Review

# Measuring Substance Use With Ecological Momentary Assessment: Scoping Review of Methods and Key Recommendations for a Methodological and Reporting Framework

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## Abstract

**Background:** Substance use disorders account for a significant portion of the disease burden attributed to mental health globally, but measurement remains suboptimal. Substance use measurement is over-reliant on retrospective recall, often over long periods of time. However, the episodic, contextual, and event- or time-contingent nature of substance use calls into question the validity of these traditional retrospective measurement methods. One method to overcome these limitations is ecological momentary assessment (EMA), which repeatedly samples participant behaviors and experiences in real time, in the context in which they occur.

**Objective:** This review aimed to systematically identify studies using EMA to measure substance use, provide a comprehensive overview of the EMA methods used, and develop a checklist for improving the reporting of methodological information for future EMA studies in this field.

**Methods:** Studies published between 2018 and 2026 were sourced from PubMed, MEDLINE, Scopus, and PsycINFO via Ovid databases on March 31, 2026, using terms related to EMA, digital phenotyping, passive sensing, daily diary, and specific terms for each drug type. Studies that actively or passively assessed thoughts and/or behavior in the participants' natural environment/daily lives, in a repeated manner, at or close to the behavior of interest (substance use), using either automatic prompts or notifications, were included. Studies were not excluded according to populations, age, setting, or study design. This study was preregistered on the International Prospective Register of Systematic Reviews (PROSPERO; CRD42023400418).

**Results:** The search identified 12,487 articles, of which 1236 were reviewed in full; 581 studies were included and extracted, resulting in 431 (n=126,733 participants) unique datasets. Most studies were conducted in the United States (348/431, 80.7%) and focused on alcohol (364/431, 84.5%) and cannabis use (172/431, 39.9%) with or without the presence of other substance use. Alcohol and cannabis measurement co-occurred the most in 128 of 431 (29.7%) unique datasets. Phencyclidine, bath salts, cough syrup, crack, depressants, prescription sedatives, prescription tranquilizers, steroids, khat, buprenorphine, gamma-hydroxybutyrate, kava, and kratom were only measured in one dataset each. This review found limited reporting consistency across compliance, completion windows, attrition rates, survey duration, and data collection technologies in EMA substance use studies.

**Conclusions:** This review provides the first comprehensive cross-substance synthesis of EMA methodologies used to measure substance use. In contrast to previous reviews focused on individual substances or narrower methodological issues, it compares methodological characteristics across substance groups and identifies common design and reporting gaps. The findings provide practical recommendations to improve the transparency, comparability, reproducibility, feasibility, and data quality of future EMA studies. Greater consistency in reporting missing data, compliance, survey duration, and prompt completion windows, alongside further integration of wearable technologies and research on underexplored substances, will be important for strengthening the real-world application of EMA in substance use research.

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**Keywords:** ecological momentary assessment; substance use; real-time data collection; ambulatory assessment; addiction; daily diary; experience sampling

## Introduction

Substance use represents a significant global health burden, with approximately 64 million people aged 15 to 64 years reporting a substance use disorder in 2024 [1]. Despite the rising prevalence and associated health impacts, treatment remains largely inaccessible, with only one in 11 people with a substance use disorder currently receiving appropriate care worldwide [1]. Compounding these challenges is the increasing prevalence of poly-substance use, the concurrent or sequential use of multiple substances, which increases associated risk, including overdose, and complicates clinical interventions due to its unpredictable and dynamic nature [2]. Traditional methods of assessing substance use typically rely on retrospective self-report measures, often covering long recall periods (ie, past 30 days or up to 12 months). Such approaches are inherently limited by recall bias and often fail to accurately capture the rapidly changing contexts and subjective experiences that influence substance use behaviors [3,4]. Given these limitations, leveraging innovative methodologies capable of better characterizing substance use with greater precision and ecological validity is vital [5-7].

One emerging method that overcomes the limitations of traditional approaches is ecological momentary assessment (EMA). Also referred to as experience sampling methods, ambulatory assessment, daily diary, and intensive longitudinal designs, EMA encompasses a set of data collection techniques designed to gather ecologically valid data on behaviors occurring in daily life [6]. Although these approaches differ in sampling schedules, recall periods, temporal resolution, and participant burden, they share the common principle of repeatedly assessing individuals in their natural environments and are considered collectively as EMA throughout this review [6]. These methods repeatedly assess participants within their natural environment at, or close to, the time when the target behavior occurs [6]. Typically, EMA studies actively prompt participants to report on the behavior of interest one or more times per day, according to interval-contingent schedules (at fixed intervals), random-contingent schedules (at random times), event-contingent schedules (following specific events, such as alcohol consumption), or a combination of event- and time-based schedules [4-6]. Due to the widespread accessibility of smartphones and smart wearables, EMA studies can make use of sensors such as accelerometers to passively and noninvasively measure behaviors relevant to substance use, such as physical activity, sleep, and heart rate variability [8]. More recently, passive sensing approaches have also been incorporated within EMA protocols to complement active self-report by providing continuous behavioral or physiological measurements in participants' natural environments.

EMA data collection has previously relied on pen and paper methods; however, portable electronic diaries, text messaging, phone calls, interactive voice recordings, and smartphone apps have significantly enhanced the feasibility and convenience of implementing EMA methods. Recently, EMA methods have been applied to diverse substance use research contexts, such as identifying real-time motives for substance use [9], monitoring the relationship between craving and contextual factors [10], ecologically validating lab assessments [11], and characterizing relationships between mental health and substance use behaviors [12]. However, few studies have been published on the synthesis of methods used in EMA substance use research.

Few reviews have explored the use of EMA in substance use research, with existing EMA research largely focused on specific substances, populations, or health outcomes, such as motives for substance use in daily life [9] or substance use craving, without comparing methods across substance types [9,10]. A methodological review by Jones et al [13] investigated design features associated with compliance among EMA substance use studies published up to 2017, providing valuable insights into participant adherence but focused less on the broader methodological characteristics. However,

since 2017, the use of EMA methods and technology has rapidly increased. Singh et al [3] reviewed the reporting of assessment periods for mood variables in EMA substance use research and found inconsistencies and lack of clarity in reporting, which can compromise interpretability and replication. However, by restricting measurement to mood variables, the broad range of substance use antecedents and outcomes was overlooked. While Serre et al [10] offers a valuable synthesis of EMA studies investigating the dynamics of craving and substance use in daily life, it primarily focuses on craving as a predictor of substance use. The review does not provide a broader methodological overview of how EMA has been used to measure substance use itself and offers limited discussion of how EMA methods vary across different substances and population groups. The lack of standardized study design and reporting practices further complicates the synthesis and comparison of findings across studies.

To date, no review has comprehensively examined EMA approaches used across all substance types, systematically assessed their methodological and reporting characteristics, or identified key areas where methodological improvements are needed, including comparisons of methodological characteristics across substance types and the use of both active and passive EMA approaches. Given the rapid expansion of EMA research across diverse substances, populations, designs, and assessment technologies, a comprehensive methodological synthesis is needed to characterize current practices, identify methodological gaps, and guide the continued adoption of approaches that improve the real-time, ecologically valid measurement of substance use. Accordingly, this review provides a comprehensive synthesis of EMA methodologies used to measure substance use and develops methodological and reporting recommendations to inform the design, conduct, and reporting of future substance use EMA studies.

This review addresses these gaps by:

1. Identifying studies that have used EMA methods to measure substance use across an 8-year period from 2018 to 2026.
2. Describing the methodological characteristics of studies using EMA methods to measure substance use, including those pertaining to participant recruitment, participant characteristics, observation periods, sampling/coverage strategy, frequency and intensity of engagement, compliance/response rates, technology and data collection (text message vs app, etc), study type, and use of reimbursement/incentive.
3. Highlighting research gaps in the EMA substance use literature.
4. Providing recommendations for an EMA study methodological reporting checklist (Table 1) to improve study designs and reporting standards for future EMA substance use research.

