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The integration of geographic methods and ecological momentary assessment in public health research: A systematic review of methods and applications

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Abstract

With the widespread prevalence of mobile devices, ecological momentary assessment (EMA) can be combined with geospatial data acquired through geographic techniques like global positioning system (GPS) and geographic information system. This technique enables the consideration of individuals' health and behavior outcomes of momentary exposures in spatial contexts, mostly referred to as "geographic ecological momentary assessment" or "geographically explicit EMA" (GEMA). However, the definition, scope, methods, and applications of GEMA remain unclear and unconsolidated. To fill this research gap, we conducted a systematic review to synthesize the methodological insights, identify common research interests and applications, and furnish recommendations for future GEMA studies.

We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analysis guidelines to systematically search peer-reviewed studies from six electronic databases in 2022. Screening and eligibility were conducted following inclusion criteria. The risk of bias assessment was performed, and narrative synthesis was presented for all studies.

From the initial search of 957 publications, we identified 47 articles included in the review. In public health, GEMA was utilized to measure various outcomes, such as psychological health, physical and physiological health, substance use, social behavior, and physical activity. GEMA serves multiple research purposes: 1) enabling location-based EMA sampling, 2) quantifying participants' mobility patterns, 3) deriving exposure variables, 4) describing spatial patterns

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Ethnics approval
This study is a systematic review. We did not collect data from human subjects.

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Yue Zhang: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Dongying Li:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Xiaoyu Li:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Xiaolu Zhou:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Galen Newman:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization.

Appendix A. Supplementary data
Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2024.117075.

of outcome variables, and 5) performing data linkage or triangulation. GEMA has advanced traditional EMA sampling strategies and enabled location-based sampling by detecting location changes and specified geofences. Furthermore, advances in mobile technology have prompted considerations of additional sensor-based data in GEMA.

Our results highlight the efficacy and feasibility of GEMA in public health research. Finally, we discuss sampling strategy, data privacy and confidentiality, measurement validity, mobile applications and technologies, and GPS accuracy and missing data in the context of current and future public health research that uses GEMA.

1. Introduction

Ecological momentary assessment (EMA) is a research method that utilizes the repeated sampling strategy to assess phenomena at the moment they occur in natural settings, thereby enhancing ecological validity (Stone and Shiffman, 1994). EMA is a powerful tool for data collection in real-world environments as participants engage in their daily activities. Subjects' self-reports of health and behavior can be collected via EMA, which provides a comprehensive understanding of how participants' experiences and behaviors vary across diverse situations and over time and reduces recall biases associated with retrospective self-reporting (Shiffman et al., 2008). The utilization of EMA data collection enables measurements of inter- and intra-individual differences, natural history, contextual associations, and temporal sequences (Shiffman et al., 2008). Accordingly, this real-time and naturalistic method has gained popularity and is also referred to as "ambulatory assessment" or the "experience sampling method (ESM)." As EMA studies usually capture momentary experiences repeatedly, EMA sampling strategies become a primary factor in collecting valid data. The previous literature classifies EMA sampling into two types, signal-triggered or event-triggered, based on the method of survey delivery (Ruwaard et al., 2018). According to this classification, existing studies mostly use signal-triggered sampling, in which participants receive a preprogrammed beep or vibration that prompts them to answer the survey questions. Some studies use event-triggered EMA, in which participants can initiate a survey when a certain behavior or health episode occurs (e.g., panic attack).

To date, the EMA technique as a vital research method has benefited numerous studies in public health. For example, the utilization of the EMA method in mood disorders research offers advantages over laboratory or questionnaire studies due to its ability to capture real-time and context-dependent data (Ebner-Priemer and Trull, 2009); EMA in substance use research has made valuable contributions in capturing drug use patterns (Shiffman, 2009); and EMA enables the detections of time- and spatially-varying factors and intra-individual fluctuations to facilitate prediction and modeling of physical and activity behaviors (Dunton, 2017). Therefore, EMA represents a scientific methodology for comprehending the dynamic nature of human behavior and experience in real-world environments, providing researchers with valuable insights into the complexities of human experience. Recent studies have provided comprehensive reviews of the application of EMA in studies on physical activities (Degroote et al., 2020), mental health (Yang et al., 2019), behaviors (Battaglia et al., 2022), and well-being (De Vries et al., 2021), indicating the advantages of EMA over traditional research design as well as challenges and limitations.

Recently, mobile technologies (e.g., handheld computers and smartphones) have been introduced to EMA data collection techniques, enabling a vast leap forward in EMA studies. The widespread adoption of mobile devices has enabled the synchronized and combined use of EMA data with other sources of data, such as passive sensor data (e.g., GPS, physiological monitoring, or accelerometer data) (Bertz et al., 2018). Recently, methods combining conventional EMA with geospatial data/approaches has also simultaneously gained in popularity, as it allows for the consideration of individuals' health and behavior outcomes of momentary exposures in spatial contexts (Chaix, 2018).

Recently, the terms geographic ecological momentary assessment and geospatially explicit EMA (GEMA) have been used repeatedly in research, but their scope and terminology remain ambiguous. Notably, although the combination of activity logs/self-reports and GPS tracking has been used for years in health geography, Epstein et al. (2014) first coined GMA to refer to the method of utilizing EMA with time-stamped GPS data. Independently, but around the same time (2013), Kirchner and Shiffman (2013) published a review on EMA methods in addiction research in which they recommended the integration of EMA within geographic information systems and further named it geospatially explicit EMA (GEMA) in 2016 (Kirchner and Shiffman, 2016). Later, Kowalczyk (2017) commented on the importance of the letter "E" in this acronym representing "explicit" in GEMA, and emphasized that such studies should not only simply add location data, but also contribute to the assessment of environment-momentary state relationships. Despite a recent surge of interest in GEMA, the definitions inherent to this approach remain unclarified.

In this review, we define "geographic ecological momentary assessment" as encompassing methods that integrate EMA and concurrent geospatial data to facilitate the assessment of contextual determinants of health and behavior. Despite this inclusive definition, this review aims to clarify the subtypes of GEMA research, including aims associated with collecting geospatial data, contributions of geospatial data to EMA sampling, and the technological approaches and limitations.

In summary, this systematic review aims to synthesize the methodological information from the studies that took advantage of GEMA to identify common research interests and implementation approaches and provide recommendations for future GEMA studies. Specific questions addressed in this study include: 1) What are the purposes and scope when using geographic approaches in EMA research on human health and behavior? 2) What are the unique contributions of GEMA to EMA sampling? 3) What are the methodological considerations and limitations regarding the use of the method integrating geographic methods and EMA?

2. Method

2.1. PECO framework and literature search

The protocol following the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines (Moher et al., 2009) was registered at the International Prospective Register of Systematic Reviews database (PROSPERO, register

ID: CRD42023387371). We conducted a rigorous systematic review according to a four-step process: identification, screening, eligibility, and inclusion.

We performed the study search on six electronic databases in January 2023: Web of Science, PubMed, EMBASE, PsycINFO, CINAHL, and Cochrane Library. These sources were selected to cover literature from a wide range of fields including public health, medicine, psychology and psychiatry, environmental science, and geography. The search captured articles from the inception of each database through to the search date. For inclusion criteria, first, we included studies that used EMA and geospatial data or methods. Secondly, we followed the population, exposure, comparator, and outcome (PECO) framework (Morgan et al., 2018).

GEMA: We included studies that explicitly use GMA, GEMA or describe their approaches as a combination of EMA and geospatial.

Population: We included studies reporting general human populations in all age groups, with or without pre-existing health conditions and behavior problems. Animal studies were excluded. We did not restrict it to specific geographical areas or sociodemographic characteristics.

Exposure: Any social and environmental factors that could affect human health and behaviors were considered exposure.

Comparators: A comparable population or repeated measures of the same population with different levels of exposure was necessary to assess the impacts on health and behaviors.

Outcome: Studies that investigated all types of health or behavioral outcomes captured by EMAs were included.

The search strategy was a combination of two major components: (1) the EMA method and (2) geographic methods. The exact terms describing the EMA methods were coupled with specific keywords identifying geographic technologies to capture all relevant studies. We developed search syntax and used wildcards to account for various forms of keywords. The search syntax used for different databases is available in Supplementary Material S1.

2.2. Study selection

After importing the retrieved articles into Endnote 20 and removing duplicates, we performed screening and eligibility procedures by examining the titles, abstracts, and full texts. Two of the three researchers made the selection decision for each record independently, with any disagreement resolved through discussion between themselves or consultation with the third researcher. The initial inter-researcher agreement was approximately 95%.

Studies were included in the review if they met all of the following criteria:

1. Study was a peer-reviewed article.

2. Study was written in English.
3. Study reported an empirical study on a human population.
4. Study assessed environmental (both physical and social) exposures.
5. Study included self-reported health and behavior outcomes via the EMA method.
6. Study included the application of geographic technology combined with the EMA method in methodology.

The search strategy and selection procedure guided by PRISMA (Moher et al., 2009) is presented in Fig. 1.

2.3. Data collection

We created a descriptive information spreadsheet in Microsoft Excel for data extraction and tabulation from the included studies. We extracted the following study characteristics into the descriptive information spreadsheet: author, citation details, publication year, study country, type of study design, population, population age, sample size, geographic method, EMA method, study result, and additional technologies for passively measured data. The geographic method category included check boxes for geographic technology, the device used for geographic data collection, mobile application, frequency/interval for data collection, and purpose for the usage of the geographic method. The EMA method category included attributes for the EMA sampling approach, frequency/interval of data collection, EMA monitoring duration, the device used for EMA reports, mobile application, mode of EMA response, outcomes measured by EMA, training, compliance, and incentive/compensation.

2.4. Risk of bias assessment

Given the methodological focus of this study, traditional quality assessment tools designed for observational and experimental studies were not applicable. Therefore, we developed a risk of bias assessment (RoB) rubric by adapting metrics and questions from the Office of Health Assessment and Translation (OHAT) Risk of Bias Rating Tool for Human and Animal Studies and the Joanna Briggs Institute (JBI) critical appraisal checklist (Moola et al., 2017; OHAT, 2019). In our RoB tool, 10 items involving five domains were considered: sampling bias, confounding bias, measurement bias, attrition bias, and selective reporting bias. Each item was answered with a four-point scale: definitely low risk, probably low risk, probably high risk, and definitely high risk. Three researchers independently rated a study and cross-checked the evaluations. Each study had an evaluation result agreed upon by all three researchers. Then, we averaged the scores of all items in each domain and rounded the value to generate the score of a domain. Finally, we presented RoB scores by item and domain, as this could uphold transparency and offer a more comprehensive representation of the methodological strengths and weaknesses of each individual article. In cases where a study referred to another publication containing relevant information about the same study, we reviewed the referenced publication to rate relevant items. Detailed RoB tool used in this study is presented in Supplementary Material S2.

