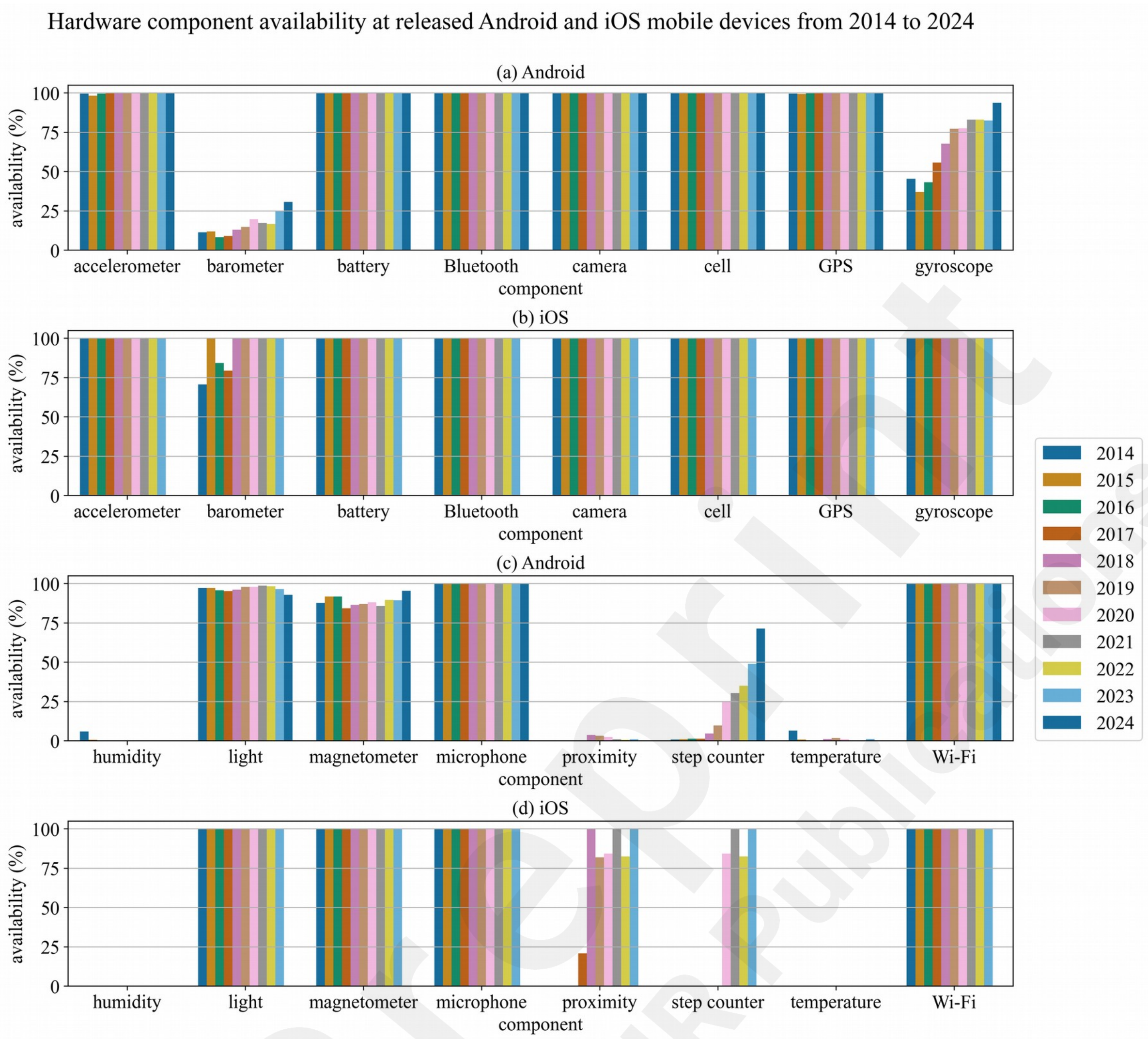
The raw data derived from the PhoneDB queries can be viewed at Multimedia Appendix 2. The appendix also contains the availability results for Android and iOS. Figure 2 depicts a condensed version of these results by showing the availability of 16 hardware components on Android and iOS smartphones from 2014 to 2024 as of September 2024.
For readability and comparability purposes the hardware components were divided into two groups, showing alternating Android and iOS results for each group. More specifically, Figure 2 includes charts:

- (a)/(b) show the availability of the first eight, Figure 2
- (c)/(d) the remaining eight hardware components of Android/iOS smartphones over the past ten years.

