The Dangers of Disquiet: A Scoping Review and Bibliometric Analysis of Digital Phenotyping in Suicide Risk Prediction

Justus L. Theiling

Department of Psychology, University of Twente

Positive Clinical Psychology & Technology

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1st Supervisor: Dr. Jannis Kraiss, Assistant Professor

2nd Supervisor: Dr. Jurrijn Koelen, Assistant Professor

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Abstract

Background: Suicide remains a major global health issue, with current predictive models and interventions showing limited success. Emerging digital phenotyping methods allow for real-time, passive monitoring of behaviour and physiology, offering potential to predict suicidality.

Aim: This study maps the characteristics of existing research, assesses the associations between and predictive validity of digital phenotyping methods with suicidality, and identifies key research trends, contributors, and themes.

Methods: This study combines a scoping review and a bibliometric analysis. The scoping review synthesises empirical studies on digital phenotyping methods in suicidality from PubMed, Web of Science, and PsycINFO. The bibliometric analysis examines trends and key contributors in research on digital phenotyping methods for suicidality.

Results: The search yielded 1120 records; 33 meet eligibility criteria for inclusion. Most studies feature small, predominantly female, white, clinical, and western samples, often with mood or anxiety disorders. Sleep and extralinguistic features (for example speech disfluency) showed the strongest associations with suicidality, while combined active and passive sensing methods achieved the highest predictive accuracy (*AUC* up to 0.84), far surpassing models based on passive data alone (*AUC* = 0.56). The bibliometric analysis revealed exponential growth in publication output after 2018 and a Western-centric authorship pattern.

Conclusion: Behavioural digital biomarkers such as sleep disturbances and speech patterns capture core clinical features of suicidality and currently show the strongest predictive potential. Combining passive sensor data with active self-reports further improves predictive accuracy, with reported *AUC* values reaching up to 0.84. The evidence is constrained by WEIRD sampling biases and critical ethical oversights, limiting generalisability. Future progress requires validating passive models that can trigger targeted, low-burden interventions within globally representative and ethically-sound frameworks.

Keywords: digital phenotyping, digital biomarkers, suicidality, suicide prediction, precision medicine

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> "There is but one truly serious philosophical problem and that is suicide. Judging whether life is or is not worth living amounts to answering the fundamental question of philosophy."

Albert Camus, *The Myth of Sisyphus* (1942/2005, p. 1)

The Dangers of Disquiet: A Scoping Review and Bibliometric Analysis of Digital Phenotyping in Suicide Risk Prediction

Every 40 seconds, someone in the world dies by suicide; a staggering statistic that underscores the urgent need for innovation in prevention. Although advances in technology and medicine are transforming mental health care, suicidality remains a deeply complex frontier where current efforts to predict and consequently prevent these deaths fall alarmingly short (Belsher et al., 2019). In their concept analysis, Keefner and Stenvig (2020) define suicidality as consisting of suicidal ideation, non-lethal and serious suicide attempts, suicidal behaviour, and completed suicide. Meta-analyses reveal that psychological interventions designed to reduce suicidality provide only modest improvements compared to control groups, while the current predictive validity of models for suicidality remain alarmingly inadequate (Belsher et al., 2019; Itzhaky et al., 2021; Kraiss et al., 2024). Moreover, Franklin et al. (2016) noted that the predictive validity of established risk factors for suicidality has not improved over the past half-century. Collectively, these findings underscore the need for innovative approaches for suicide prediction that move beyond traditional models and are tailored to the complex interplay of individual risk factors. This paper maps current research and interventions to assess the associations and the predictive validity of digital phenotyping methods for suicidality.

Precision medicine and suicidality

Precision medicine offers an innovative perspective by tailoring healthcare to individual characteristics, such as genetic makeup, behavioural patterns, and environmental influences. Unlike traditional interventions, which often rely on assumptions about a generalised or prototypical patient (Barrigon et al., 2019, p. 2), precision medicine aims to deliver interventions based on a detailed understanding of a person's unique risk profile (Ashley, 2016; Naithani et al., 2021). This approach is grounded in the 4 Ps of precision medicine: prediction, which involves identifying risk before symptoms emerge; prevention, which focuses on intervening early to reduce risk; personalization, which tailors interventions to individual characteristics; and participation, which actively involves individuals in managing their own health (Flores et al., 2013; Baiardini & Heffler, 2018). Precision medicine might combine digital technologies, such as smart watches, with previous clinical assessments to identify individuals at heightened suicide risk (Nabipour & Assadi, 2016). By integrating biological, psychological, and social variables, precision medicine enables the development of comprehensive risk assessment models that account for distal predispositions such as genetic

vulnerability, family history, and developmental experiences including early attachment disruptions and childhood trauma, as well as proximal triggers such as acute stress and recent interpersonal conflict (Kosorok & Laber, 2019). While traditional approaches have struggled to reduce suicide rates over the past 40 years (Franklin et al., 2016; Roza et al., 2023), precision medicine shifts the paradigm by focusing on the individual level and engages in new methods like digital phenotyping for the prediction of suicidality.