3. Results

3.1. Literature search and selection results

The initial search process resulted in 957 publications. After removing duplicates, screening titles and abstracts, and reviewing full text, a total of 47 articles met all our inclusion criteria. Basic information was extracted from each study (Table 1), including publication year, the geographical distribution of the study area, study type, sample characteristics, and participant characteristics.

The earliest two articles were published in 2013. There was a steady growth in the number of publications from 2018 to 2022, with a surge of studies on this topic in 2021 (n = 10, 22.2%). Fig. 2 displays the yearly distribution of the studies. The vast majority of included research was observational studies (n = 45,95.7%), and only two (4.3%) (Beres et al., 2022; Kirchner et al., 2013) adopted experimental research designs. With respect to geographical distribution, most studies were conducted in North America (n = 28, 59.6%), followed by Europe (n = 10,21.7%), Asia (n = 6,12.8%), Australia (n = 1,2.1%), and Africa (n = 1, 2.1%).

Most included studies focused on adults (n = 19, 40.4%), ten (17.8%) focused on teens and young adults (e.g., 12–25), and three (6.4%) examined older middle-aged (50–65) and older adults (65+). While the majority of studies targeted healthy populations, 11 studies (23.4%) focused on patients with various clinical diagnoses, such as psychiatric disorders (e.g., mood disorder, schizophrenia, anxiety disorder, attention deficit hyperactivity disorder) (Bolte et al., 2019; Jacobson and Bhattacharya, 2022; McIntyre et al., 2021; Parrish et al., 2020) or physical health conditions (Mardini et al., 2021). Of them, three studies (6.4%) included clinical populations and healthy controls to compare differences between groups (Pellegrini et al., 2022; Raugh et al., 2020, 2021). The sample sizes of included studies varied between 10 and 21, 947 (mean = 586.7, sd = 3187.2).

3.2. Health outcomes measured through EMA

EMA offers versatility in acquiring self-reported measures related to health and behavior. Studies mostly used EMA to assess outcomes such as psychological health (e.g., Ben-Zeev et al., 2015; Jacobson and Bhattacharya, 2022) (n = 34, 72.3%), followed by psychoactive substance use (e.g., Kirchner et al., 2013; Lipperman-Kreda et al., 2020) (n = 12, 25.5%), eating and sleeping behavior (e.g., Pellegrini et al., 2022; Roy et al., 2019) (n = 10, 21.3%), social behavior (e.g., Cornwell and Goldman, 2020; Kamalyan et al., 2021; Pellegrini et al., 2022) (n = 9, 19.1%), environmental perception (e.g., Cornwell and Goldman, 2020; Kou et al., 2020) (n = 11, 23.4%), physical activity (e.g., Pellegrini et al., 2022; Raugh et al., 2020) (n = 6, 12.8%), physical and physiological health (e.g., Mardini et al., 2021) (n = 4, 8.5%), sexual behavior (i.e., sexual activity and condom use) (Beres et al., 2022; Wray et al., 2019) (n = 2, 4.3%), and medication adherence (Yerushalmi et al., 2021) (n = 1, 2.1%).

State mood, affect, and stress —transient or short-term psychological reactions to situations —are the most common outcomes of interest (Kondo et al., 2020; McIntyre et al., 2021; Xia et al., 2022). In addition, a few studies used EMA to capture fluctuations in physiological distress (i. e., pain and fatigue) or other physical symptoms, such as tinnitus, dizziness or light-headedness (Bolte et al., 2019).

Another application of EMA is to examine the rhythms and characteristics of behaviors, including eating, sleeping, substance use, and social behavior (MacKerron and Mourato, 2013; Raugh et al., 2020). Social interactions were also often included in EMA surveys as secondary outcomes or covariates related to the primary outcome. These include items asking about companions (Cornwell and Goldman, 2020), intensity of social interaction (Kamalyan et al., 2021), social interest (Pellegrini et al., 2022), and social avoidance (Jacobson and Bhattacharya, 2022).

In recent years, increasing attention has been given to using EMA in assessing perceived contextual characteristics. These measures include perceived exposure to food, tobacco, and alcohol marketing, ambient noise, and neighborhood disorders (Byrnes et al., 2017; Kowitt et al., 2021; Roy et al., 2019; Zhang et al., 2020). Occasionally, EMA was also used to gather information on participants' perceptions of surrounding populations (Wray et al., 2019) and the atmosphere of the setting (e.g., “romantic” and “formal”) (Labhart et al., 2020).

3.3. Purposes of GEMA

As the integration of geographic methods with EMA has emerged as an innovative approach for measuring subjects' health and behaviors in real-time, capturing current contextual characteristics, and understanding space-time patterns of exposure-outcome pairs (Boettner et al., 2019; Kanning et al., 2022). Both global positioning system (GPS) technology and GIS technology enable the detection of rich and complex spatial contexts to which humans are exposed (Mennis et al., 2017); meanwhile, GPS methods also allow the tracking of precise locations and exposure time and duration in such a context (Duncan et al., 2019). As such, 20 (42.6%) of the studies integrated GPS and GIS technologies to enrich the data describing the environments with which subjects interacted (Elliston et al., 2020; Kondo et al., 2020; Lipperman-Kreda et al., 2022; Rhew et al., 2022).

By incorporating geographic methods (i.e., GPS and GIS), multifold research purposes can be fulfilled:

I. *Enabling location-based EMA sampling*. Location technology enabled spatial sampling and surveys were triggered by geographic location changes or geofences (Koch et al., 2018; Shoval et al., 2018) (n = 7, 14.9%).

II. *Quantifying participants' mobility patterns*. Such studies used geographic locations to derive measures related to mobility and activity space, such as distance traveled, homestay duration, location variance, unique location clusters, and location entropy (variance of time spent in different clusters), through computation of GPS data (Kamalyan et al., 2021; Mardini et al., 2021) (n = 11, 23.4%).

III. *Deriving exposure variables*. Studies used geographic locations, along with publicly available GIS databases, to derive environmental or social characteristics of concurrent exposures. Such exposure variables included green space, land use, walkability score, neighborhood disorders, and ambient weather conditions (Bollenbach et al., 2022; Roy et al., 2019) (n = 19, 40.4%).

IV. *Describing spatial patterns of outcome variables*. Studies used this method to map subjects' spatial activity (Doherty et al., 2014) and emotional characteristics (Shoval et al., 2018) in urban environments (n = 4, 8.5%).

V. *Performing data linkage or triangulation*. Several studies used GPS data to verify the quality of other sensor data (Bolte et al., 2019) or self-reports (Crochiere et al., 2021; Tao et al., 2021). Another study employed GPS records to identify instances of co-location between participants and their partners during EMA surveys (Yerushalmi et al., 2021) (n = 1, 2.1%).

Some studies (n = 4, 8.5%) combined multiple of the use cases mentioned above to realize multifold aims (Bollenbach et al., 2022; Glasgow et al., 2019; Shoval et al., 2018; Tornros et al., 2016). Additionally, some studies (n = 5, 10.6%) merely exploited the features to record location coordinates without further analysis of the information (Labhart et al., 2020; Meyerhoff et al., 2021). Fig. 3 presents the purposes of geographic methods in EMA studies.

3.4. Traditional EMA sample and GEMA spatial sampling

Although existing literature has classified EMA sampling into two types according to the survey delivery method (i.e., signal-triggered or event-triggered), the two become less discernible when passive sensing is involved (e.g., using ambient or physiological sensors), during which an event is detected, and a signal sent. By the actual mechanism of the EMA trigger, we classify the sampling strategies used in studies reviewed into four primary sampling approaches: time-contingent (n = 37, 78.7%), location-contingent (n = 7,14.9%), event-contingent (n = 3, 6.4%), and other user-initiated (n = 11, 23.4%). Those basic methods were often combined and utilized in some studies; for example, the location-contingent method in combination with user-initiated strategy would enhance the validity of studies investigating drinking behavior (Wray et al., 2019), concurrent application of location-based and time-based methods would benefit the assessment of psychological health (Koch et al., 2020; Reichert et al., 2017), and integrating user-initiated methods with time-based and event-contingent approaches could facilitate the understanding of the tobacco use (McQuoid et al., 2018, 2019).

With respect to the primary categories, the first three are passive triggers, while the last is initiated by users based on any rule. A time-contingent sampling scheme is suitable for monitoring variations of a particular health or behavior outcome by triggering questionnaires on a predefined time window (Tornros et al., 2016), and achieved through fixed-time (Lipperman-Kreda et al., 2022), random-time (Parrish et al., 2020) or semi-random triggers (Crochiere et al., 2021). Both location-based and event-triggered sampling schemes rely on a sensor (e.g., GPS tracker or smartphone-embedded sensor) to detect the situation of interest in real-time (Koch et al., 2020; Reichert et al., 2017). Additionally, to capture data under specific events that may not be accurately sensed passively, user-initiated reports are used, requiring participants to register specific situations by themselves (Kanning et al., 2022; Tornros et al., 2016). A combination of different sampling approaches in a single study could advance unique research objectives for assessing health and behavior outcomes (Bollenbach et al., 2022; Koch et al., 2020; Raugh et al., 2021; Wray et al., 2019). Fig. 4 shows the descriptions of multiple sampling strategies.

The EMA surveys often assess participants' conditions "right now" to capture state affect or momentary behaviors (Crochiere et al., 2021; Seto et al., 2016), but they can also assess conditions retrospectively of short recall periods. For instance, the recall periods of various studies range from one day (Lipperman-Kreda et al., 2022; Wray et al., 2019) to one week (Beres et al., 2022).