**Table 1.** Review-derived reporting recommendations and proposed extensions to CREMAS[a] for EMA[b] studies assessing substance use[c].

| Domain | Reporting item | Recommendation[c] | Link to CREMAS | Basis for inclusion |
|---|---|---|---|---|
| Study design | Sample size justification | Report how target sample size was determined, accounting for the multilevel/clustered structure of EMA data where appropriate. | Additional item | Sample-size justification/power procedures were inconsistently reported in reviewed studies. |
| Data completeness | Compliance rates | Report the proportion of EMA assessments completed, clearly specifying the numerator and denominator used to calculate compliance. | Reinforces CREMAS item 13 | Compliance was frequently unreported and inconsistently operationalized. |
| Data completeness | Attrition | Report participant attrition across the monitoring period and, where applicable, across study waves. | Reinforces CREMAS item 10 | Attrition was frequently incompletely reported. |
| Data completeness | Missing data | Report the extent of missing EMA data and describe procedures used to manage missing observations, including imputation or exclusion where applicable. | Extends CREMAS item 14 | Existing CREMAS guidance focuses on predictors of compliance rather than analytical handling of missing EMA observations. |
| Substance use measurement | Substance use measurement | Report all substances assessed and describe how substance use was operationalized and measured, including timing, quantity/frequency, route, or objective measurement where relevant. | Substance use specific addition | Considerable heterogeneity was observed in how substance use was measured and reported. |
| EMA measurement | Survey items | Report the EMA items or item sets used and indicate whether they were validated, adapted, piloted, or developed specifically for EMA administration. | Additional item | Measurement items, their provenance, and whether they were developed for EMA designs were inconsistently reported. |
| Prompting | Prompt completion window | Report the period during which participants were permitted to respond following delivery of an EMA prompt. | Extends CREMAS item 12 | Response windows were frequently unreported despite influencing the temporal resolution of EMA data. |
| Participant burden | Survey length | Report the approximate duration required to complete each EMA assessment. | Extends CREMAS item 9 | Survey duration was infrequently reported, limiting assessment of participant burden. |

| Domain | Reporting item | Recommendation[c] | Link to CREMAS | Basis for inclusion |
|---|---|---|---|---|
| Technology | EMA platform | Report the platform/application and device or technology used to administer EMA assessments. | Reinforces CREMAS item 4 | Technology/platform reporting remained incomplete despite existing guidance. |

[a]CREMAS: Checklist for Reporting Ecological Momentary Assessment Studies.
[b]EMA: ecological momentary assessment.
[c]Recommendations were mapped against the 16-item Checklist for Reporting Ecological Momentary Assessment Studies (CREMAS). "Reinforces" indicates that an existing CREMAS recommendation was retained because the corresponding reporting deficiency remained evident in the present review; "extends" indicates that the recommendation addresses an aspect related to, but not explicitly specified by, an existing CREMAS item; and "additional" indicates a reporting recommendation arising from the present review that was not explicitly addressed in CREMAS. These review-derived recommendations are intended to complement existing ecological momentary assessment reporting guidance rather than constitute a formally validated reporting guideline.

# Methods

## Protocol and Registration

This review follows the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) guidelines according to the PRISMA-ScR checklist in Checklist 1 and was preregistered on International Prospective Register of Systematic Reviews (PROSPERO; masked for blind review) [14].

## Eligibility Criteria

Eligibility criteria were developed according to the Population, Concept, and Context (PCC) framework.

## Population

Studies including participants of any age, population, or clinical group, in any setting, were eligible.

## Concept

Studies were included if they used EMA or a related intensive longitudinal method, with a minimum assessment frequency of once per day to ensure that included studies reflected intensive longitudinal assessment methods with high temporal resolution. Eligible methods included active or passive assessment of thoughts and/or behaviors within participants' natural environments at, or close to, the behavior of interest (substance use), using automatic prompts, notifications, or ongoing passive sensing. Studies using continuously collected data from digital devices (eg, wearable sensors or smartphone sensing data) to measure substance use or proxy indicators of substance use were also eligible. Studies were eligible if they used EMA to measure substance use, regardless of whether substance use represented the primary outcome, exposure, or a secondary study variable. Studies were required to report explicit measures of substance use (eg, any use, quantity, frequency, and passive proxy measures) at full-text review.

## Context

Studies conducted in any geographical or clinical context and using any study design, including observational, experimental, and randomized controlled trials, were eligible. Systematic reviews were included solely for hand-searching reference lists to identify additional eligible primary studies.

Eligible substances included alcohol and drugs listed in the Alcohol, Smoking, and Substance Involvement Screening Test (ASSIST), including cannabis, cocaine, amphetamine-type stimulants (including 3,4-methylenedioxymethamphetamine [MDMA]), inhalants, sedatives, hallucinogens, opioids, and other drugs. Nicotine-only studies were excluded because EMA methodologies in nicotine research have been comprehensively reviewed elsewhere [9,14] and represent a well-established area of EMA research. Further, the high-frequency, habitual pattern of nicotine use typically requires distinct EMA sampling strategies and measurement approaches compared with alcohol and other psychoactive substances, limiting methodological comparability.

## Exclusion Criteria

Studies were excluded if they:

- did not explicitly measure substance use at the individual level;
- did not use EMA or another eligible intensive longitudinal assessment method;
- collected data less frequently than once per day;
- reported only a single cross-sectional or one-off assessment;
- described interventions delivered via mobile apps without ongoing repeated assessment or surveillance;
- did not include original empirical data (eg, study protocols, theoretical papers, and commentaries); or
- did not involve human participants.

## Information Sources and Search Strategy

We searched PubMed, MEDLINE, Scopus, and PsycINFO via Ovid databases on January 31, 2023, using terms related to EMA, digital phenotyping, passive sensing, daily diary, and specific terms for each drug type (Table S1 in Multimedia Appendix 1 for the full table of search terms). A hand search of the reference lists of relevant systematic reviews was conducted to identify any additional papers that may have been missed during the electronic search. Our protocol did not include search limits by date; however, we deviated from the protocol and imposed a date restriction of January 31, 2018, to January 31, 2023. This decision was made to build upon a recent review of compliance in EMA methodologies for substance use, which synthesized studies published up to 2017, while specifically focusing on methodological developments, reporting practices, and assessment technologies reported in the contemporary literature [12]. An updated search was conducted to capture any additional studies published from January 31, 2023, to March 31, 2026.

## Study Selection

Citations were imported into, and deduplicated in, EndNote (version 20.6; Clarivate) and exported and uploaded into the web-based screening platform Covidence (Future Evidence Foundation) for screening [15]. Each article was double-screened for relevance based on titles and abstracts by 6 independent reviewers (ZB, JW, JH, GD, KP, and AN). An identical process was conducted for full-text screening, and any interreviewer disagreement was discussed to reach consensus (interrater reliability: 86%-100%). Reviewers nominated reasons for exclusion at the full-text stage. If consensus could not be reached, a third reviewer (ZB, JW, and JH) was consulted to resolve the discrepancy.

## Data Charting Process

Study data were single-extracted by any one of 5 reviewers (ZB, JW, GD, KP, or AN) using a prepiloted data extraction form in Microsoft Excel. Prior to formal data extraction, reviewers completed a calibration exercise to ensure consistent interpretation of the extraction variables, with uncertainties resolved through discussion among the review team. The extraction template_was iteratively refined during the original extraction, where necessary during the review process to improve clarity and consistency of variable definitions, as well as the inclusion of any additional relevant variables. Previously extracted studies were updated where changes were made to the extraction template. Following the updated search, which identified an additional 310 eligible studies, an AI-assisted extraction protocol was implemented in accordance with the Cochrane Responsible Use of AI in Evidence Synthesis (RAISE) guidelines and recommendations [16]. We used *Systematic Review Extractor Pro,* a custom GPT-based tool developed using OpenAI's GPT builder, which had previously demonstrated high performance in extracting participant and methodological characteristics from research articles [17]. The tool extracts prespecified variables directly from article PDFs according to a review-specific extraction template. Further details regarding its development and evaluation have been reported elsewhere [17].

The performance of the AI-assisted extraction procedure was evaluated within this review using a stratified (by publication year) random sample of 95 of the 310 (30.6%) newly included studies. For each study, AI-extracted items were independently checked against the source articles by a human reviewer (ZB and JW) and classified as concordant or discordant. Consistent with the RAISE framework, concordance was based on factual agreement with the source information and did not require identical wording, formatting, structure, or level of detail for free text responses [16]. An item was considered discordant when the extracted value was factually inconsistent with the source article and therefore required human correction. The item-level correction rate was calculated as the number of extracted items requiring correction divided by the total number of extracted items assessed across the validation sample. Fewer than 1% (29/3492) of assessed items required correction. Based on this within-review validation, the AI-assisted extraction procedure was subsequently applied to the remaining 215 newly included studies. Variable-specific correction rates were also examined to identify fields with comparatively lower performance . Ambiguous or insufficiently supported outputs were classified as discordant rather than accepted as correct. No extraction variables were designated a priori as high-risk or requiring additional verification because the extraction framework predominantly comprised directly reported participant and methodological characteristics.