Digital phenotyping, digital biomarkers and suicidality

The use of digital devices in everyday settings has increased drastically since the start of the digital revolution in the 1940s with the construction of the first computing system. Since then, the potential digital methods offer in obtaining information about characteristics, traits, or behaviours of an individual has significantly expanded, enabling more precise and scalable assessments (Burkey, 2021; Chao et al., 2024). The method of collecting moment-by-moment data using digital tools such as smartphones and wearable devices is referred to as digital phenotyping (De Boer et al., 2022; Oudin et al., 2023). The data gathered by digital phenotyping, e.g. heart rate variability, total sleep time or the total number of steps, is referred to collectively as digital biomarkers (Nugent et al., 2022; Oudin et al., 2023). Sameh et al. (2024), in a systematic review of 66 studies, found that digital phenotyping methods can objectively track health outcomes and stress levels by analysing passive data from smartphones and wearable devices, suggesting the potential utility in real-time monitoring and early detection of mental health changes. The Sameh et al. (2024) review particularly underlines the advantages of continuous and unobtrusive measurement in real-world settings, which could improve early detection of mental disorders, including high levels of stress and even suicidality.

Building on these capabilities, depressive behaviours and environmental factors that trigger suicidal thoughts and intentions can be assessed through digital phenotyping methods, offering the possibility to better predict suicidality. Digital phenotyping methods often tries to assess an individual's current depressive symptoms, as these hold significant predictive validity for suicidality (Melhem et al., 2019; Fredriksen et al., 2022). Additionally, Fredriksen et al. (2022) found that self-reported suicidal ideation, suicide planning, and self-harm were not reliable predictors of suicide, largely due to issues such as underreporting, recall bias, and the fluctuating nature of suicidal thoughts. This underscores the need for passive data collection methods, which can provide continuous, real-time insights into behavioural and physiological changes without relying on individuals to self-disclose.

Several digital biomarkers have emerged as promising indicators of suicidality, reflecting physiological and behavioural patterns that can be passively monitored through smartphones and wearable devices. In response to the developed focus on passive data, sleep has emerged as a frequently studied biomarker for suicidality, as it is often disrupted in individuals with depression (Bernert, 2008; Glenn et al., 2021; Burke et al., 2022). A recent meta-analysis by Romier et al. (2023) reviewed 11 studies and identified a decreased total sleep time measured by digital devices as a promising predictive biomarker linked to suicidality. Notably, this association remained significant even after controlling for gender, age, and depression scores. Similarly to sleep, heart rate variability (HRV) is often used as a valid index of current stress level: Wilson et al. (2016) found that lower HRV was associated with subsequent self-harm behaviours, suggesting its potential utility as a stress-related biomarker, although its direct predictive power for suicidality remains limited. This is particularly crucial, because the HRV score can be measured by several wearable devices (Li et al., 2023). Additionally, Knol et al. (2024) demonstrated that smartphone keystroke dynamics, such as slower typing speed and increased inter-key latency, can be used to predict changes in affective states associated with suicidal ideation. These affective states refer to emotional conditions such as sadness, hopelessness, or emotional numbness, which are commonly linked to heightened suicide risk. Slower typing speed, in particular, may reflect anhedonia, a core symptom of depression characterised by a reduced ability to experience pleasure (Cooper et al., 2018). This underlines the value of passive data collection for detecting subtle behavioural markers of depressive symptoms, which digital biomarkers can provide. Moreover, extralinguistic features like voice speech quality have been utilised as a digital biomarker, serving as a feature set for machine-learning models which assisted clinicians in identifying elevated suicide risk from speech patterns (Galatzer-Levy et al., 2021; Stasak et al., 2021). Consequently, digital biomarkers offer a wide range of potential applications, with ongoing advancements continually expanding their scope.