Particularly, GEMA could enable location-contingent EMA sampling with sophisticated algorithms, allowing for the detection of participants' real-time locations and the release of EMA prompts. Two types of location-contingent EMA sampling have been used: geographic location change and geofencing. The location change-triggered EMA sampling approach detects participants' movement by triggering surveys when they move a specific distance (e.g., 500 m) away from their previous locations (Bollenbach et al., 2022; Koch et al., 2018, 2020; Reichert et al., 2017; Tornros et al., 2016). Other studies utilized geofencing-triggered surveys. For example, the survey can be triggered when the user enters and spends a certain amount of time within a specific area of interest (Shoval et al., 2018; Tornros et al., 2016; Wray et al., 2019).

3.5. Advancements in technology supporting GEMA

To date, advances in mobile technology have allowed mobile phones to be embedded with a GPS sensor to record accurate spatial data. Therefore, most studies (n = 41, 87.2%) used smartphones as a convenient device to collect data on geospatial information. A few studies (n = 5, 10.6%) also used a separate GPS logger to keep track of daily movement (Bolte et al., 2019; Epstein et al., 2014; Mitchell et al., 2014; Rhew et al., 2022; Roy et al., 2019), and only one (2.1%) study used a GPS-enabled smartwatch (Mardini et al., 2021). Of the studies using smartphone-based methods, most used mobile applications to facilitate GPS data logging and storage. To reduce participant burden, the majority of these studies (n = 22, 46.8%) used one particular application that collected both EMA and GPS data (Bollenbach et al., 2022; Doherty et al., 2014; Koch et al., 2020; Raugh et al., 2021; Sukei et al., 2021), and only a few (n = 4, 8.5%) used separate applications to acquire EMAs and GPS information (Crochiere et al., 2021; Jacobson and Bhattacharya, 2022; Kamalyan et al., 2021; Parrish et al., 2020). Table 2 shows the characteristics of mobile applications used in these studies.

Among the selected studies, 22 (46.8%) studies also utilized additional smartphone-embedded or portable sensors for other measures. The use of additional sensors can strengthen human-environment assessment, allowing environmental exposure variables to be assessed and controlled, and outcomes to be simultaneously measured and modeled statistically. As such, combining GEMA with passive sensing can reduce users' workload while encouraging the collection of diverse data to enrich the descriptions of real-time behaviors. Furthermore, passive sensing data has improved the reliability of the detection and contributed to research on health and behavior in GEMA studies by incorporating objective measures from a variety of sensors. Assorted types of objective measures are identified in Table 3.

3.6. Risk of bias

Fig. 5 presents the results of the risk of bias assessment. The individual scores for each item are provided in Supplementary Material S3 Figs. S3–1. The major bias concerns in included studies are related to confounding factors, exposure/outcome measurement, and missing data (Supplementary Material S3 Figs. S3–2). Regarding confounding bias, most studies considered time-invariant factors associated with participants' demographic characteristics, such as age and sex, as well as timevariant factors, such as hours of the day, while those that did not adjust for any confounders were deemed to have a probably high risk of bias. In addition, those studies in the review that only reported descriptive statistics to interpret data were not rated for the performance of confounding factors due to their inapplicability. In the measurement bias domain, studies that utilized invalidated assessment tools by EMA application were considered to have a probably high risk of bias. Furthermore, studies that did not provide adequate information on GPS settings related to GPS accuracy were also graded as having a probably high risk of bias. For missing data, each study should report evidence of whether there was a loss of subjects during the study and whether outcome data were complete. Studies that did not mention whether missing data existed were rated as a probably high risk of bias. Studies that acknowledged missing data but failed to indicate how to address it were considered to have a probably low risk of bias. Studies were considered to have a definitely low risk of bias if they reported no missing data or if they reported missing data with descriptions and justifications of approaches to handling it.

4. Discussion

4.1. Main findings

The GEMA method has become a cutting-edge technique for monitoring individuals' real-time health and behaviors. This approach combines EMA with GPS and GIS technologies to capture current contextual characteristics and identify spatiotemporal patterns in exposure-outcome relationships, offering valuable insights into the complex dynamics of health and behavior. As the first methodological review of GEMA, this study clarified the definition and scope of GEMA, summarized its type of application in public health research, and synthesized important issues related to technology use and challenges.

GEMA studies have used geospatial technologies to achieve a diverse set of research aims that include: 1) enabling location-based EMA sampling, 2) quantifying participants' mobility patterns, 3) deriving exposure variables, 4) describing spatial patterns of outcome variables, and 5) performing data linkage or triangulation. Furthermore, it is worth noting that the GEMA technique takes advantage of geographic methods to advance traditional EMA sampling methods. Specifically, in the location-contingent EMA sampling strategy, EMA prompts are triggered by detecting geographic location changes or entering/staying/exiting predefined geofences, increasing the ecological validity of data collection in naturalistic settings. Advances in mobile technologies have allowed mobile phones to be equipped with multiple functions due to various embedded sensors (e.g., GPS, accelerometers, and microphones).

Overall, GEMA is a versatile technique used to acquire self-reported measures associated with health and behavior. Studies included in this review have revealed a wide range of GEMA applications in a variety of outcomes, including psychological health, physical and physiological health, psychoactive substance use, medication adherence, eating and sleeping behavior, sexual behavior, social behavior, environmental perception, and physical activity. The most common outcome of interest is psychological health (e.g., mood, affect, depression, stress, and anxiety) and the rhythms and characteristics of physical behaviors. In those studies, social behaviors (e.g., social interaction) were often included in GEMA surveys as secondary outcomes or covariates related to primary outcomes. In addition, GEMA is also an ideal approach to compare the subjectively perceived contextual characteristics with the objectively measured ones.

4.2. Important methodological considerations

Despite the growing interest in using the GEMA approach and sensor networks in public health, methodological concerns that affect the validity and reliability of such research need to be examined and carefully addressed. In this section, we summarize these concerns and potential solutions and discuss future directions of GEMA studies.

Disclosing and improving GEMA compliance.—As repeated measures of EMA and the use of apps/sensors may increase user burden compared to traditional survey approaches, addressing compliance in the research design phase is critical. In the GEMA studies, the statistical power of a study is not only related to the number of participants but also to the number of EMA responses from participants. In our review, only 16 (35.6%) of the studies reported a measure of compliance, and the average compliance rate was 80.5%. Reported compliance rates varied between studies ranging from 50% to 98.7%. Strategies aimed at enhancing compliance could involve reduced study duration or frequency of EMA prompts (Colombo et al., 2019), proper training sessions (De Vries et al., 2021), ongoing compliance monitoring, and incentives (Heron et al., 2017). In our reviewed GEMA studies, we observed that the studies with higher compliance rates generally reported training processes and compensation for participation, as well as lower frequencies of prompts, typically around 4–7 per day. However, the previous review of smartphone-based EMA studies indicated no link between compliance level and incentives (De Vries et al., 2021). Further, a meta-analysis of EMA protocol compliance in substance use studies did not find a significant association between prompt frequency and compliance rate (Jones et al., 2019). More methodological studies examining the effects of study duration, sampling strategies, training, and compensations on compliance are warranted. Empirical studies using GEMA should utilize strategies to improve adherence to distinguish the actual effect of environmental exposure accurately and validly on health and behavior outcomes.

Protecting privacy and confidentiality associated with geographic location data.—Because GEMA studies use spatial information on individuals, protection of privacy and confidentiality should be a critical consideration. In reviewed studies, 31 (68.9%)

studies reported obtaining institutional review board approval for the research; however, the majority did not describe data management and security measures, especially the ones using customized platforms for data collection. Several studies mapped out example participant trajectories without mentioning whether locations have been adjusted for confidentiality purposes. Other studies reported aggregated geospatial characteristics but did not mention whether small counts were suppressed or addressed.

Sampling based on environmental exposure.—GEMA provides an important way of sampling the various levels of environmental exposure that exhibit geographical changes. By combining GEMA with other sensors or sampling approaches, more complex sampling schemes can be created to account for the space-time dynamics of behavior and health. It is worth noting, however, that a few studies have directly sampled environmental conditions through triggers set off by continuous sensor data streams. For example, studies used accelerometers and exposimeter sensors to capture the moments of transient events (Dunton et al., 2016; van Wel et al., 2017) following the Context-Sensitive Ecological Momentary Assessment (CS-EMAs). In this review, a few studies combined GPS with sensor information, but only four used it to sample behavioral outcomes (Crochiere et al., 2021; Jacobson and Bhattacharya, 2022; Pellegrini et al., 2022; Sukei et al., 2021). Future studies integrate GPS with environmental sensors as a sampling strategy, as controlling over levels of independent variables typically allows better internal validity than over outcome variables.

Improving measurement validity.—Studies with GEMA have utilized validated scales such as the RAND 36-Item Health Survey for general health status (Hays et al., 1993), the Patient Health Questionnaire (PHQ-9) for depression symptoms (Kroenke et al., 2001), or the positive and negative affect schedule (PANAS) for subjective feelings (Watson et al., 1988), to assess the physical and mental health conditions. However, some instruments in their original forms are not suitable for GEMA methodologies because of the typical look-back periods and therefore need to be adapted or calibrated; for example, the PHQ-9 asks about major depressive symptoms in the past two weeks (Kroenke et al., 2001), might not be appropriate for momentary assessment or daily diaries. Additionally, in studies with GEMA, the length of questionnaires is typically restricted; nevertheless, the validity of scales, especially psychometric scales, should not be compromised. But many studies often used single-item questions or items not validated for outcomes such as affect, stress, food intake, or substance use. Therefore, as GEMA and other methods of repeated measures become prevalent, the importance of scale validity should not be neglected. Also, the existing scales need to be adapted for GEMA studies, and in certain circumstances, the development of short versions of existing scales would be necessary.

Mobile applications and technologies for GEMA research.—In the reviewed studies, mobile applications can be categorized into two types: 1) commercial/open-source applications and 2) customized applications. Commercial off-the-shelf applications (e.g., MoviSens and Daynamica) offer features such as GPS tracking, geofencing, EMA prompts, data storage, data visualization, and additional passive sensors (Reichert et al., 2017; Tornros et al., 2016). However, they may suffer limitations such as poor customizability, higher cost, and data ownership and privacy concerns. Custom-developed applications may be a choice for investigators in GEMA research to overcome these defects, although the development, testing, and deployment may be a lengthy process that requires cross-disciplinary collaboration and user experience may not be optimized without professional interface designs. The advancement in artificial intelligence (AI) offers potential for scene understanding and health symptom/episode detection. For example, digital biosensing technologies have been utilized in discerning mood and emotion, and detecting the onset and duration of various episodes for populations with mental and developmental disorders (Albinali et al., 2009; Osmani, 2015; Torrado et al., 2017). With the wide application of generative AI technologies, GEMA approaches could incorporate more computing to gain more interactivity.