The following data were extracted from general study characteristics: aims/objectives, study design (EMA, daily diary [DD], or sensor data), ecological momentary intervention (0=no and 1=yes), intervention type (0=personalized feedback, 1=just-in-time adaptive intervention (JITAI), sample size, substance use measurement, reimbursement/incentive, and sample characteristics. The following methodological characteristics were extracted; sample characteristics, technology used, collection device (EMA and DD studies: 0=phone/smartphone, 1=electronic diary/personal digital assistant, 2=iPod touch, 3=tablet, and 4=paper; SD studies: 0=ankle-worn device, 1=breathalyzer, and 2=wrist-worn device), survey duration (0=less than or equal to 3 minutes, 1=greater than 3 to less than 5 minutes, and 2=greater than or equal to 5 minutes per survey), prompt window, sample strategy/coverage, statistical analyses, frequency, and intensity of data collection. Sample size, age (years), gender (%), compliance (%), attrition rate (%), assessment period (days), number of daily assessments, survey duration (minutes), completion window duration (hours), and reimbursement (USD) were extracted as numeric. All other data were extracted as free text. Definitions, coding rules, and derivation of extracted variables are provided in the

Extracted variable synthesis section in Multimedia Appendix 1.

## Synthesis of Results

Following data synthesis, methodological and reporting recommendations were developed using an iterative, review-informed process. Candidate items were identified from methodological characteristics that were frequently missing, inconsistently reported, or difficult to synthesize across included studies. These items were then mapped against existing EMA reporting guidance, including the Checklist for Reporting Ecological Momentary Assessment Studies (CREMAS), an EMA-specific adaptation of the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting framework [18]. Recommendations were classified as either (1) existing CREMAS items reinforced by findings from this review; (2) extensions or adaptations of existing CREMAS items; or (3) additional recommendations arising from reporting issues identified in substance use EMA studies that were not explicitly addressed by CREMAS. The resulting recommendations were reviewed by members of the research team with expertise in EMA methodology and substance use research for relevance and clarity. They were synthesized into a review-derived reporting checklist intended to complement, rather than

replace, existing EMA reporting guidance. Per the protocol, individual assessment of risk of bias of the included studies was not assessed in this scoping review, as the primary aim was to describe and synthesize methodologies, rather than to assess intervention efficacy and the impact of risk on outcomes. To handle the anticipated high heterogeneity of included studies, data were synthesized and described qualitatively into the following categories (as seen in [18]):

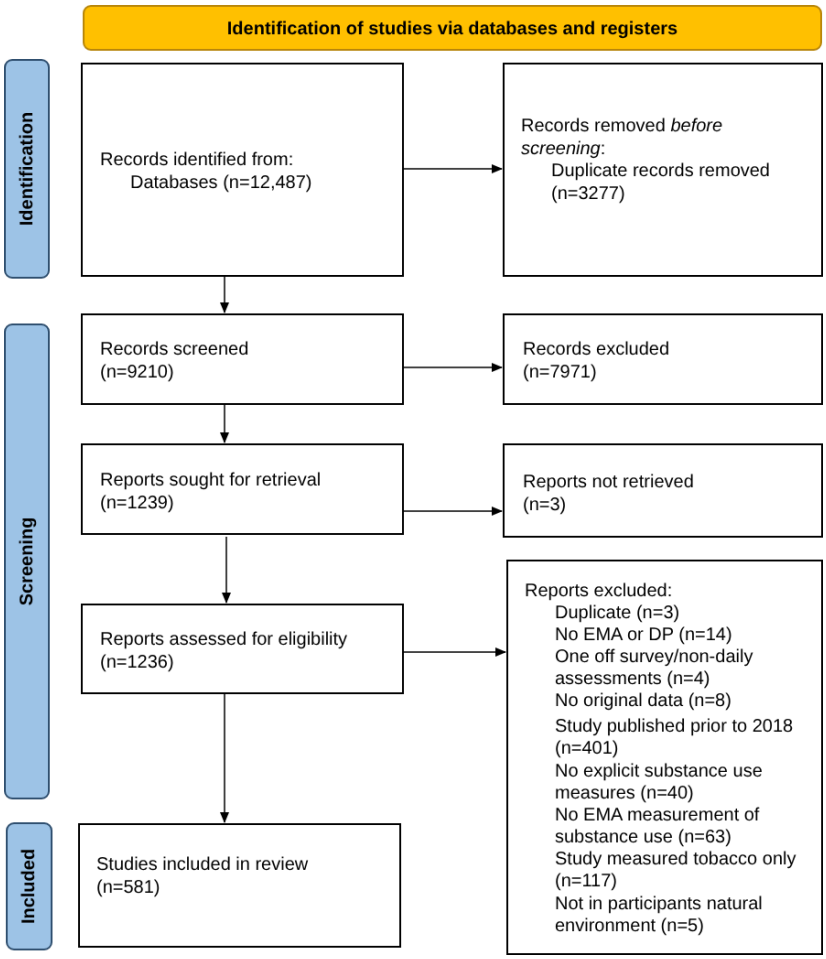
1. *Sampling and sample characteristics*: sample strategy/coverage, sample characteristics, sample, substance measured (including identifying studies where multiple substances were measured, described using a heatmap), and sample size.
2. *EMA protocol scheduling*: monitoring periods, prompt frequency and intensity, prompt interval/window, and study duration.
3. *Prompting strategy*: interval type (fixed vs random), use of event-based recording (yes/no).
4. *Technology and administration*: technology used, collection device, and survey duration.
5. *Compliance and attrition*: compliance rates, attrition, and reimbursement.

# Results

## Study Selection

Of the 9210 studies screened at the title and abstract stage, 1236 progressed to the full-text review, with 581 meeting criteria and included in the current review (Figure 1 and Multimedia Appendix 2). Of the 581 included publications, 395 (67.9%) were primary analyses. The remaining 187 publications comprised 84 (14.4%) secondary analyses of another included publication, 45 (7.7%) secondary analyses of EMA datasets whose parent publication was not included in the review, and 58 (10.0%) sibling publications drawing on the same underlying dataset as another included publication. Across all included publications, 431 unique EMA datasets were identified. Of these, 348 (80.7%) contributed a single publication to the review and 83 (19.3%) contributed 2 or more publications.

**Figure 1.** PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram. DP: digital phenotyping; EMA: ecological momentary assessment.




Among the unique datasets, most studies were conducted in the United States (348/431, 80.7%), followed by European countries (30/431, 7.0%), Canada (16/431, 3.7%), the United Kingdom (13/431, 3.0%), Australia/New Zealand (11/431, 2.6%), Asia (7/431, 1.6%), Middle Eastern countries (4/431,

0.9%), Central America (1/431, 0.2%), and Africa (1/431, 0.2%).

## Characteristics of Studies

### Sampling and Sample Characteristics

Across the 431 unique datasets, there were a total of 126,733 participants. The mean number of participants per study was 294 (range 9-24, 250; median 100, IQR 137.5), with an average 54.0% (SD 22, range 0%-100%) female participants. The average participant age across EMA studies was 29.2 (SD 10.3, range 10-83) years. In terms of population groups, studies most commonly sampled community-dwelling participants who regularly engage in substance use behaviors (84/431, 19.5%), followed by university/college students (76/431, 17.6%), the general population (71/431, 16.5%), high-risk populations (60/431, 13.9%), clinical samples (73/431, 16.9%; 55/73, 75.3% in treatment vs 18/73, 24.7% not in treatment), and with 1.9% (8/431) focusing on specialist groups (Table S2 in Multimedia Appendix 1). According to age classifications reported in included studies, most studies sampled adults (217/431, 50.3%), followed by young adults (186/431, 43.2%), and adolescents (23/431, 5.3%), while only 3 studies (431, 0.7%) examined older adults. Overall, 2 of 431 (0.5%) studies did not report age classification details.

Regarding substance use measurement, 31 unique substances were measured using EMA methods (Table 2). Most unique datasets assessed alcohol use (364/431, 84.5% of total studies accounting for 114,753/126,733, 90.5% of total participants) and cannabis (172/431, 39.9% of studies; 40,572/126,733, 32.0% of participants). The next largest grouping of substances was “other drugs” where the substance under investigation was not explicitly described in the studies (Table S3 in Multimedia Appendix 1 for summary of substance types and definitions).