Each bar corresponds to the percentual availability of a hardware component on Android and iOS systems in a particular year. The bars of each hardware component and operating system are plotted in chronologically ascending order to depict the availability trend throughout the years. Charts in Figure 2 (b) and (d) are missing a bar for year 2024 due to no existing iOS specifications for 2024 as of September 22nd, 2024.

As seen in Figure 2, the hardware components accelerometer, battery, Bluetooth, camera, cell network support, GPS, microphone and Wi-Fi were available at almost every Android and iOS smartphone the past ten years. Since 2018 iOS smartphones have been equipped with barometers. In contrast, only 31 percent of Android devices came with barometers in 2024, but a positive trend is identifiable. Similarly, iOS smartphones already provided gyroscopes for the past 9 years, while not all Android devices were shipped with gyroscopes in 2024. With more than 80 percent from 2021 to 2023 and approximately 94 percent in 2024, a positive trend regarding gyroscope installations at Android smartphones is visible. Besides a few recognizable Android devices in 2014, almost no Android or iOS smartphone provided a humidity sensor in the past years. Almost the same pattern applied to the temperature sensor with several years of availability at a low percentage level at Android systems and no coverage at iOS systems the past years at all. When it comes to light sensors, iOS devices provided full coverage for the past 9 years, whereas Android devices also mostly provided light sensors in the past with 95 percent availability from 2014 to 2023 and an all-time low of approximately 93 percent in 2024. Similarly, while magnetometers were found in every iOS smartphone, not every Android device came with magnetometers the past years. The trend of magnetometers at Android phones experienced a slow increase from 2017 to 2023 and ended with a 95-percent-availability in 2024. Since 2018 an iOS smartphone came with a proximity sensor of at least 80 out of 100 times, whereas almost no Android phones provided a proximity sensor the past five years. Step counters are usually derived by sensor fusion of multiple other (hardware) sensors, but modern smartphones are equipped with dedicated motion coprocessors to perform this task more energy-efficient [27]. Those coprocessors for efficiently estimating step counts were present in iOS phones more than 80 percent of time since 2017, while Android system rapidly caught-up the past years with an average availability of 71 percent in 2024.

Figure 2: Hardware component availability at released Android and iOS smartphones from 2014 to 2024 as of September 2024.



Discussion

Principal Results

To highlight the potential of sensors for building reliable mental health monitoring systems across smartphone platforms, we focused on answering three research questions in the course of this work: (1) Which data streams provided by smartphones have been used in literature to build models for depression monitoring? (2) Which smartphone data streams are available across smartphone vendors and operating systems to build robust platform-independent software systems for depression monitoring? (3) Which proxies have been constructed from raw smartphone data streams to build key figures for depression models?

To address research question (1), an umbrella literature review aligned with the PRISMA workflow was conducted and nine articles were included that ensure high methodological quality according to the AMSTAR results. From each of the included articles the referred smartphone data streams were extracted, resulting in a list of:

1. 16 hardware data streams
2. 3 software data streams.

To consider research question (3), the data stream purposes regarding mental health monitoring were extracted from literature and assigned to similar purpose clusters. In summary, smartphone data was used in literature to build key figures for 1) circadian rhythm, 2) environment 3) mobility, 4) mood, 5) physical activity, 6) sleep, 7) social activity, 8) speech, 9) stress and 10) well-being to support the insights into the mental state of individuals.

To provide answers to research question (2) the identified smartphone hardware data streams were assessed regarding their availability at Android and iOS platforms.
Summing up, the hardware components accelerometer, battery, Bluetooth, camera, cell receiver, GPS, microphone and Wi-Fi were available at every Android or iOS device the past decade. Due to the presence on every smartphone, data streams from those components are promising candidates for the construction of robust cross-platform software systems.