Optimizing GPS accuracy and geocomputing for missing data.—GPS accuracy varies based on the hardware and software, as well as environmental conditions. However, many studies reported using apps without reporting the precision, reliability, or missingness of the GPS devices. Studies generally noted a trade-off between obtaining high geospatial resolution and maintaining manageable data volume/preserving battery life when using continuous high-frequency GPS logging (Krenn et al., 2011). In the reviewed studies, 28 (59.6%) indicated the time interval programmed for GPS receivers. There was wide variability among intervals set in different studies, ranging from every second to 4–6 h (mean = 18.0 min, sd = 10.7). Furthermore, phone type (i.e., IOS and Android) would influence the accuracy of geographic location measurements given that the strategies applied for location geotracking of both platforms might be different (Elevelt et al., 2021). Also, it is noteworthy that the accuracy of GPS receivers may vary across different environmental conditions. In areas with high atmospheric refraction, dense tree canopy, or buildings, communication with satellites would be attenuated, resulting in increased incidences of missing data or positional errors (Schipperijn et al., 2014). Errors in satellite-receiver synchronization and errors in ephemeris information on satellite position may also lead to inaccuracies (Osmani, 2015). Pretesting and recording GPS and geofencing accuracy is highly recommended for future studies examining health and behavior outcomes to assess and reduce bias in GEMA studies. Geographic imputation approaches could be utilized to address missing locational or activity space data (Osmani, 2015).

Analyzing time-variant variables and relationships.—GEMA not only supports geospatial characterization, but also allows higher temporal resolution and data linking. As Kirchner et al. recommended (Kirchner and Shiffman, 2013), the passage of time can be treated as the dependent variable or a dimension along with other factors vary. Repeated measures approaches, survival models, and time series methods could be applied to GEMA data, with attention to differences in sampling frequencies, and conducting resampling/interpolation. Cumulative exposure may play a stronger role than momentary exposure for many phenomena, and therefore the analysis should consider exposure-lag-response associations (e.g., with distributed lag models) or time-to-event models (e.g., Cox proportional hazards models) (Kirchner and Shiffman, 2013). In other scenarios, the trajectory or specific sequence of exposure may be related to the outcomes, and advancements in time fragmentation and sequence analysis can contribute to such assessments (Shi et al., 2022).

4.3. Limitations of the present study

It should be acknowledged that the current review has several limitations. Firstly, our search syntax covered a variety of terms used for GEMA and similar approaches (e.g., ecological momentary assessment, experience sampling, ambulatory assessment), but there are other similar approaches that have not been considered (e.g., diary-related methods). Despite the different terms, these studies often share similar methodologies of sensor use and geospatial integration. Secondly, we specified that the study has to present data related to our PECO guideline in order to be included, therefore, proof of concept studies and protocol papers without empirical data were not included. Nevertheless, these studies may have also addressed important issues (Bruening et al., 2016; Fore et al., 2020; Poelman et al., 2020) Thirdly, as a methodological review, this study did not consider a meta-analysis to quantify the association of the GEMA method performance with the study characteristics and examine the factors that could affect the successful application of GEMA in public health research. Finally, although our review included all studies assessing health and behavior outcomes, we did not clarify the specific characteristics of the GEMA approach applied in each field (e.g., mental health, physical activity, or eating behavior) and distinguish the potential differences of key factors in different fields. As the use of GEMA continues to grow, future studies should pay attention to identifying the strengths and weaknesses of the GEMA method in distinct research areas and the particular contributions in different research, thus providing recommendations and suggestions for continuous improvement in the GEMA methods.

5. Conclusion

With the incorporation of mobile technologies into EMA studies and the promotion of geospatial and contextual data in the field of public health, a comprehensive investigation of GEMA research in public health would facilitate a better understanding of the scope, research methods, and implementation approaches, and provide recommendations for future GEMA studies. Based on the PRISMA framework, this systematic review synthesized the methods and applications of GEMA research on human health and behavior, especially the unique contributions of GEMA to conventional EMA sampling. Particularly, location-contingent sampling strategies (i.e., geographic location change and geofencing) enable the release of EMA prompts based on the detection of participants' real-time locations. Notably, besides spatial data recorded by a GPS sensor, GEMA was often combined with other objectively-measured data to encourage the collection of diverse data to enrich the description of subjects' real-time behaviors. Our summary of all mobile applications and their characteristics for GEMA would also provide references for future study. Finally, our review raised methodological considerations in advancing this area of research, involving GEMA compliance, privacy and confidentiality of geospatial data, sampling strategies, measurement validity, development of mobile applications, GPS accuracy and missing data, and time-variant measures in GEMA.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Data availability

No data was used for the research described in the article.

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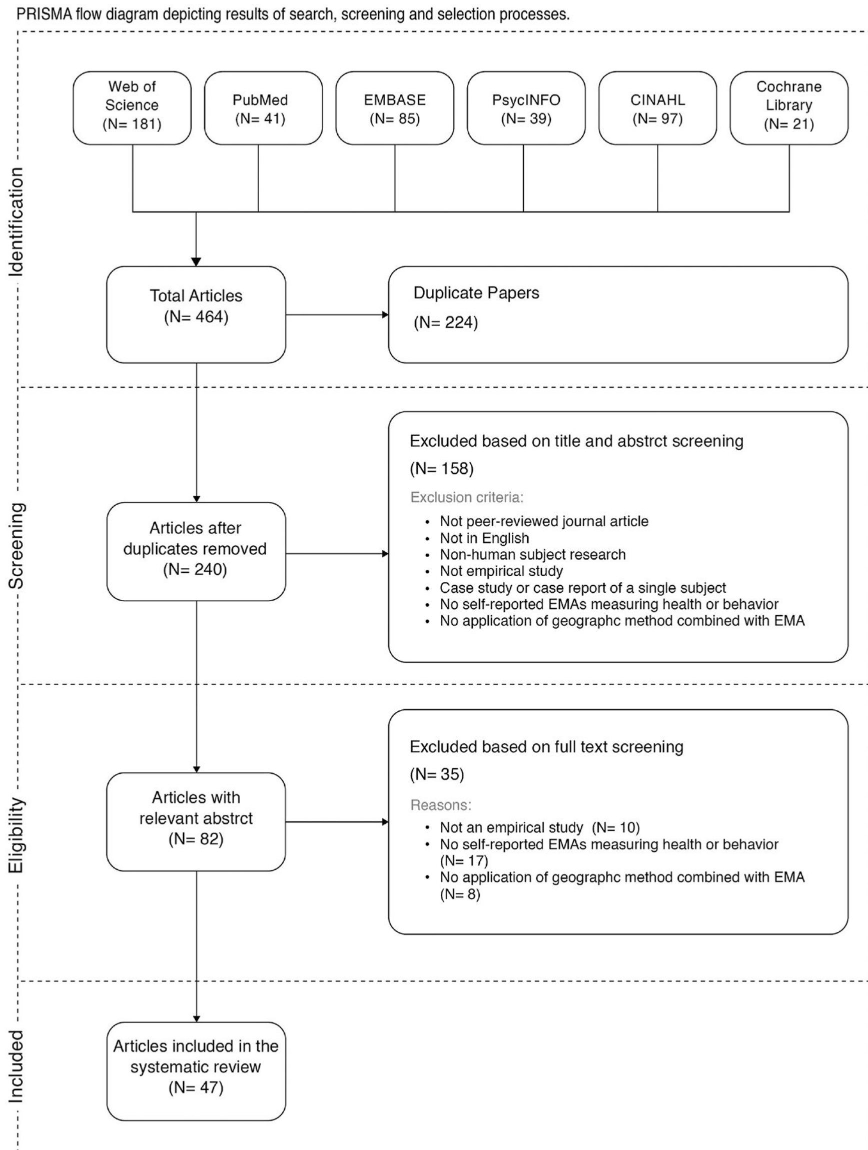

Fig. 1.

PRISMA flow diagram depicting the process of identification, screening, eligibility, and inclusion.

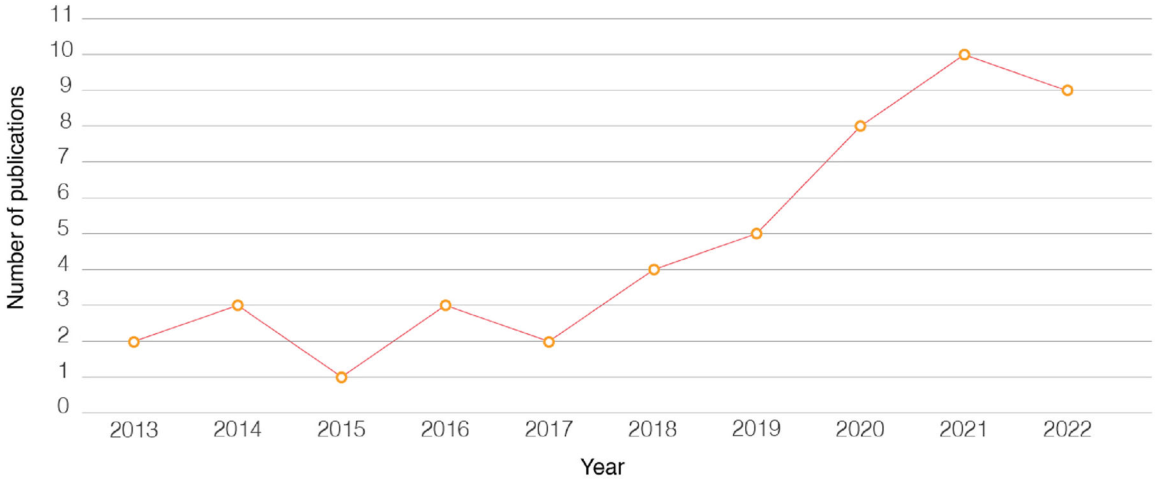

Fig. 2.

Number of GEMA studies published by year.