**Table 2.** Unique substances measured using EMA[a] methodologies.

| Substances[b] | Studies, n (%)[c] | Total participants, n (%)[d] |
|---|---|---|
| Alcohol | 364 (84.5) | 114,753 (90.5) |
| Cannabis | 172 (39.9) | 40,572 (32) |
| Other drugs | 87 (20.2) | 20,280 (16) |
| Nonprescription opioids | 33 (7.7) | 9727 (7.7) |
| Cocaine | 30 (7) | 9989 (7.9) |
| Meth/amphetamines | 20 (4.6) | 8748 (6.9) |
| Prescription drug use | 18 (4.2) | 4892 (3.9) |
| Psychedelics | 14 (3.2) | 7627 (6) |
| Heroin | 13 (3) | 3574 (2.8) |
| MDMA/ecstasy[e] | 12 (2.8) | 4622 (3.6) |
| Sedatives | 12 (2.8) | 6947 (5.5) |
| Stimulants | 10 (2.3) | 3046 (2.4) |
| Benzodiazepine | 6 (1.4) | 739 (0.6) |
| Prescription opioids | 6 (1.4) | 3210 (2.5) |
| Prescription stimulants | 6 (1.4) | 5175 (4.1) |
| Injection drug use | 4 (0.9) | 571 (0.5) |
| Fentanyl | 3 (0.7) | 687 (0.5) |
| Inhalants | 3 (0.7) | 2855 (2.3) |
| Bath salts | 1 (0.2) | 74 (0.1) |
| Buprenorphine | 1 (0.2) | 117 (0.1) |
| Cough syrup | 1 (0.2) | 74 (0.1) |
| Crack | 1 (0.2) | 74 (0.1) |
| Depressants | 1 (0.2) | 36 |
| GHB[f] | 1 (0.2) | 272 (0.2) |
| Kava | 1 (0.2) | 395 (0.3) |
| Kratom | 1 (0.2) | 395 (0.3) |
| PCP[g] | 1 (0.2) | 74 (0.1) |
| Prescription sedatives | 1 (0.2) | 300 (0.2) |
| Prescription tranquilizer | 1 (0.2) | 300 (0.2) |
| Steroids | 1 (0.2) | 744 (0.6) |
| khat | 1 (0.2) | 60 |

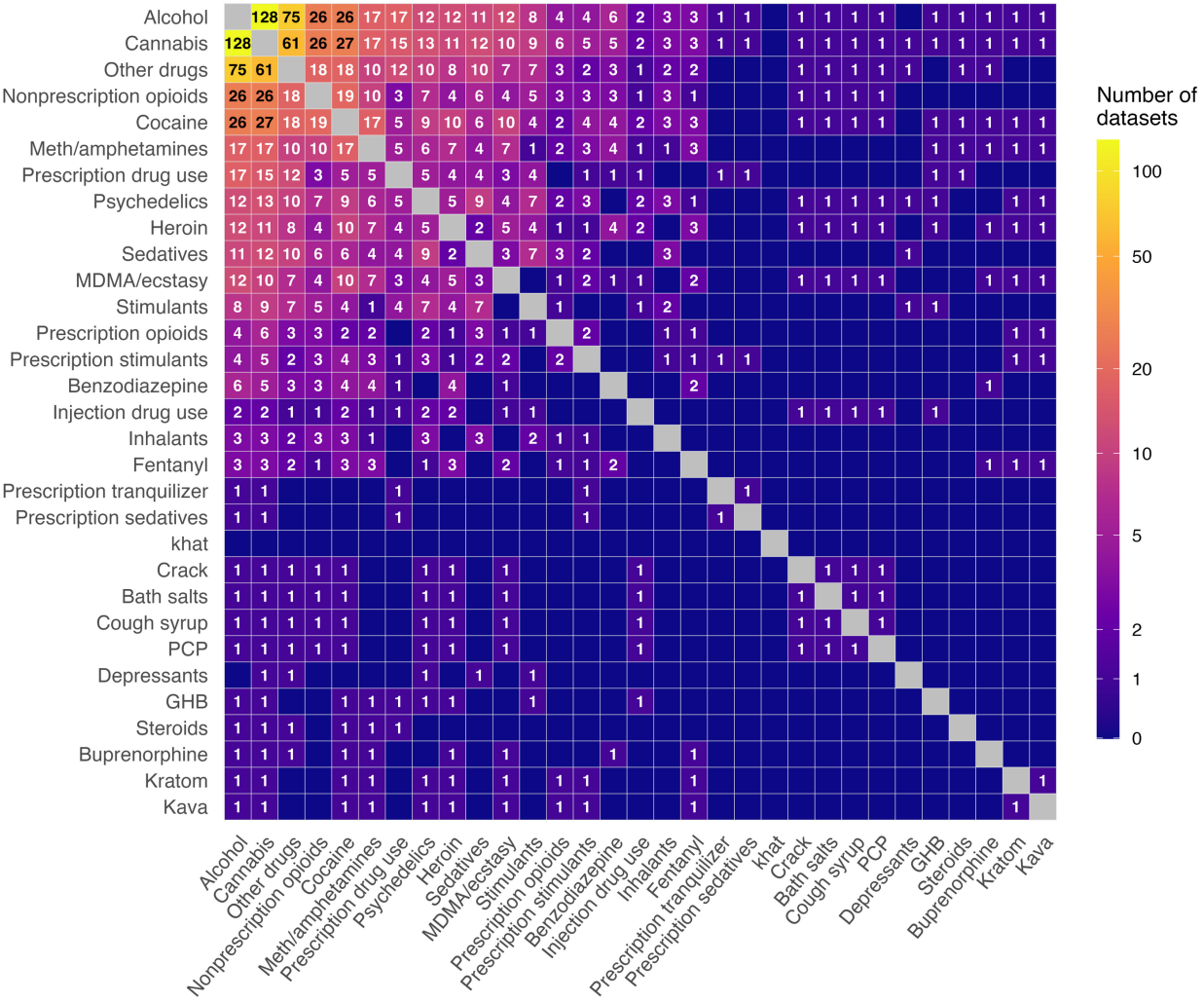
[a]EMA: ecological momentary assessment.

[b]Frequency of individual substances measured across the 431 unique datasets included in this scoping review of EMA methodologies for substance use.
[c]Counts represent the number and percentage of unique datasets assessing each substance.
[d]Participant totals reflect the cumulative number of participants contributing to studies measuring each substance. Individual datasets may appear in multiple substance categories where more than one substance was assessed.
[e]MDMA: 3,4-methylenedioxymethamphetamine.
[f]GHB: gamma-hydroxybutyrate.
[g]PCP: phencyclidine.

## Co-Occurrence of Substances

Figure 2 presents a heatmap illustrating the co-occurrence of substances measured together across included studies. The color intensity represents the frequency with which 2 substances were assessed within the same study, with darker shades indicating more frequent comeasurement. Alcohol and cannabis were most frequently measured together (128 datasets; Figure 2), followed by alcohol and "other drugs" (75 datasets), cannabis and "other drugs" (61 datasets). Cocaine was also commonly comeasured with alcohol and cannabis (26 and 27 datasets, respectively) as were nonprescription opioids (26 datasets with each). Prescription drug use was less frequently measured in combination with other substances, with the strongest co-occurrence observed with alcohol (17 datasets) and cannabis (15 datasets). Several substances, including phencyclidine, bath salts, inhalants, cough syrup, steroids, buprenorphine, kratom, and kava, were rarely comeasured with other substances, typically appearing in only one or a few datasets.

**Figure 2.** Co-occurrence matrix of substances measured together. Co-occurrence of substances measured within the same ecological momentary assessment protocol across the 431 unique datasets included in the review. Cell values indicate the number of unique datasets in which each pair of substances was measured together. Lighter colors represent a greater frequency of comeasurement. Diagonal cells are omitted because they represent self-occurrence. GHB: gamma-hydroxybutyrate; MDMA: 3,4-methylenedioxymethamphetamine; PCP: phencyclidine.



## Measurement of Substance Use

Among the 424 of 431 unique datasets using self-reported EMA or daily diary methods (Table 3), any use (eg, binary yes/no measures) was the most commonly assessed dimension of substance use, reported in 296 of 431 (68.7%) datasets. This was followed by quantity of use, which was measured in 280 of 431 (65.0%) datasets. Far fewer datasets assessed more specific dimensions of substance use, including type or mode of administration (68/431, 15.8% datasets), frequency of use (38/431 datasets, 8.8%), subjective intoxication (29/431 datasets, 6.7%), duration of use (25/431, 5.8% datasets), time since last use (10/431, 2.3% datasets), and substance potency (12/431, 2.8% datasets). These measurement dimensions varied across substance groups. Compared with other substance groups, cannabis studies more frequently assessed type or mode of administration, frequency of use, subjective intoxication, duration of use, and potency (Table 3).