While existing studies have examined individual biomarkers (such as sleep, HRV, voice features, and mobile sensor data like activity or location) for the prediction of suicidality (Bidargaddi et al., 2024; Sameh et al., 2024), a comprehensive, systematic overview that synthesises the types of biomarkers studied, the technologies used, and their predictive validity across diverse populations is currently lacking. Foundational questions remain unanswered regarding the key characteristics of studies and interventions in this field, such as the demographics of participants, the geographical distribution of research, the study designs

employed, and the extent to which ethical issues like data privacy are addressed (RQ1). Currently, there is no systematic synthesis of these aspects, which limits the ability to assess the generalisability, equity, and ethical robustness of digital phenotyping research. This lack of clarity also impairs the understanding of how these tools are associated with suicidality, and how their predictive validity may vary across different populations, psychiatric diagnoses, and clinical or non-clinical settings (RQ2). Here, it is crucial to differentiate between two distinct analytical goals. Predictive validity specifically refers to the ability of digital phenotyping methods to forecast a future event, such as a suicide attempt, over a defined period. Concurrent associations, on the other hand, describe the strength of the relationship between a digital phenotyping method and the state of suicidality at the same point in time.

To address its research questions, this study uses a dual methodological approach. The primary method is a scoping review that systematically maps the literature to provide an in-depth synthesis of individual studies. This review addresses the first two research questions by investigating the key characteristics of studies and interventions (RQ1) and examining how digital methods are associated with suicidality across various groups and settings (RQ2). To complement this review with a quantitative overview of the field's structure and evolution, a bibliometric analysis provides further insight. This secondary method addresses the final research question by systematically mapping publication patterns to uncover research trends, influential contributors, and thematic focuses (RQ3) (Donthu et al., 2021). By integrating the in-depth findings from the scoping review with the broad structural insights from the bibliometric analysis, this study offers a comprehensive, integrated overview of the field. This dual approach identifies overlooked populations, exposes methodological gaps, and outlines priorities for future empirical investigations. Hence, this study is guided by the following research questions:

1. What are the key characteristics of studies and interventions investigating digital phenotyping methods for suicidality?
2. How are digital phenotyping methods associated with suicidality (including suicidal ideation, suicide risk, and self-harm), and how do their associations vary across diverse populations (clinical, sub-clinical, or non-clinical), diagnoses, and contexts (geographic, cultural, and clinical)?
3. What are the research trends, influential contributors, and thematic focuses in the field of digital phenotyping methods for suicidality as revealed by a bibliometric analysis?

Methods

Research design

The current study employed a scoping review following the Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) guidelines (Tricco et al., 2018) to address the first two research questions and a bibliometric analysis for the third research question.

Search strategy

A systematic search was conducted using the three databases “PubMed,” “Web of Science” and “PsycInfo”. PubMed offered extensive access to biomedical and clinical research, including studies on mental health and digital health interventions (National Library of Medicine, 2025). PsycInfo focused on psychology and behavioural sciences, capturing research on suicidality, psychological assessment, and digital mental health tools (American Psychological Association, 2025). Web of Science provided broad multidisciplinary coverage, with high-influence journals across health sciences, technology, and social sciences (Clarivate, 2025). The search string was designed to capture studies that use digital and passive data collection methods. Digital phenotyping, ecological momentary assessment (EMA), and wearable sensors for monitoring mental health were included. Following the Population, Concept, and Context (PCC) framework, the search strategy was built around a central Concept comprising two keyword groups: digital monitoring technologies (e.g., "digital phenotyping," "wearable sensor") and suicidality outcomes (e.g., "suicidal ideation," "self-harm") (University of South Australia, 2025). The population and context were deliberately left unrestricted to capture a broad range of studies across diverse participant groups and settings, ensuring a comprehensive dataset for analysis. The search was conducted on February 2, 2025, and the following search string was used:

("digital phenotyping" OR "digital biomarker" OR "ecological momentary assessment" OR "EMA" OR "experience sampling" OR "ESM" OR "wearable sensor" OR "continuous monitoring" OR "mobile sensing" OR "smartphone-based monitoring" OR "real-time monitoring") AND ("suicidality" OR "suicidal behavior" OR "suicide risk" OR "suicide prediction" OR "suicide prevention" OR "self-harm" OR "suicidal ideation").