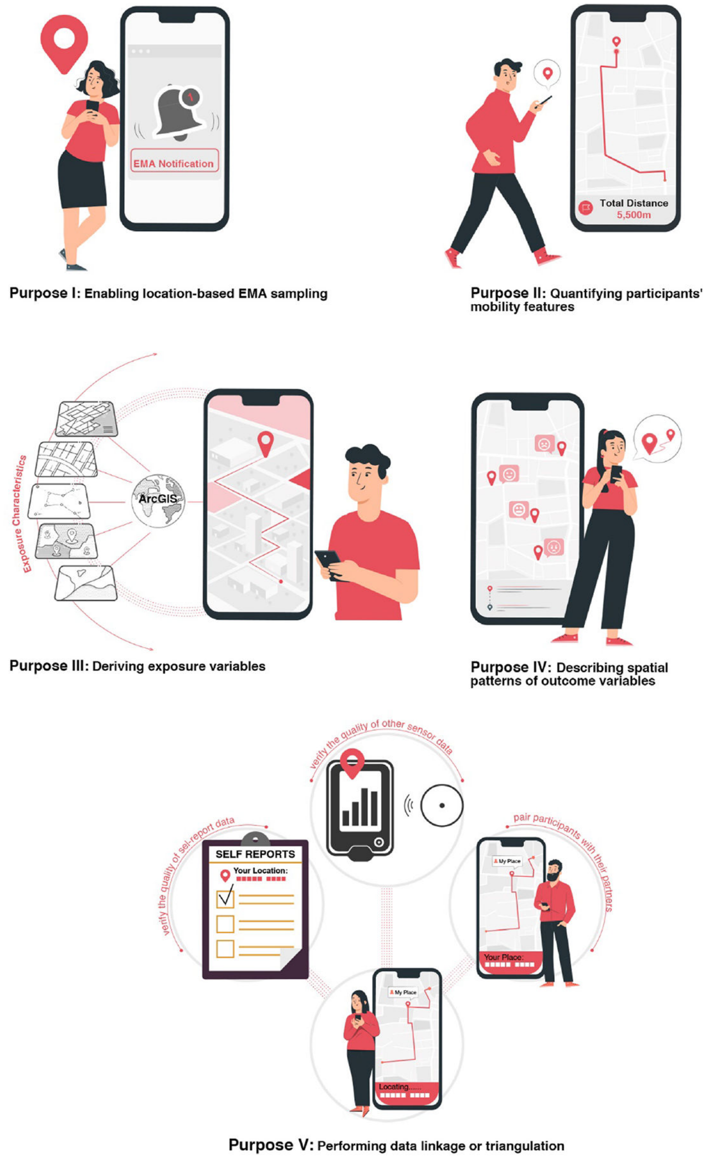

Fig. 3.

Purposes of utilizing geographic methods in GEMA studies.

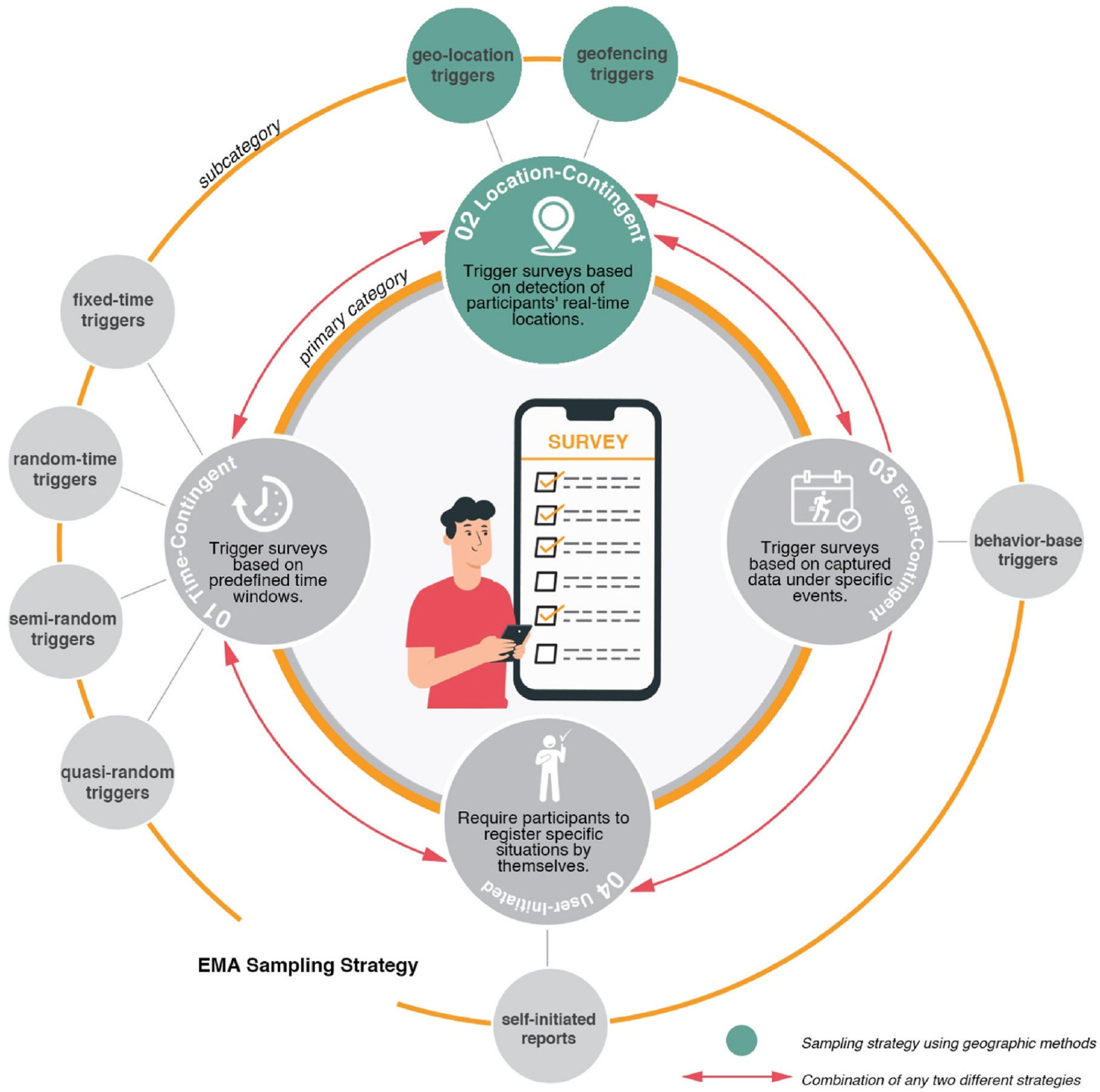

Fig. 4.
Multiple sampling strategies.

Study	Selection bias	Confounding bias	Measurement bias	Attrition bias	Selective reporting bias
Ben-Zeev et al., 2015	++	++	+	++	++
Beres et al., 2022	++	-	+	+	++
Bollenbach et al., 2022	++	++	+	++	++
Bolte et al., 2019	++	++	++	++	++
Byrnes et al., 2017	++	++	+	-	++
Cornwell & Goldman, 2020	++	++	+	+	++
Crochiere et al., 2021	++	-	+	++	++
Doherty, Lemieux, &Canally, 2014	++	NA	+	+	++
Elliston, Schuz, & Ferguson, 2020	++	-	+	++	++
Epstein et al., 2014	++	-	+	-	++
Glasgowet al., 2019	++	-	+	++	++
Jacobson & Bhattacharya, 2022	++	++	++	++	++
Kamalyan et al., 2021	++	++	++	-	++
Kirchner et al., 2013	++	++	++	+	++
Koch et al., 2018	++	++	+	++	++
Koch et al., 2020	++	++	+	++	++
Kondo et al., 2020	+	++	+	++	++
Kou et al., 2020	++	++	+	++	++
Kowitt et al, 2021	++	++	+	++	++
Labhart et al., 2020	++	-	-	+	++
Lipperman-Kreda et al., 2020	++	++	+	++	++
Lipperman-Kreda et al., 2022	++	++	+	++	++
MacKerron & Mourato, 2013	++	++	+	++	++
Mardini et al., 2021	++	++	++	+	+
McIntyre et al., 2021	++	-	+	-	+
McQuoid, Thrul, & Ling, 2018	++	-	+	-	++
McQuoid et al., 2019	++	-	+	-	++
Mennis et al., 2016	++	++	+	++	++
Meyerhoff et al., 2021	++	-	-	++	++
Mitchell et al., 2014	++	NA	++	+	++
Parrish et al., 2020	++	-	+	++	++
Pellegrini et al., 2022	+	++	++	++	++
Raugh et al., 2020	++	++	++	++	++
Raugh et al., 2021	++	-	++	-	++
Reichert et al., 2017	++	-	+	+	++
Rhew et al., 2022	++	-	++	+	+
Roy et al., 2019	++	++	++	+	++
Seto et al., 2016	++	++	+	++	++
Shoval, Schvimer, & Tamir, 2018	++	NA	+	-	++
Su et al., 2022	++	++	+	++	++
Sukei et al., 2021	++	++	+	++	++
Tao et al., 2021	++	++	+	++	++
Tornros et al., 2016	++	-	+	++	++
Wray et al., 2019	++	++	-	+	++
Xia et al., 2022	++	++	+	++	++
Yerushalmi et al., 2021	++	-	+	+	++
Zhang et al., 2020	++	++	+	++	++

Judgement:

++ Definitely Low

+ Probably Low

- Probably high

-- Definitely High

NA Not Applicable

Fig. 5.

Risk of bias assessment results.

Table 1

Study characteristics (N = 47).