**Table 3.** Substance use measurement by substance group.

| Substance[a] | Alcohol (n=364) | Cannabis (n=172) | Other drugs[b] (n=96) | Opioids[c] (n=44) | Stimulants[d] (n=42) | Psychedelics[e] (n=22) | Depressants and sedatives[f] (n=21) | All datasets (n=431) |
|---|---|---|---|---|---|---|---|---|
| Active self-report (EMA[g] or DD[h]), n (%) | | | | | | | | |
| Quantity of use | 255 (70.1) | 50 (29.1) | 9 (9.4) | 6 (13.6) | 2 (4.8) | 1 (4.5) | 1 (4.8) | 280 (65) |
| Any use | 222 (61) | 148 (86) | 75 (78.1) | 42 (95.5) | 41 (97.6) | 20 (90.9) | 20 (95.2) | 296 (68.7) |
| Type/mode of administration | 25 (6.9) | 36 (20.9) | 11 (11.5) | 4 (9.1) | 1 (2.4) | 1 (4.5) | 1 (4.8) | 68 (15.8) |
| Frequency of use | 18 (4.9) | 25 (14.5) | 2 (2.1) | 2 (4.5) | 1 (2.4) | 1 (4.5) | 1 (4.8) | 38 (8.8) |
| Subjective intoxication | 18 (4.9) | 16 (9.3) | 2 (2.1) | 1 (2.3) | 1 (2.4) | —[i] | — | 29 (6.7) |
| Duration of use | 16 (4.4) | 11 (6.4) | 1 (1.0) | — | — | — | — | 25 (5.8) |
| Time since last use | 5 (1.4) | 7 (4.1) | 2 (2.1) | 2 (4.5) | 1 (2.4) | — | 1 (4.8) | 10 (2.3) |
| Potency | 4 (1.1) | 8 (4.7) | — | — | — | — | — | 12 (2.8) |
| Active or passive SD[j] | | | | | | | | |
| Breath alcohol concentration | 15 (4.1) | — | — | — | — | — | — | 15 (3.5) |
| Transdermal alcohol concentration | 20 (5.5) | — | — | — | — | — | — | 20 (4.6) |
| Sensor other[k] | 3 (0.8) | 3 (1.7) | — | — | 1 (2.4) | — | — | 6 (1.4) |

[a]Substance use measurement dimensions are reported across the 431 unique self-report ecological momentary assessment, daily diary, and sensor data datasets, stratified by substance group. Values are presented as n (%) of datasets within each substance group. Substance categories are not mutually exclusive, and individual datasets may contribute to multiple substance groups where more than one substance was measured.
[b]Other drugs include unspecified "other drugs," unspecified prescription drugs, injection drug use, inhalants, cough syrup, and steroids.
[c]Opioids include nonprescription opioids, prescription opioid use, heroin, fentanyl, buprenorphine, kratom, and prescription pain reliever use.
[d]Stimulants include cocaine/crack, methamphetamines, amphetamines, prescription stimulants, unspecified stimulants, khat, and bath salts (synthetic cathinones).
[e]Psychedelics include unspecified psychedelics, 3,4-methylenedioxymethamphetamine, and phencyclidine.
[f]Sedatives and depressants include unspecified sedatives, benzodiazepines, prescription sedatives, prescription tranquilizers, unspecified depressants, gamma-hydroxybutyrate, and kava.
[g]EMA: ecological momentary assessment.
[h]DD: daily diary.
[i]Not applicable.
[j]SD: sensor data.
[k]Sensor other contains smartphone passive sensing for alcohol; smartphone passive sensing, puff count, puff duration, and product potency for cannabis; and heart rate variability for stimulants.

Substance use was measured using sensor data in a small number of datasets and was almost exclusively limited to alcohol studies. Transdermal alcohol concentration was measured in 20 datasets and breath alcohol concentration in 15 datasets. One cannabis dataset measured puff dura-

tion/count and potency, while one stimulant dataset measured heart rate variability to assess intoxication.

## Design

### Overview

Of the 431 unique datasets included, 359 (82.0%) were observational, 31 (7.1%) were randomized controlled trials, 28 (6.4%) were feasibility studies, 12 (2.7%) were pilot studies, and one (0.2%) was an open trial design. As seen in Table 4, most unique datasets used an EMA-only (212 studies) approach to data collection. There were 60 unique datasets that included intervention components with psychological/behavioral interventions (22/60, 36.7%) most commonly reported, followed by mobile health (mHealth) interventions (14/60, 23.3%). EMA-specific intervention methodologies, including ecological momentary interventions (EMIs), JITAIs, and EMA-informed personalized feedback, were used less frequently (Table 5).

**Table 4.** Characteristics of studies by substance group[a].

| | Alcohol (n=364) | Cannabis (n=172) | Other drugs (n=96) | Opioids (n=44) | Stimulants (n=42) | Psychedelics (n=22) | Depressants and sedatives (n=21) | All datasets (n=431) |
|---|---|---|---|---|---|---|---|---|
| Characteristic, mean (SD) | | | | | | | | |
| Assessment period (days) | 28.5 (25.7) | 29 (28) | 33.9 (33.2) | 28.5 (27.8) | 33.4 (27.4) | 25.2 (12.3) | 28.2 (23) | 27.9 (25) |
| Assessments per day | 2.7 (3.5) | 2.9 (2.2) | 2.4 (2) | 2.5 (1.8) | 2.7 (2) | 2.1 (2.1) | 2.4 (2.2) | 2.8 (3.3) |
| Completion window (hours) | 6.2 (10.5) | 5 (6) | 5.5 (6.7) | 5.8 (7.8) | 6.3 (7.8) | 7.7 (9.2) | 4.5 (4.7) | 5.4 (9.6) |
| Study design, n (%) | | | | | | | | |
| EMA[b] only | 166 (45.6) | 91 (52.9) | 46 (47.9) | 20 (45.5) | 21 (50) | 7 (31.8) | 7 (33.3) | 212 (49.2) |
| DD[c] only | 102 (28) | 48 (27.9) | 29 (30.2) | 12 (27.3) | 14 (33.3) | 10 (45.5) | 8 (38.1) | 110 (25.5) |
| SD[d] only | 11 (3) | 0 | 0 | 0 | 0 | 0 | 0 | 11 (2.6) |
| Combination | 82 (22.5) | 32 (18.6) | 21 (21.9) | 12 (27.3) | 7 (16.7) | 4 (18.2) | 6 (28.6) | 95 (22) |
| Missing/did not report | 3 (0.8) | 1 (0.6) | 0 | 0 | 0 | 1 (4.5) | 0 | 3 (0.7) |
| Sampling strategy, n (%) | | | | | | | | |
| Interval contingent only | 217 (59.6) | 98 (57) | 55 (57.3) | 21 (47.7) | 26 (61.9) | 14 (63.6) | 13 (61.9) | 248 (57.5) |
| Random contingent only | 45 (12.4) | 25 (14.5) | 13 (13.5) | 6 (13.6) | 4 (9.5) | 2 (9.1) | 0 | 55 (12.8) |
| Event contingent only | 9 (2.5) | 5 (2.9) | 1 (1) | 2 (4.5) | 2 (4.8) | 0 | 0 | 14 (3.2 |
| Combination | 89 (24.5) | 44 (25.6) | 27 (28.1) | 15 (34.1) | 10 (23.8) | 6 (27.3) | 8 (38.1) | 110 (25.5) |
| Missing/did not report | 4 (1.1) | 0 | 0 | 0 | 0 | 0 | 0 | 4 (0.9) |
| Max. survey duration, n (%) | | | | | | | | |
| <=3 minutes | 30 (8.2) | 16 (9.3) | 9 (9.4) | 5 (11.4) | 3 (7.1) | 2 (9.1) | 1 (4.8) | 36 (8.4) |
| >3<5 minutes | 52 (14.3) | 25 (14.5) | 18 (18.8) | 5 (11.4) | 7 (16.7) | 6 (27.3) | 4 (19) | 60 (13.9) |
| >5 minutes | 14 (3.8) | 8 (4.7) | 7 (7.3) | 5 (11.4) | 5 (11.9) | 3 (13.6) | 6 (28.6) | 15 (3.5) |
| Missing/did not report | 268 (73.6) | 123 (71.5) | 62 (64.6) | 29 (65.9) | 27 (64.3) | 11 (50) | 10 (47.6) | 320 (74.2) |

[a]Methodological characteristics of the 431 unique datasets included in the review, stratified by substance group. Values are presented as mean (SD) for continuous variables and n (%) for categorical variables.
[b]EMA: ecological momentary assessment.
[c]DD: daily diary.
[d]SD: sensor data.