The same applies to data from gyroscopes, light sensors and magnetometers, which are installed at every iOS and almost every Android smartphone. Despite the fact that step counts are already provided by the operating systems through sensor fusion of other hardware components, the availability trend of motion coprocessors for more accurate step counters at Android and iOS increased significantly the past years, making it also a promising candidate for the establishment of robust software systems.

As of September 2024, barometers, humidity, proximity and temperature sensors are not consistently installed across Android and iOS mobile phones and have therefore limited use for reliable cross-platform mental health monitoring systems.

Limitations

While this work strives to provide a complete picture of the smartphone data available for the development of reliable cross-platform depression indication systems, it does not consider the quality and uniformity of data streams. The work considers a data stream for a particular hardware component to be available if any type of hardware component has been installed. Due to the broad spectrum of installed hardware components in the considered time frame, the data stream signals will vary significantly, which limits the comparability and interpretability of raw values across mobile phones. Therefore, future works may focus on improving operating systems and middleware to provide comparable data streams derived from different hardware component types. Furthermore, the work lacks in-depth analysis on how the data streams were exactly used in literature to calculate key figures for representing mental health. Future works may fill this gap by focusing on the preparation of smartphone data streams for the construction of representative mental health key figures across platforms.

Comparison with Prior Work

Through the course of this work, plenty of reviews were found that already summarize the potential of smartphone data for mental health monitoring. To our knowledge, there is no umbrella review to give a complete picture of the research in this field. Therefore, this work consolidates the literature findings with respect to the development of cross-platform mental health monitoring systems. The studies of the umbrella review mostly highlight the potential of smartphone data for mental health monitoring, but little research has been performed on the availability of underlying data sources across mobile platforms. This work closes this research gap by providing the availability of smartphone hardware data streams at the predominating smartphone platforms Android and iOS for the past ten years. Vendors and researchers may make use of the availability results to build reliable and robust mental health monitoring software systems in the future.

Conclusions

Research in the field of digital phenotyping for mental health and depression modeling is an emerging and complex field that integrates insights from psychiatry, technology, and health informatics [33]. Currently, the literature lacks information on passive smartphone data for reliable key figures that represent mental health. This work started to address this gap by analyzing the cross-platform availability of relevant smartphone data. The results are expected to support the informed decisions concerning the best data collection setup for apps and trials focusing on the value of long-term complex time series analyses of such data in people living with depression and other mental health issues. Nevertheless, further research is needed to streamline smartphone data across varying mobile hard- and software configurations to provide reliable digital mental health for everyone. Therefore, future works may investigate improving frameworks and operating systems to easily provide comparable data streams for mental health monitoring independent of the underlying smartphone.

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JL conducted the umbrella review, the cross-platform availability analysis and the main writing of the manuscript. MP worked on the overall study design, validated the decisions throughout the umbrella review and fine-tuned the manuscript. AD, DH and UH supervised and reviewed the work from technical and medical perspective.

Conflicts of Interest

The authors declare no conflicts of interest.

Abbreviations

AMSTAR: A MeaSurement Tool to Assess systematic Reviews
GPS: Global Positioning System
LED: Light Emitting Diode
ML: Machine Learning
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
Wi-Fi: Wireless Fidelity

Multimedia Appendix 1

The excluded studies of the umbrella review and reasons for exclusion.

Multimedia Appendix 2

The full version of PhoneDB raw data and analysis results of the cross-platform availability analysis.