	Citation	Participants' Characteristics		Geographic Method			Ecological Momentary Assessment						Other Passively Sensor-Based Data	Research Objectives
		Population	Sample size	Technology	Device	Purpose	Sampling method	Frequency/ Interval	Monitoring duration	Device	Mobile APP	Outcome measures		
1	Ben-Zeev et al., 2015; Ben-Zeev et al., 2015)	College students: A cohort of undergraduate and graduate students recruited through class announcements	47 persons	GPS	Mobile phone	Deriving activity's space/space time characteristics; Quantifying participants' mobility	Random-time	NR	10 weeks	Mobile phone	Unspecified	Stress	Physical activity pattern, smartphone communication pattern	Examine the relationship between Daily Stress (outcome) and several covariates derived from smartphone sensing-Geospatial Activity, Kinesthetic Activity, Speech Duration, and Sleep Duration.
2	Beres et al., 2022; Beres et al. (2022)	General population aged 18+: A cohort of adult participants from the Rakai Community Cohort Study (RCCS)	48 persons	GPS	Mobile phone	Recording location coordinates without further analysis	Fixed-time, Random-time, User-initiated	2/day, 1/ week	90 days	Mobile phone	Unspecified	Food intake, Alcohol use, Smoking, Sexual activity, Condom use	None	Examine the feasibility and acceptability of EMA and the feasibility of geospatial data collection.
3	Bollenbach et al., 2022; Bollenbach et al. (2022)	General population aged 18+: A cohort of population living in a (sub)-urban residential areas in Germany	46 persons	GPS, GIS	Mobile phone	Deriving environmental exposure; Triggering EMA surveys	Event-contingent, location-change	5/day	9 days	Mobile phone	movisensXS	Affective states, Social interaction	Physical activity pattern	Examine associations between social- and physical environmental factors and affective states during walking episodes.
4	Bolte et al., 2019; Bolte et al. (2019)	General population: A cohort of participants who were self-declared electrosensitive	57 persons	GPS	GPS logger	Interpreting and checking the quality of the sensor data	Random-time	A 2- or 3-h interval	5 days	Mobile phone	Unspecified	Physical symptoms, Stress, Cognitive deficit in attention	Environmental condition	Examine association between the measured exposure to radiofrequency electromagnetic

	Citation	Participants' Characteristics		Geographic Method		Ecological Momentary Assessment							Other Passively Sensor-Based Data	Research Objectives
		Population	Sample size	Technology	Device	Purpose	Sampling method	Frequency/ Interval	Monitoring duration	Device	Mobile APP	Outcome measures		
		all over the Netherlands												fields and nonspecific physical symptoms.
5	Byrnes et al., 2017; Byrnes et al., 2017	Teens aged 14–16: A cohort of teens in a longitudinal study (the Healthy Communities for Teens study) and from 10 cities in the San Francisco, CA area in U.S.	170 persons	GPS, GIS	Mobile phone	Deriving environmental exposure	Random-time	2/day	1 month	Mobile phone	NR	Alcohol use, other problem behaviors	None	Examine the relationships between observed and objective indicators of contextual risks, and the relations of indicators of contextual risks with teen alcohol use and problem behavior.
6	Cornwell and Cagney (2020); Cornwell and Goldman (2020)	General population aged 55+: A cohort of older adults in the Realtime Neighborhoods and Social Life Study (RNSLS)	61 persons	GPS, GIS	Mobile phone	Deriving environmental exposure	Random-time	4/day	1 week	Mobile phone	Survey Swipe	Pain, Fatigue, Affect, Stress, Sense of safety, Social interaction	None	Examine the relationships between observed and objective indicators of contextual risks, and examine the relationships between observed and objective indicators of contextual risks with teen alcohol use and problem behavior.
7	Crochiere et al. (2021); Crochiere et al. (2021)	Adults with obesity aged 18–70: A cohort of adults reporting BMI 25 50 kg/m2	15 persons	GPS	Mobile phone	Creating a geographic location pair by linking the GPS coordinates with spatial data reported by EMA	Semirandom-time, User-initiated	6/day	6 weeks	Mobile phone	Paco	Dietary lapse	Physical activity pattern, Sleep pattern	Compare the burden and accuracy of commercially available sensors (i. e., GPS, (accelerometer) versus

	Citation	Participants' Characteristics		Geographic Method		Ecological Momentary Assessment							Other Passively Sensor-Based Data	Research Objectives
		Population	Sample size	Technology	Device	Purpose	Sampling method	Frequency/ Interval	Monitoring duration	Device	Mobile APP	Outcome measures		
														established EMA in dietary lapse prediction.
8	Doherty et al., 2014; Doherty et al., 2014)	General population: A group of visitors to the Pinery Provincial Park in Canada	72 persons	GPS	Mobile phone	Mapping participants' spatial activity	Random-time, User-initiated	An interval of 35 min plus a random number	1 day	Mobile phone	Unspecified	Mood/ Emotion	None	Demonstrate how passive tracking of human activity using GPS/ accelerometers can be combined with ESM to explore the perceived health and well-being impacts of contact with nature.
9	Elliston et al., 2020; Elliston et al., (2020)	General population aged 18+: A cohort of participants recruited by looking at everyday food choices through social media advertising and a university staff newsletter in Tasmania	79 persons	GPS, GIS	Mobile phone	Deriving environmental exposure	Random-time	5/day	2 weeks	Mobile phone	Unspecified	Mood, Food and drink intake, Food craving	None	Compare the subjective and GIS assessments of the momentary food environment and assess the feasibility of using GIS data to predict eating behavior and inform geofenced interventions.
10	Epstein et al., 2014; Epstein et al., 2014	Outpatients aged 18–65: A cohort of outpatients admitted for methadone maintenance at a research clinic in Baltimore, MD	27 persons	GPS, GIS	GPS logger	Deriving environmental exposure	Random-time	3/day	16 weeks	PalmPilot	Unspecified	Mood, Stress, Drug craving	None	Examine the relationship between the neighborhood surroundings and mood and behavior in drug misusers.

	Citation	Participants' Characteristics		Geographic Method		Ecological Momentary Assessment							Other Passively Sensor-Based Data	Research Objectives
		Population	Sample size	Technology	Device	Purpose	Sampling method	Frequency/ Interval	Monitoring duration	Device	Mobile APP	Outcome measures		
11	Glasgow et al., 2019; Glasgow et al. (2019)	General population aged 18+: A cohort of population living in three metropolitan areas in U.S	229 persons	GPS, GIS	Mobile phone	Deriving environmental exposure	User-initiated	NR	1 week	Mobile phone	Daynamica	Mood, Physical activity	None	Explore the relationship between mood during travel and transport modes, activity, and the built and natural environments.
12	Jacobson and Bhattacharya, 2022; Jacobson and Bhattacharya (2022)	College students with clinical anxiety disorder symptoms: A cohort of students from a psychology subject pool	32 persons	GPS	Mobile phone	Deriving environmental exposure	NR	A 1-h interval	1 week	Mobile phone	Mood Triggers	Anxiety, Depression, Behavioral avoidance	Physiological outcomes, smartphone communication pattern, Environmental condition	Predict future anxiety symptoms among a sample reporting clinical anxiety disorder symptoms by using smartphone sensor-based data and personalized deep learning models.
13	Kamalyan et al., 2021; Kamalyan et al. (2021)	Patients aged 50+: A cohort of patients from a participant pool at the University of California San Diego (UCSD) HIV Neurobehavioral Research Program (HNRP) or through the community (HIV clinics, flyers, and community centers)	88 persons	GPS	Mobile phone	Quantifying participants' mobility	Unspecified	4/day	2 weeks	Mobile phone	NR	Mood, Fatigue, Pain, Social interaction	None	Examine real-time relationships between life-space, mood, fatigue, and pain, and assess the moderating effect of social interactions on the effect of life-space on mood.
14	Kirchner et al., 2013;	Smokers aged 18+: A cohort of smokers who	475 persons	GPS, GIS	Mobile phone	Deriving environmental exposure	Random-time, User-initiated	3–4/day	1 month	Mobile phone	mEX system	Craving to smoke,	None	Examine the association between the

	Citation	Participants' Characteristics		Geographic Method		Ecological Momentary Assessment							Other Passively Sensor-Based Data	Research Objectives
		Population	Sample size	Technology	Device	Purpose	Sampling method	Frequency/ Interval	Monitoring duration	Device	Mobile APP	Outcome measures		
	Kirchner et al., 2013	lived in Washington DC (DC) and contacted the DC Tobacco Quitline (DCQL)										smoking status		real-time geospatial exposure to point-of-sale tobacco (POST) and subjective craving to smoke.
15	Koch et al., 2018; Koch et al., 2018	General population aged 12–17: A cohort of Adolescents from the URGENCY study (Impact of Urbanicity on Genetics, Cerebral Functioning and Structure and Condition in Young People) in Germany.	113 persons	GPS	Mobile phone	Triggering EMA surveys	Fixed-time, location-change	4–7/day, 8–17/day	1 week	Mobile phone	movisensXS	Mood	Physical activity pattern	Investigate the association of mood with non-exercise activity in adolescents.
16	Koch et al., 2020; Koch et al., (2020)	General population aged 12–17: A cohort of Adolescents from the URGENCY study (Impact of Urbanicity on Genetics, Cerebral Functioning and Structure and Condition in Young People) in Germany.	134 persons	GPS	Mobile phone	Triggering EMA surveys	Random-time, location-change	4–7/day	1 week	Mobile phone	movisensXS	Mood	Physical activity pattern	Investigate the association of mood incidental activity, exercise activity, and sports in adolescents.
17	Kondo et al., 2020; Kondo et al. (2020)	General population aged 18–75: A cohort of participants from the PHENOTYPE (The Positive Health Effects	368 persons	GPS, GIS	Mobile phone	Deriving environmental exposure	Random-time	NR	1 week	Mobile phone	CalFit	Mood	Physical activity pattern	Examine the association between mood and exposure to green space.