**Table 5.** Intervention types integrated with EMA[a] protocols across unique datasets[b].

| Intervention type | Description | n (%) |
|---|---|---|
| EMI[c] | Real-time interventions delivered in response to participants' EMA responses or behaviors such as personalized coping messages, motivational prompts, or behavioral support in naturalistic settings. | 6 (10.2) |
| JITAI[d] | Adaptive interventions that used real-time EMA and/or sensor data to deliver the right type and amount of support precisely when an individual is identified to be at increased risk. | 2 (3.3) |
| EMA-informed personalized feedback | Interventions using participants' EMA data to generate personalized feedback, dashboards, visualizations, or summaries intended to increase self-awareness and support behavior change. | 10 (16.7) |
| Sensor-based intervention | Interventions using wearable or sensor technologies (eg, heart rate variability biofeedback, transdermal alcohol sensors, and wearable monitoring) to trigger support. | 8 (13.3) |
| mHealth[e] interventions | Smartphone applications, web-based platforms, SMS or text messaging, and mHealth interventions used to deliver behavioral support, reminders, or treatment content. | 14 (23.3) |
| Contingency management | Incentive-based interventions where financial or other rewards were dependent on abstinence, treatment adherence, or EMA compliance. | 9 (15) |
| Psychological/behavioral interventions | Conventional behavioral interventions delivered alongside EMA, including CBT[f], MI[g], MET[h], counseling, relapse prevention, and coping-skills training. | 22 (36.7) |
| Pharmacotherapy | Medication-based interventions delivered alongside EMA, including medications such as naltrexone, topiramate, NAC[i], ibudilast, and varenicline. | 10 (16.7) |
| Harm reduction interventions | Interventions designed to reduce drug- or alcohol-related harms, including drug checking, breath alcohol concentration warnings, and safer use strategies. | 5 (8.3) |

[a]EMA: ecological momentary assessment.
[b]Intervention types integrated with ecological momentary assessment protocols across unique datasets employing interventions. Values represent the number and percentage of unique datasets incorporating each intervention type. Intervention categories were not mutually exclusive; individual datasets could incorporate multiple intervention approaches.
[c]EMI: ecological momentary intervention.
[d]JITAI: just-in-time adaptive intervention.
[e]mHealth: mobile health.
[f]CBT: cognitive behavioral therapy.
[g]MI: motivational interviewing.
[h]MET: motivational enhancement therapy.
[i]NAC: N-acetylcysteine.

Sensor data were collected in 40 of 431 (9.3%) unique datasets, predominantly among studies assessing alcohol. Sensor data were also used in a small number of cannabis and stimulant datasets (Table 3).

## EMA Protocol, Scheduling, and Prompt Strategy

The average assessment period across studies was 28 (range 1-180; median 21, IQR 16) days, with an average of 3 (range 1-13) assessments per day. Reporting on number of daily assessments was relatively high with only a small percentage (50/431, 11.6%) not reporting the number of assessments per day as set out in their protocol. Of the 11 sensor data-only studies (Table 4) that measured behavior continuously, the frequency of measurement ranged from every 20 seconds to every 30 minutes. Of the 156 EMA- and DD-only studies (n=56, 35.6%) that reported strict prompt completion windows for self-report measures, participants were given on average 5 hours and 24 minutes (SD 9.6 hours) to complete a momentary prompt before it expired (range 15-1440 minutes). There were 284 (431, 65.9%) studies that did not report details on prompt completion windows. Most studies (248/431, 57.5%) used a sampling strategy that prompted participants to complete surveys at fixed time intervals (interval contingent only; Table 4).

## Technology and Administration

Of the 431 unique datasets, 323 collected self-report data using mobile phones, followed by electronic diaries or personal digital assistant (PDA) devices (30 unique datasets; Table 6). Among studies using smartphones for data collection, 64 distinct smartphone apps and software platforms were used to measure target behaviors. However, a proportion of studies (99/431, 23.0%) did not specify the EMA software or app used for data collection. Web-based surveys (64/431, 14.8%) and email, SMS messaging, or interactive voice response (IVR) systems (57/424, 13.2%) were the most commonly reported nonapp-based data collection methods. A total of 2 studies (0.4%) used smartwatch-based EMA, mostly in conjunction with a companion smartphone app. Among the 111 studies that provided information on momentary survey duration, 60 reported a maximum duration of greater than 3 and less than 5 minutes. See Table 4 for further details.

**Table 6.** Data collection devices[a].

| Collection device | n (%) |
|---|---|
| Self-report (EMA/DD)[b,c] | |
| Phone/smartphone | 323 (74.9) |
| Electronic diary/PDA[d] | 30 (7.0) |
| Computer | 6 (1.4) |
| Tablet | 5 (1.2) |
| iPod touch | 2 (0.5) |
| Paper | 2 (0.5) |
| Smartwatch | 2 (0.5) |
| Missing | 56 (13.0) |
| Sensor data | |
| Ankle-worn device | 16 (3.7) |
| Breathalyzer | 14 (3.2) |
| Wrist-worn device | 8 (1.9) |
| Smartphone sensors | 3 (0.7) |
| Smart vaporizer | 1 (0.2) |
| Chest-worn device | 1 (0.2) |

[a]Devices used to collect EMA, DD, and passive sensor data across the included studies. Values represent the number and percentage of studies using each data collection device. Self-report devices were used for EMA/DD studies, whereas sensor devices were used for passive or active sensing studies.
[b]EMA: ecological momentary assessment.
[c]DD: daily diary.
[d]PDA: personalised digital assistant.

Among the 40 unique datasets that used active or passive sensor data to measure substance use behaviors, 16 used ankle-worn devices, 14 used breathalyzers, 8 used wrist-worn devices, 3 used smartphone sensors to collect objective indicators of substance use, one used a smart vaporizer, and one used a chest-worn device (Table S4 in Multimedia Appendix 1 for an extensive list of apps and technologies used to collect data).

### Compliance, Attrition, and Reimbursement

Compliance rates were not applicable or not conventionally calculable for 6.0% (26/431) datasets that used event-contingent and/or sensor-only designs. Among the remaining datasets, 109 of 431 (25.3% of all datasets) did not report sufficient information to determine compliance. Across 74.7% (322/431) of the studies that reported compliance rates, these rates were relatively high, with participants completing on average 79.1% (SD 13.5%; range 22.8%-100%) of triggered assessments. Of the 325/431 (75.4%) studies that reported the number of missing datapoints or excluded participants from analyses, the average attrition and/or exclusion rate was 14.9% (SD 16.5; range 0%-86.7%). Common reasons reported for excluding participants included low response rates, failing to report outcome of interest, and equipment malfunction or technical issues. There were 297 of 431 (68.9%) studies that offered financial reimbursement. The maximum potential reimbursement available to participants averaged USD $166 (SD US $152; range USD $0-1130); although reimbursement structures varied considerably between studies, including fixed payments, payments contingent on survey completion, and compliance-based bonuses. Among the studies offering nonmonetary incentives, university course credits were offered in 19 of 431 (4.4%) studies, 2 of 431 (0.5%) studies offered prize draws, 1 of 431 (0.2%) study offered a festival ticket, and one study (0.2%) offered a Fitbit as reimbursement for study participation.

## Discussion

### Summary of Evidence

#### Overall Findings

This study comprehensively reviewed recent studies using EMA to measure substance use, focusing on methodological characteristics such as sampling strategies, engagement frequency, compliance, and data collection methods. Overall, 431 unique datasets were included in the review, predominantly observational studies conducted in the United States. The included studies measured 31 unique licit and illicit substances and, despite considerable variation in the effects and patterns of use across substances, EMA study designs were broadly comparable. However, this may partly reflect protocols measuring multiple substances within the same study.