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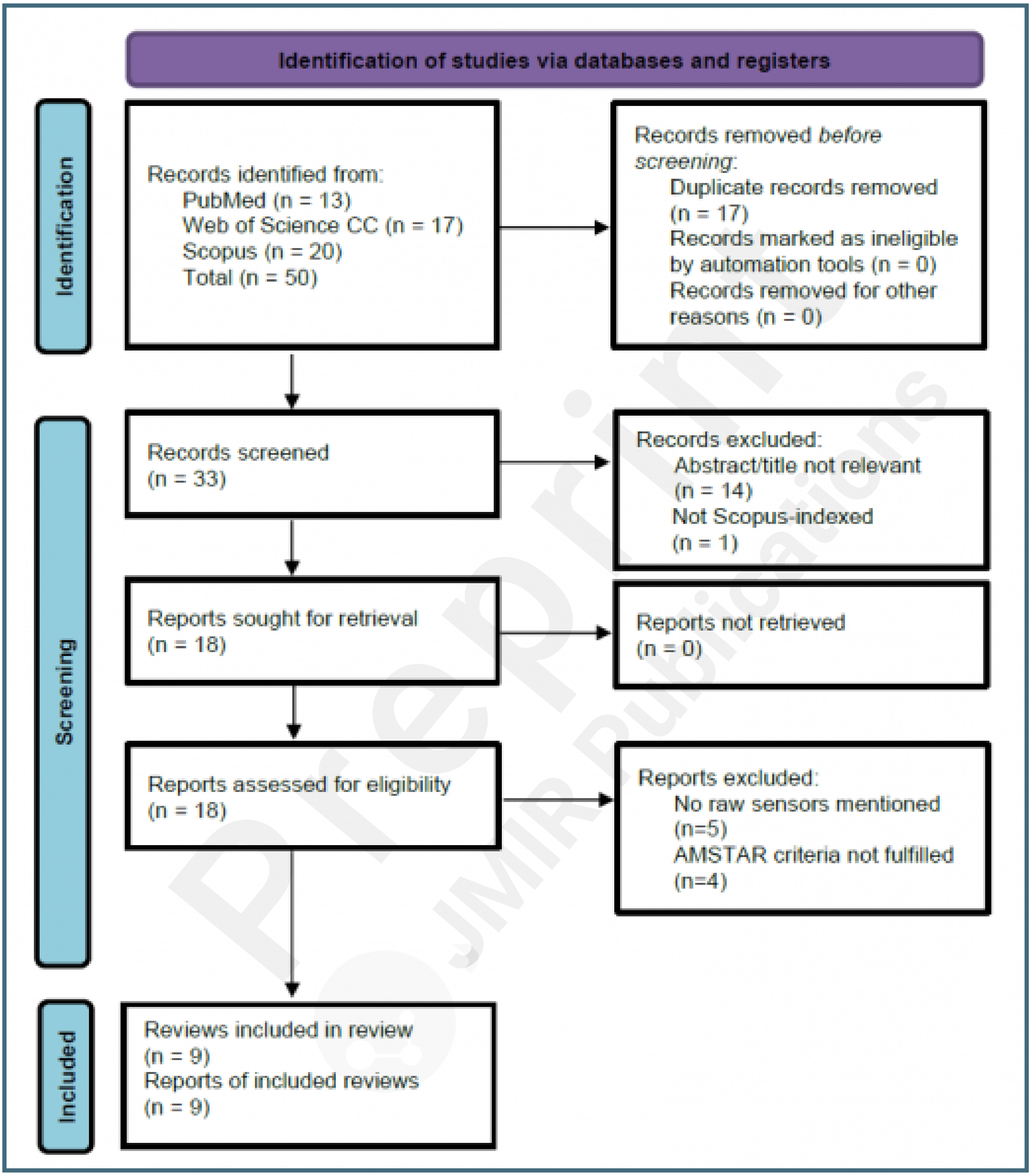
Supplementary Files

Figures

PRISMA flow chart based on the PRISMA flow chart template [25].



Hardware component availability at released Android and iOS smartphones from 2014 to 2024 as of September 2024.

Multimedia Appendixes

The excluded studies of the umbrella review and reasons for exclusion.
URL: http://asset.jmir.pub/assets/9b658e4defc4b118c0b98c9c8fa45c6d.docx

The full version of PhoneDB raw data and analysis results of the cross-platform availability analysis.
URL: http://asset.jmir.pub/assets/c02fb275594f8d9524190626eeb14bf5.xlsx