	Citation	Participants' Characteristics		Geographic Method		Ecological Momentary Assessment							Other Passively Sensor-Based Data	Research Objectives
		Population	Sample size	Technology	Device	Purpose	Sampling method	Frequency/ Interval	Monitoring duration	Device	Mobile APP	Outcome measures		
		on the Natural Outdoor environment in Typical Populations) project												
18	Kou et al., 2020; Kou et al. (2020)	General population aged 18–60: A cohort of population residing Meiheyuan community for over 1 year in Beijing, China	101 persons	GPS	Mobile phone	Deriving activity space/ space time characteristics; Validating and correcting the data of participants' activity-travel dairies	Fixed-time	4/day	2 days	Mobile phone	NR	Stress, Environmental perception	None	Examine the relationships among contextual effects, momentary measured noise, perceived noise, and psychological stress.
19	Kowitt et al., 2021; Kowitt et al. (2021)	General population aged 16–20: A cohort of youth in California city areas	83 persons	GPS, GIS	Mobile phone	Deriving environmental exposure	Fixed-time	1/day	2 weeks	Mobile phone	Unspecified	Cigar use, Environmental perception	None	Examine associations between perceived and objective exposure to tobacco marketing and cigar use.
20	Labhart et al., 2020; Labhart et al. (2020)	General population aged 16–25: A cohort of population in the nightlife districts of the two major nightlife hubs in Switzerland, Lausanne, and Zurich	241 persons	GPS	Mobile phone	Recording location coordinates without further analysis	Fixed-time, Random-time	2/day	1 week	Mobile phone	Youth@Night	Drinking behaviors, Environmental perception	Physical activity pattern, Smartphone communication pattern, Smartphone usage	Describe a smartphone application developed to document young adults' nightlife and drinking behaviors and investigate the impact of this application on participants' lives.
21	Lipperman-Kreda et al., 2020; Lipperman-	General population aged 16–20: A cohort of youth in	100 persons	GPS, GIS	Mobile phone	Deriving environmental exposure	Fixed-time	1/day	2 weeks	Mobile phone	Unspecified	Smoking	None	Examine whether daily exposure to tobacco outlets within activity

	Citation	Participants' Characteristics		Geographic Method		Ecological Momentary Assessment							Other Passively Sensor-Based Data	Research Objectives
		Population	Sample size	Technology	Device	Purpose	Sampling method	Frequency/ Interval	Monitoring duration	Device	Mobile APP	Outcome measures		
	Kreda et al. (2020)	California city areas												spaces is associated with cigarette smoking and with the number of cigarettes smoked by youth that day.
22	Lipperman-Kreda et al., 2022; Lipperman-Kreda et al. (2022)	General population aged 16–20: A cohort of youth in California city areas	100 persons	GPS, GIS	Mobile phone	Deriving environmental exposure	Fixed-time	1/day	2 weeks	Mobile phone	Unspecified	Tobacco and cannabis use and co-use, Environmental perception	None	Investigated the association of tobacco and cannabis use and co-use with youth daily activity spaces, travel patterns, and exposure to tobacco retail marketing.
23	MacKerron and Mourato 2013; MacKerron and Mourato 2013	General population: A cohort of participants recruited by coverage in traditional and social media	21947 persons	GPS, GIS	Mobile phone	Deriving environmental exposure	Random-time	2/day	6 months	Mobile phone	Mappiness	Happiness, Physical activity, Social interaction	None	Explore the relationship between happiness and individuals' immediate environment.
24	Mardini et al., 2021; Mardini et al. (2021)	Patients aged 65+: A cohort of older adults with knee osteoarthritis	19 persons	GPS	Smartwatch	Quantifying participants' mobility	Random-time	3/day	NR	Smartwatch	ROAMM	Pain	None	Examine the temporal association between ecological momentary assessments of pain and GPS metrics in older adults with symptomatic knee osteoarthritis.
25	McIntyre et al., 2021; McIntyre et al. (2021)	Patients aged 18–65: A cohort of adults diagnosed with Major	200 persons	GPS	Mobile phone	Quantifying participants' mobility	NR	NR	90 days	Mobile phone	mind.me	Depression	None	Validate the accuracy of the mind.me application for the assessment

	Citation	Participants' Characteristics	Geographic Method			Ecological Momentary Assessment							Other Passively Sensor-Based Data	Research Objectives
		Population	Sample size	Technology	Device	Purpose	Sampling method	Frequency/ Interval	Monitoring duration	Device	Mobile APP	Outcome measures		
		Depressive Disorder by a healthcare provider												of depressive symptoms in adults.
26	McQuoid et al., 2018; McQuoid et al., 2018	Young adults aged 18–26: A cohort of young adult bisexual smokers in a larger GEMA study	17 persons	GPS, GIS	Mobile phone	Mapping participants' spatial activity	User-initiated, Random-time	3/day	30 days	Mobile phone	PiLR Health	Smoking, Cigarette craving, Mood, Environmental perception	None	Investigate participants' spatial and temporal patterns of smoking and cravings, situational factors and place-based practices driving patterns of smoking and cravings, and how bisexual identity interplays with situational factors and place-practices of smoking and cravings.
27	McQuoid et al., 2019; McQuoid et al. (2019)	Young adults aged 18–26: A cohort of young adult bisexual smokers in a larger GEMA study	17 persons	GPS, GIS	Mobile phone	Mapping participants' spatial activity	User-initiated, Random-time	3/day	30 days	Mobile phone	PiLR Health	Smoking, Cigarette craving, Mood, Environmental perception	None	Investigate participants' spatial and temporal patterns of smoking and cravings, situational factors and place-based practices driving patterns of smoking and cravings, and how bisexual identity interplays with situational factors and place-practices

	Citation	Participants' Characteristics		Geographic Method			Ecological Momentary Assessment						Other Passively Sensor-Based Data	Research Objectives
		Population	Sample size	Technology	Device	Purpose	Sampling method	Frequency/ Interval	Monitoring duration	Device	Mobile APP	Outcome measures		
														of smoking and cravings.
28	Mennis et al., 2016; Mennis et al., 2016	General populations aged 13–14: A cohort of participants enrolled in a study of urban adolescent substance use	139 persons	GPS, GIS	Mobile phone	Recording location coordinates without further analysis	NR	3–6/day	1 year	Mobile phone	NR	Stress	None	Investigates the association of activity space-based exposure to neighborhood disadvantage with momentary perceived stress and safety, and the moderation of substance use on those association.
29	Meyerhoff et al., 2021; Meyerhoff et al. (2021)	General population aged 18+: A cohort of population recruited through ResearchMatch and the Center for Behavioral Intervention Technologies research registry.	282 persons	GPS	Mobile phone	Quantifying participants' movement/ mobility	NR	NR	16 weeks	Mobile phone	Passive Data Kit	Depression	None	Evaluate the association of changes in phone sensor-derived behavioral features with the subsequent changes in mental health symptoms (i. e., anxiety and social Anxiety).
30	Mitchell et al., 2014; Mitchell et al., 2014	Patients aged 18–50: A cohort of adults with attention deficit hyperactivity disorder enrolled in a larger EMA study on smoking and psychiatric symptoms in U.S.	10 persons	GPS	GPS logger	Recording location coordinates without further analysis	User-initiated	5/day	1 week	Handheld computer	Entryware Designer	Smoking	Smartphone communication pattern, Smartphone usage	Assess the acceptability and feasibility of acquiring and combining EMA and GPS data from adult smokers with attention deficit hyperactivity disorder.

	Citation	Participants' Characteristics		Geographic Method		Ecological Momentary Assessment							Other Passively Sensor-Based Data	Research Objectives
		Population	Sample size	Technology	Device	Purpose	Sampling method	Frequency/ Interval	Monitoring duration	Device	Mobile APP	Outcome measures		
31	Parrish et al., 2022; Parrish et al. (2020)	Patients aged 18–65: A cohort of adults with schizophrenia or schizoaffective disorder	105 persons	GPS	Mobile phone	Quantifying participants' movement/ mobility	Random-time	7/day	1 week	Mobile phone	Samplex	Emotion	None	Evaluated the associations between emotional experiences in relation to life-space among people with schizophrenia compared to healthy controls
32	Pellegrini et al., 2022 (Pellegrini et al., 2022)	Patients versus Health control aged 18+: A cohort of outpatients from Massachusetts General Hospital with major depressive disorder, bipolar I or II disorder, schizophrenia or schizoaffective disorder vs. A cohort of population with no axis I psychiatric disorder	45 persons	GPS	Mobile phone	Quantifying participants' movement/ mobility	Unspecified	At least 5/ week	8 weeks	Mobile phone	Beiwe	Mood, Sleep quality, Physical activity, Social interaction	Physical activity, Smartphone communication pattern	Predict depression severity based on phone-based PHQ-8 and passive measures.
33	Raugh et al., 2020; Raugh et al. (2020)	Patients versus Health control: A cohort of patients with psychiatric diagnoses from local community outpatient mental health centers vs. A cohort of population without psychiatric	105 persons	GPS	Mobile phone	Quantifying participants' movement/ mobility	Quasi-random time	8/day	6 days	Mobile phone	mEMA	Avolition, Asociality, Anhedonia, Physical activity, Social interaction	None	Evaluated the psychometric properties of a novel "passive" digital phenotyping method: Geolocation.

	Citation	Participants' Characteristics		Geographic Method		Ecological Momentary Assessment							Other Passively Sensor-Based Data	Research Objectives
		Population	Sample size	Technology	Device	Purpose	Sampling method	Frequency/ Interval	Monitoring duration	Device	Mobile APP	Outcome measures		
		diagnoses from local community												
34	Raugh et al., 2021; Raugh et al. (2021)	Patients versus Health control: A cohort of patients with psychiatric diagnoses from local community outpatient mental health centers vs. A cohort of population without psychiatric diagnoses from local community	109 persons	GPS	Mobile phone	Recording location coordinates without further analysis	Quasi-random time, user-initiated	8/day	6 days	Mobile phone	mEMA	Anhedonia	Physiological outcomes, Physical activity pattern, smartphone communication pattern	Evaluated levels of adherence, feasibility, and tolerability for active and passive digital phenotyping methods recorded from smartphone and smartband devices.
35	Reichert et al., 2017; Reichert et al., 2017	General population aged 18–28: A cohort of Adolescents from the URGENCY study (Impact of Urbanicity on Genetics, Cerebral Functioning and Structure and Condition in Young People) in Germany.	93 persons	GPS	Mobile phone	Triggering EMA surveys	Fixed-time, location-change	9–22/day	1 week	Mobile phone	movisensXS	Mood	Physical activity	Assess the association of exercise and non-exercise with mood and investigate differential effects of exercise and non-exercise on mood.
36	Rhew et al., 2022; Rhew et al. (2022)	General population aged 21–27: A cohort of young adults participating in two separate research projects related to substance use in U.S.	14 persons	GPS, GIS	GPS logger	Deriving environmental exposure	Fixed-time, Random-time	4/day	2 weeks	Mobile phone	NR	Marijuana use, Craving to marijuana	None	Examine spatio-temporal exposures associated with marijuana use among young adults.