This review highlighted the predominant focus on alcohol and cannabis in EMA-based substance use research, with relatively little examination of other psychoactive substances. Several reasons may explain this oversaturation, such as broader research priorities, funding availability, and the

relative prevalence and legal status of these substances, but it also introduces a potential research bias [19,20]. Expanding EMA research across a broader range of substances will be important to determine whether existing methodological approaches are transferable or whether substance-specific protocols are required.

Most studies assessed substance use over a multiweek period, typically using several prompts per day. While the length of assessment and number of daily surveys varied considerably across studies, overall compliance rates were generally high, with most studies reporting moderate-to-strong participant engagement.

Overall, compliance rates of included studies were high. This may be driven by the short nature of the studies and may speak to the general acceptability and ease of usability of EMA methods in substance use research [13]. This finding may also reflect the acceptability of collecting substance use data through personal mobile devices, which enable relatively discreet, real-time self-reporting without requiring repeated face-to-face or telephone contact with researchers [6]. While good, compliance rates still fell below the suggested 80% compliance benchmark for optimizing data quality [5]. This was particularly evident in studies measuring depressant and sedative use, which reported the lowest average compliance rates. These findings suggest that future EMA research in this area should carefully consider feasibility and adopt strategies to improve participant engagement, such as tailored or indirect notification schedules, flexible completion windows, or enhanced incentives to optimize compliance and data quality [21]. While prior research has found no consistent association between shorter study durations and survey compliance, adjusting reimbursement schedules to better reward sustained participation may offer an alternative approach to improving adherence [13]. Further, this review describes design and participant characteristics (ie, by substance type) in relation to compliance; however, factors associated with compliance were not formally analyzed. Jones et al [13] discuss a detailed overview of factors associated with compliance in EMA studies of substance use.

## Methodological Characteristics by Substance Type

Alcohol was the most frequently studied substance, followed by cannabis and other drugs. Given alcohol's global prevalence and significant public health impact, and the increasing legalization and accessibility of cannabis, it is unsurprising that these substances have been prioritized in EMA research [22,23]. Unique to alcohol studies, one cannabis and one stimulant study were the measurement of sensor-based technologies to objectively measure substance use. These included wrist and ankle-worn transdermal alcohol concentration (TAC) monitors and breathalyzers to quantify alcohol use, as well as smartphone sensing data (ie, accelerometers, GPS, number of outgoing calls, etc) to passively detect biologically confirmed or subjective intoxication. Notably, one cannabis study used a smart vaporizer to objectively measure use characteristics, such as puff count and product potency.

While still limited in number, this likely reflects the relative maturity of validated biosensors in alcohol research and, to a lesser extent, cannabis and stimulant research, whereas equivalent technology for substances like cannabis, psychedelics, stimulants, or opioids remains underdeveloped, with a focus on detection rather than level of intoxication [8,24]. As wearable and smartphone sensing technologies continue to evolve, passive sensing has the potential to complement self-reported EMA by reducing participant burden, providing continuous behavioral data, and facilitating more objective measurement of substance use and related behaviors. However, challenges relating to sensor validity across different substances, user acceptability, privacy, and integration with active EMA protocols remain important considerations for future research.

EMA has seen increasing application in studies measuring opioid use, with most focusing on clinical samples or vulnerable populations. This growing body of research signals an important and emerging role for EMA in understanding opioid use patterns in real-world settings. Prior reviews have demonstrated that EMA is both feasible and acceptable among individuals receiving treatment for opioid use disorder, with evidence pointing to its potential utility in predicting and intervening on relapse in a naturalistic setting [25]. Further, EMA has been proposed as a valuable clinical tool to support treatment retention and improve patient outcomes by enabling more responsive, individualized care [26]. Given the scale of the opioid crisis in many parts of the world, there is a compelling case to continue expanding EMA research to better understand opioid use patterns, cravings, and relapse [1]. Doing so may strengthen harm reduction and prevention efforts, support personalized interventions, and potentially improve the delivery of evidence-based care [25,27].

Psychedelic use is of increasing interest due to recent regulatory changes in access to therapeutic psychedelic drugs in several countries and increasing global prevalence rates [1,28]. Despite this, psychedelics were measured in relatively few studies, and in most cases, they were not the primary substance being targeted. Instead, psychedelics were typically measured as either confounding variables or to describe substance use patterns of participants. For instance, Bragard et al [29] grouped psychedelics with all substances except cannabis to examine associations between drug use and loneliness during COVID-19. Paolillo et al [30] included psychedelics in their dichotomous variable describing any substance use but reported only on alcohol and cannabis outcomes. Similarly, Santa Maria et al [31] reported lysergic acid diethylamide (LSD), MDMA, and phencyclidine use descriptively but aggregated all substances into a single variable in predictive models. Weiss et al [32] and Yeater et al [33,34] measured psychedelic use but excluded it from both descriptive statistics and main analyses. Pop et al [35] used EMA to measure the effects of microdosing psychedelics on state authenticity; however, they did not differentiate between substance type despite distinct variation in nature and duration of effects.

Given recent regulatory changes in some jurisdictions permitting substances like psilocybin, MDMA, and ketamine to be used clinically for conditions like posttraumatic stress disorder (PTSD) and depression [36,37], EMA could offer valuable real-world insights on short-term effects of psychedelics both within and beyond clinical settings. Such research may help to unpack therapeutic mechanisms, inform safer clinical protocols and harm reduction strategies, and improve understanding of recreational use patterns including risk and protective factors.

## Reporting Methodological Information

Inconsistent reporting of methodological information posed a key challenge when synthesizing study characteristics. Compliance information was not reported for approximately one quarter of datasets for which it could reasonably be assessed, and many studies also omitted details on attrition, raising concerns about potential reporting bias. This is consistent with EMA research in other areas that have also identified compliance reporting issues, which is not unique to EMA substance use research [18,38,39]. Although reported compliance was generally high and attrition was generally low among studies providing these data, the substantial amount of missing reporting limits confidence in these estimates and may result in overly favorable representation of study performance. More broadly, compliance should be interpreted as an indirect indicator of participant engagement rather than definite evidence of acceptability. Improved and standardized reporting of compliance and attrition is therefore needed to enable more reliable assessment of EMA feasibility, data completeness, and study quality [18].

Reporting of prompt completion windows is another important factor in EMA research [40,41]. This parameter directly impacts the temporal resolution and ecological validity of the data and is especially important when assessing behaviors that are time- and context-dependent like substance use [41]. When completion windows are long or nonexistent, responses may be temporally distant from the behavior of interest, calling into question how "momentary" the data truly are [21]. On the contrary, extending completion windows may be a pragmatic strategy to reduce missing data. Notably, the majority of studies in this review did not report prompt completion windows, highlighting a significant gap in methodological transparency. Thus, researchers must strike a balance between minimizing recall bias and maximizing data retention whilst ensuring that details of prompt completion windows and latency are reported to ensure reproducibility of findings and protocols.

Despite some evidence suggesting that the specific delivery platform can influence compliance and data quality in EMA studies, a small minority of studies did not specify the EMA platform used for data collection [40]. Reporting detailed information on tools used to collect data is important, not only to support replication and confidence in findings, but also to prevent unnecessary duplication of data collection tools when existing platforms may suffice. We recommend that future studies report detailed information on the platform, application, or technology used to deliver EMA prompts.

Participant burden is an important consideration in EMA studies, as it may contribute to attrition, although it remains difficult to quantify. Momentary survey duration may serve as a useful proxy, yet just over 3-quarters of included studies did not report this metric. Although existing literature presents mixed findings on whether or not survey duration is associated with compliance, transparent reporting of momentary survey length is important for evaluating feasibility and participant burden [13,39,42]. Future EMA studies in substance use research should prioritize consistent reporting of survey duration to support comparability with other studies as well as transparency, reproducibility, and consistency of research methods.

Collectively, these reporting limitations have implications beyond methodological transparency. Incomplete reporting limits the ability to critically appraise study quality, assess potential sources of bias, and determine whether EMA protocols were implemented in a manner consistent with their intended design. Further, inconsistent reporting limits meaningful comparisons across studies, the reproducibility of EMA protocols, and opportunities to identify methodological features associated with improved data quality and participant engagement. As EMA methods continue to evolve, more complete and standardized reporting will be essential to maximize the validity, interpretability, and cumulative value of findings for substance use research.

## Future Directions

Despite the ubiquity of smartphones and consumer wearables over the past decade, only 3 studies passively assessed substance use with smartphone smart sensors and only 2 studies used a commercially available device, such as Apple Watches (Apple Inc), Fitbits (Google LLC), or Oura Rings (Oura Inc). The majority of studies measuring sensor data used specialized wearables like wrist or ankle bracelets developed specifically to monitor transdermal alcohol concentration [43,44]. This represents a missed opportunity for leveraging widely accessible technologies to capture unobtrusive real-time physiological, behavioral, and environmental markers of substance use as well as potential digital phenotypes related to substance use behaviors. Future EMA-substance use research should therefore prioritize systematically evaluating the feasibility, validity, and eventual clinical utility of integrating smartphone sensors and consumer-grade wearables to passively capture indirect indicators of substance use and their effects, such as heart rate variability, electrodermal activity, circadian rhythm, speech or keystroke dynamics, and geolocation [45,46]. Achieving this will require multidisciplinary collaboration, particularly with substance use researchers, data scientists, and machine-learning experts, capable of handling highly dimensional and complex sensor data.

Expanding sensor-based methods across different drug classes could not only enhance the ecological validity of EMA but also support the identification of (additional) objective biomarkers of use. This, in turn, may contribute to the development of standardized units of measurement, an approach long established in alcohol research through

the concept of a "standard drink," but still largely absent for most illicit substances [47]. Additionally, efforts to quantify substance potency, as seen in a small subset of cannabis studies, are crucial for improving our understanding of dose-response relationships and should be more widely adopted [48]. However, we acknowledge that not all wearables provide raw data and data security issues might hinder research from including this type of data source. Expanding EMA research beyond alcohol and cannabis is also important to ensure that methodological advances are applicable across the broader spectrum of substance use research. Stimulant use, including cocaine, methamphetamine, and amphetamine use, represents an important opportunity for future EMA research. The episodic and context-dependent nature of stimulant use, characterized by rapid fluctuations in craving, affect, and environmental influences, is well suited to high-frequency EMA designs, which may provide greater temporal resolution than current retrospective assessment methods for understanding patterns of use and relapse.

Further, as evidenced in this review, EMA methods offer ample opportunity to support the development and delivery of a broad range of interventions (Table 5) [49]. By leveraging contextual and behavioral data, these approaches have the potential to deliver personalized, context-specific support and intervention at moments of heightened risk or need. Although EMIs and JITAIs were relatively uncommon in included studies, they represent a promising application of EMA methodologies offering researchers the opportunity to intervene within the daily lives of participants in response to real-time behavioral and contextual changes. Taken together, these directions highlight the opportunity for innovation in EMA data collection methods that align with technological advancements and the complexity of substance use behaviors.

## Limitations

Methodological and practical limitations within the field of EMA-based research have been reported in detail elsewhere [6,50,51]. There were also several limitations inherent to our own review process. Due to the wide scope of the review and the large number of included studies, we were limited in the number of methodological variables that could be extracted within our time and resource constraints. For example, we restricted the publication timeframe of studies to the last 8 years (2018-2026). Additionally, we did not assess whether studies provided participant training for EMA protocols, standardization of included items, nor did we examine in detail the use of burst designs in included studies. These aspects may influence feasibility, participant burden, compliance, and data quality and should be considered in future reviews [50]. Power and sample size calculations remain a common challenge in EMA design due to the intensive, multilevel nature of the data [52]. We did not extract whether included studies performed a priori or post hoc power calculations, nor the method (eg, formula-based vs simulation-based) used to determine sample size. Future syntheses should aim to capture these variables to inform best practice in EMA study planning.

Missing data is a well-known issue in EMA research. Whilst our review did collect information on the proportion of missing data and the number of excluded participants postbaseline, we did not collect information on whether studies reported the mechanisms of missingness (ie, missing completely at random), nor on the statistical techniques used to address it (eg, multiple imputation and maximum likelihood). Given the implications of missing data on validity and inference, future studies should systematically assess and report on these practices. We caution against making value judgments without further context. Nonetheless, our findings reinforce the need for clearer guidance and more consistent application of statistical methods that address the correlated nature of EMA data such as mixed-effects or multilevel models [52].

Although duplicate independent data extraction of all included studies was not undertaken, multiple quality assurance procedures, including reviewer training, calibration, and validation of AI-assisted extraction against a stratified human-reviewed sample, were implemented to minimize extraction errors.

Cross-substance comparisons should be interpreted cautiously because substance categories were not mutually exclusive and many studies measured multiple substances within the same EMA protocol, resulting in overlapping datasets across substance categories. Further, the methodological recommendations and common design practices identified in this review are likely to be most representative of alcohol and cannabis research and may not fully reflect the unique methodological considerations associated with less frequently investigated substances, such as opioids, psychedelics, or novel psychoactive substances.

Finally, we did not extract detailed metrics on response latency (ie, time between prompt and participant response). While such data could inform the ecological validity of EMA responses, we did collect information on prompt completion windows, which may serve as a proxy for temporal proximity between behavior and measurement. Future studies should consider collecting and investigating response latency variables.

## Conclusions

This review provides the first comprehensive cross-substance synthesis of EMA methodologies used to measure substance use, offering valuable insight into current design practices, strengths, and areas requiring improvement. Unlike previous reviews, which have focused on individual substances or narrower methodological aspects, this review systematically compared methodological characteristics across substance groups and developed methodological and reporting recommendations for future EMA studies. While EMA is increasingly recognized as a powerful tool for capturing dynamic, context-dependent substance use behaviors, findings from this study highlight several methodological inconsistencies, particularly in reporting practices and design transparency. Although broad methodological similarities were observed across substance categories,

cross-substance comparisons should be interpreted cautiously because many studies assessed multiple substances within the same EMA protocol. There were emerging trends in the application of EMA to underexplored substances such as opioids and a lack of studies focusing on psychedelics. Yet, key gaps remain, including limited use of wearable technologies, underreporting of missing data and compliance, limited reporting of momentary survey duration, and prompt completion window metrics. By identifying current methodological practices, reporting gaps, and emerging trends in EMA technologies, this review provides practical guidance to improve the transparency, reproducibility, and comparability of future substance use research. Addressing these limitations and following the reporting and methodological recommendations provided within this review (Table 1) may improve feasibility, data quality, and reproducibility in future EMA studies. As the field evolves alongside digital health technologies, ongoing methodological refinement will be critical to fully realizing the potential of EMA in substance use research.

## Generative AI Use

The authors declare the use of generative AI (GenAI) in the research and writing process. According to the Generative AI Delegation Taxonomy (GAIDeT) taxonomy (2025), the following tasks were delegated to GenAI tools under full human supervision: code optimization and proofreading and editing. The GenAI tool used was ChatGPT-5.6 Sol. Responsibility for the final manuscript lies entirely with the authors. GenAI tools are not listed as authors and do not bear responsibility for the final outcomes. This declaration was submitted by Zachary Bryant. Additional note: As described in the Data Extraction and Synthesis section, a custom GPT (Systematic Review Extractor Pro) was used to assist with data extraction. All other AI-assisted outputs were critically reviewed and verified by the authors for accuracy, errors, and potential bias, and were revised as appropriate.

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## Conflicts of Interest

None declared.

## Multimedia Appendix 1

Search strategy, data extraction and categorization procedures, identification of linked publications and unique datasets, study population and substance classifications, and extraction quality control procedures.
[DOCX File (Microsoft Word File), 39 KB-Multimedia Appendix 1]

## Checklist 1

PRISMA-ScR checklist.
[PDF File (Adobe File), 531 KB-Checklist 1]

## Multimedia Appendix 2

Bibliographic references, study characteristics, and publication-to-dataset mapping for the 581 included publications.
[DOCX File (Microsoft Word File), 749 KB-Multimedia Appendix 2]

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## Abbreviations

**ASSIST:** Alcohol, Smoking Substance Involvement Screening Test
**CREMAS:** Checklist for Reporting Ecological Momentary Assessment Studies
**DD:** Daily diary
**EMA:** ecological momentary assessment
**EMI:** ecological momentary intervention
**IVR:** interactive voice response
**JITAI:** just-in-time adaptive intervention
**LSD:** lysergic acid diethylamide
**MDMA:** 3,4-methylenedioxymethamphetamine
**mHealth:** mobile health
**PCC:** population, Concept and Context
**PDA:** personalized digital assistant
**PRISMA-ScR:** Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews
**PROSPERO:** International Prospective Register of Systematic Reviews
**PTSD:** posttraumatic stress disorder
**RAISE:** responsible use of AI in evidence synthesis
**STROBE:** Strengthening the Reporting of Observational Studies in Epidemiology
**TAC:** transdermal alcohol concentration

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