	Citation	Participants' Characteristics		Geographic Method			Ecological Momentary Assessment						Other Passively Sensor-Based Data	Research Objectives
		Population	Sample size	Technology	Device	Purpose	Sampling method	Frequency/ Interval	Monitoring duration	Device	Mobile APP	Outcome measures		
37	Roy et al., 2019; Roy et al. (2019)	General population aged 25–65: A cohort of population enrolled in the African American Women's Daily Life Study	79 persons	GPS	GPS logger	Deriving environmental exposure	Random-time	5/day	1 week	Mobile phone	NR	Snack and sweetened beverage intake, Physical activity, Social interaction, Environmental perception	None	Examined relationships between contextual factors and within-person variations in snack food and sweetened beverage intake in African American women.
38	Seto et al., 2016; Seto et al., 2016	College students: A cohort of students at the Kunming Medical University in China	12 persons	GPS, GIS	Mobile phone	Deriving environmental exposure	NR	5/day	2 weeks	Mobile phone	CalFit Chi and Dong	Emotion, Meal and snack intake	Physical activity pattern	Demonstrate individual-based modeling methods relevant to a person's eating behavior and compare such approach to typical regression models.
39	Shoval et al., 2018; Shoval et al., 2018	General population: A group of tourists visiting Jerusalem and residing at a centrally located youth hostel in Israel	144 persons	GPS	Mobile phone	Triggering EMA surveys; Mapping participants' emotional characteristics of urban environments	Geofencing, Random-time	NR	1 day	Mobile phone	Sensometer	Emotion	Physiological outcomes	Map the emotional characteristics of a large-scale urban environment using aggregative measures of emotion.
40	Su et al., 2022; Su et al. (2022)	General population: A cohort of population residing in Tangxia Street in Tianhe District in Guangzhou, China	144 persons	GPS, GIS	Mobile phone	Deriving environmental exposure	Fixed-time	4/day	2 days	Mobile phone	NR	Emotion	Environmental condition	Examine the association of momentary happiness with immediate urban environments.

	Citation	Participants' Characteristics		Geographic Method		Ecological Momentary Assessment							Other Passively Sensor-Based Data	Research Objectives
		Population	Sample size	Technology	Device	Purpose	Sampling method	Frequency/ Interval	Monitoring duration	Device	Mobile APP	Outcome measures		
41	Sukei et al., 2021; Sukei et al. (2021)	Outpatients aged 18+: A cohort of outpatients recruited from community clinics	943 persons	GPS	Mobile phone	Quantifying participants' movement/ mobility	NR	NR	At least 30 days	Mobile phone	eB2 MindCare	Emotion, Sleep	Sleep pattern, Smartphone usage	Present a machine learning-based approach for emotional state prediction that uses passively collected data from mobile phones and wearable devices and self-reported emotions.
42	Tao et al., 2021; Tao et al. (2021)	General population: A cohort of population residing in Meiheyuan Community in Beijing, China	120 persons	GPS	Mobile phone	Recording the precise activity and travel location to correct the detailed spatiotemporal information of activity-travel dairies	Fixed-time	4/day	2 days	Mobile phone	NR	Stress	environmental condition	Assess the associations of co-exposures to air pollution and noise with psychological stress.
43	Tornros et al., 2016; Tornros et al., 2016	General population: A cohort of Adolescents from the URGENCY study (Impact of Urbanicity on Genetics, Cerebral Functioning and Structure and Condition in Young People) in Germany.	143 persons	GPS, GIS	mobile phone	Deriving environmental exposure; Triggering EMA surveys	Fixed-time, location-change	NR	1 week	Mobile phone	movisensXS	Mood	None	Compare temporal and location-based sampling strategies for global positioning system-triggered electronic diaries.
44	Wray et al., 2019; Wray et al. (2019)	General population aged 18+: A cohort of population using gay-oriented smartphone	76 persons	GPS	mobile phone	Triggering EMA surveys	Geofencing, User-initiated	NR	30 days	Mobile phone	MetricWire	Alcohol use, Sexual activity, Social interaction, Environmental perception	None	Examine the feasibility of using geofencing to examine social/ environmental factors related to alcohol use

	Citation	Participants' Characteristics		Geographic Method		Ecological Momentary Assessment							Other Passively Sensor-Based Data	Research Objectives
		Population	Sample size	Technology	Device	Purpose	Sampling method	Frequency/ Interval	Monitoring duration	Device	Mobile APP	Outcome measures		
		dating applications												and sexual perceptions in a sample of gay and bisexual men.
45	Xia et al., 2022; Xia et al. (2022)	Adolescent patients: A cohort of adolescents and young adults with affective instability from the Penn/CHOP Lifespan Brain Institute or through the Outpatient Psychiatry Clinic at the University of Pennsylvania.	41 persons	GPS	Mobile phone	Quantifying participants' movement/ mobility	Fixed-time	NR	3 months	Mobile phone	Beiwe	Mood, Sleep	Physical activity pattern	Examined whether individuals have person-specific mobility pattern by linking individual distinctiveness in mobility patterns to mood, sleep, and brain functional connectivity.
46	Yerushalmi et al., 2021; Yerushalmi et al. (2021)	Patients and their partners: A cohort of population with bipolar disorder and their partners living together	8 persons	GPS	Mobile phone	Deriving environmental exposure	Random-time, User-initiated	2/day	An average of 123 days	Mobile phone	BADAS	Depression, Mania, Sleep, Medication adherence	None	Assess the association of BD symptoms (both depression and hypo/mania) with partner mood (positive and negative affect.
47	Zhang et al. 2020; Zhang et al., 2020)	General population aged 18+: A cohort of population residing in Tangxia Street in Tianhe District in Guangzhou, China		GPS, GIS	Mobile phone	Linking participants with their respective partners; Determining whether participants were with their partners during EMA surveys	Fixed-time	4/day	2 days	Mobile phone	NR	Annoyance, Environmental perception	Environmental condition	Examine the influence of the geographic context of the activity places and daily acoustic environment on participants' real-time annoyance.

Table 2

Characteristics of mobile applications used in GEMA studies.

Application Name	Mobile Devices	Mobile Operating System	Collected Data Types	Studies
BADAS	Mobile phone	iOS	location, EMAs (bipolar affective disorder)	Yerushalmi et al. (2021)
Beiwe	Mobile phone	iOS, Android	location, EMAs	(Pellegrini et al., 2022; Xia et al., 2022)
CalFit	Mobile phone	iOS, Android	location, physical activity	Kondo et al. (2020)
CalFit Chi and Dong	Mobile phone	Android	location, physical activity, EMAs (diet)	Seto et al. (2016)
Daynamica	Mobile phone	Android	location, physical activity, EMAs (mood)	Glasgow et al. (2019)
eB2 MindCare	Mobile phone	iOS, Android	location, physical activity, social activity, hours of sleep, EMAs (emotion)	Sukei et al. (2021)
Entryware Designer	Handheld computer	N/A	EMAs	Mitchell et al. (2014)
Mappiness	Mobile phone	iOS	location, EMAs (happiness)	MacKerron and Mourato (2013)
mEMA	Mobile phone	iOS, Android	location, EMAs	(Raugh et al., 2020, 2021)
MetricWire	Mobile phone	iOS, Android	location, EMAs	Wray et al. (2019)
mind.me	Mobile phone	iOS, Android	location, physical activity, social activity, EMAs	McIntyre et al. (2021)
Mood Triggers	Mobile phone	Android	location, weather, Physiological outcomes, EMAs (mood)	Jacobson and Bhattacharya (2022)
movisensX	Mobile phone	Android	location, physical activity, EMAs	(Bollenbach et al., 2022; Koch et al., 2018, 2020; Reichert et al., 2017; Tornros et al., 2016)
Paco	Mobile phone	iOS, Android	EMAs (behavior)	Crochiere et al. (2021)
Passive Data Kit	Mobile phone	iOS, Android	location, physical activity, social activity, EMAs	Meyerhoff et al. (2021)
PiLR Health	Mobile phone	iOS, Android	location, EMAs	(McQuoid et al., 2018, 2019)
ROAMM	Smartwatch	N/A	location, physical activity, EMAs	Mardini et al. (2021)
Samplex	Mobile phone	Android	EMAs	Parrish et al. (2020)
Senso Meter	Mobile phone	Android	location, physiological outcomes, EMAs	Shoval et al. (2018)
Survey Swipe	Mobile phone	iOS	EMAs	Cornwell and Goldman (2020)
Youth@Night	Mobile phone	Android	location, physical activity, social activity, EMAs (young adults' nightlife behaviors)	Labhart et al. (2020)

Note. N/A: not applicable; EMA: ecological momentary assessment.

Table 3

Assorted types of additional sensors and other passively collected in GEMA studies.

Domain	Measures obtained with passive sensors	Studies
Physical activity pattern	pedometer, accelerometry, physical activity intensity or duration, total energy expenditure, device wear time,	(Ben-Zeev et al., 2015; Bollenbach et al., 2022; Crochiere et al., 2021; Doherty et al., 2014; Koch et al., 2018, 2020; Kondo et al., 2020; Labhart et al., 2020; Pellegrini et al., 2022; Raugh et al., 2021; Reichert et al., 2017; Seto et al., 2016; Xia et al., 2022)
Environmental/ ambient condition	weather information (e.g., temperature, humidity, precipitation, light level), noise, air pollutant (e.g., PM2.5); ambient silence, ambient darkness, or radiofrequency electromagnetic field (12 radio frequency bands for communication)	(Ben-Zeev et al., 2015; Bolte et al., 2019; Jacobson and Bhattacharya, 2022; Kou et al., 2020; Su et al., 2022; Tao et al., 2021; Zhang et al., 2020)
Smartphone communication pattern	number of incoming and outgoing text messages, message length, number of phone calls, duration of phone call, number of unique phone numbers dialed, call duration,	(Ben-Zeev et al., 2015; Jacobson and Bhattacharya, 2022; Labhart et al., 2020; Meyerhoff et al., 2021; Pellegrini et al., 2022; Raugh et al., 2021)
Sleep pattern	duration of sleep, sleep efficiency, number or duration of nighttime awakenings, or duration of restlessness periods	(Ben-Zeev et al., 2015; Crochiere et al., 2021; Sukei et al., 2021)
Physiological outcome	skin conductance, skin temperature, heart rate, heart rate variability,	(Jacobson and Bhattacharya, 2022; Shoval et al., 2018)
Smartphone usage	battery status, signal strength, WiFi, Bluetooth, daily app use duration	(Labhart et al., 2020; Meyerhoff et al., 2021)