Eligibility criteria

Studies were considered eligible if they investigated digital phenotyping methods or specific digital biomarkers, such as wearable sensors, smartphone-based monitoring, or real-time tracking, in relation to suicidality, including suicidal ideation, suicide risk, and suicidal behaviour, such as self-harm. Additionally, studies needed to examine the relationship between digital phenotyping methods and suicidality. Both clinical, subclinical and nonclinical samples were included to ensure a comprehensive understanding of the research landscape. Eligible study designs included empirical studies, such as observational, case-control, experimental, or cross-sectional research, feasibility studies. The outcome measures of the studies had to assess suicidality (ideation, attempt, suicidal behaviour, actual suicide) using validated clinical scales (e.g. Columbia Suicide Severity Rating Scale) or self-reports, and include quantitative evaluations of prediction accuracy, sensitivity, specificity, effectiveness or correlations between digital phenotyping methods and suicidality. Only peer-reviewed publications were considered, and only studies in English were included.

Studies were excluded if they did not specifically address suicidality or did not utilise digital phenotyping methods. Non-empirical publications, such as case reports, commentaries, or theoretical papers were also excluded. Additionally, studies that focused solely on general mental health outcomes (e.g., depression, anxiety) without explicit suicidality-related metrics were not considered for inclusion.

Study selection

After conducting searches in the three specified databases using the defined search string, the resulting articles were exported, including their titles, keywords, abstracts, authors' names, DOIs, and journal names, and then imported into the Covidence program (Covidence, 2025). The program automatically removed any duplicates during the import process. The researcher screened the remaining articles by reviewing their titles and abstracts to identify studies relevant to the research question. Relevant studies were saved for full-text evaluation. During the full-text screening, the researcher carefully reviewed the methods, results, and discussion sections to determine whether each study met the predefined eligibility criteria. In cases of uncertainty regarding inclusion, the researcher revisited the eligibility criteria and cross-checked with similar studies to ensure consistency in decision-making. This process involved compiling a list of the ambiguous articles and reviewing the inclusion criteria according to the new challenges posed by said articles. These cases were then presented to other

researchers to reach a consensus, ensuring the consistent application of the eligibility criteria. If ambiguity remained, the researcher documented the rationale behind the decision before making a final decision.

Data charting process

The relevant information was extracted manually from the full texts of all included studies into a structured Excel spreadsheet. No automated tools were used during this process. To answer the first research question (RQ1), data was collected on publication year, country of publication, study design, sample characteristics (sample size, age, gender, ethnicity), population (clinical, subclinical, or non-clinical), incentives, study setting (real world, hospital, laboratory), data processing methods, privacy, funding sources and intervention characteristics where applicable. For RQ2 (associations and predictive validity), information was extracted on the type of digital biomarkers or phenotyping modalities assessed, device used (e.g. smartphone, Fitbit), suicidality outcomes measured (e.g., ideation, self-harm, risk levels), reported statistical associations (e.g., correlations, p-values, odds ratios, confidence intervals), and predictive metrics (e.g., sensitivity, specificity, AUC), as well as key findings.

Synthesis of results

A narrative synthesis was utilised to integrate the outcomes across studies, chosen specifically for its suitability in handling the diverse range of study designs and the expansive scope of the included research. A narrative synthesis is a systematic approach to summarising and interpreting findings from heterogeneous studies, making it particularly valuable for scoping reviews (Lisy & Porritt, 2016). It facilitates the identification of patterns, gaps, and trends in research, allowing for a structured, yet flexible integration of evidence without the necessity of statistical meta-analysis.

Bibliometric analysis

To address the third research question about examining research trends, key contributors, and thematic emphases in digital phenotyping methods for suicide prevention, a bibliometric dataset was retrieved on 2 February 2025. The predefined search string was applied sequentially to Web of Science, PubMed, and PsycINFO; Web of Science yielded the most comprehensive result set, consisting of 440 records. To eliminate redundancy, only the Web of Science export was retained. The researcher used the recommendations about analysis and software tools of Moral-Muñoz et al. (2020) and Donthu et al. (2021) as a guideline.

Consequently, the data was exported in RIS format and imported into Microsoft Excel 2021 (Version 16) for processing. Using PivotTable functionality, the following variables were extracted and tabulated: country of origin, author keywords, publication year, author name, and journal title. These variables were deemed most pertinent for mapping geographic distribution, temporal trends, prolific authorship, and leading outlets. For visualisation, bar charts were generated in Excel, with publication or keyword-occurrence counts on the y-axis and the variable of interest on the x-axis.

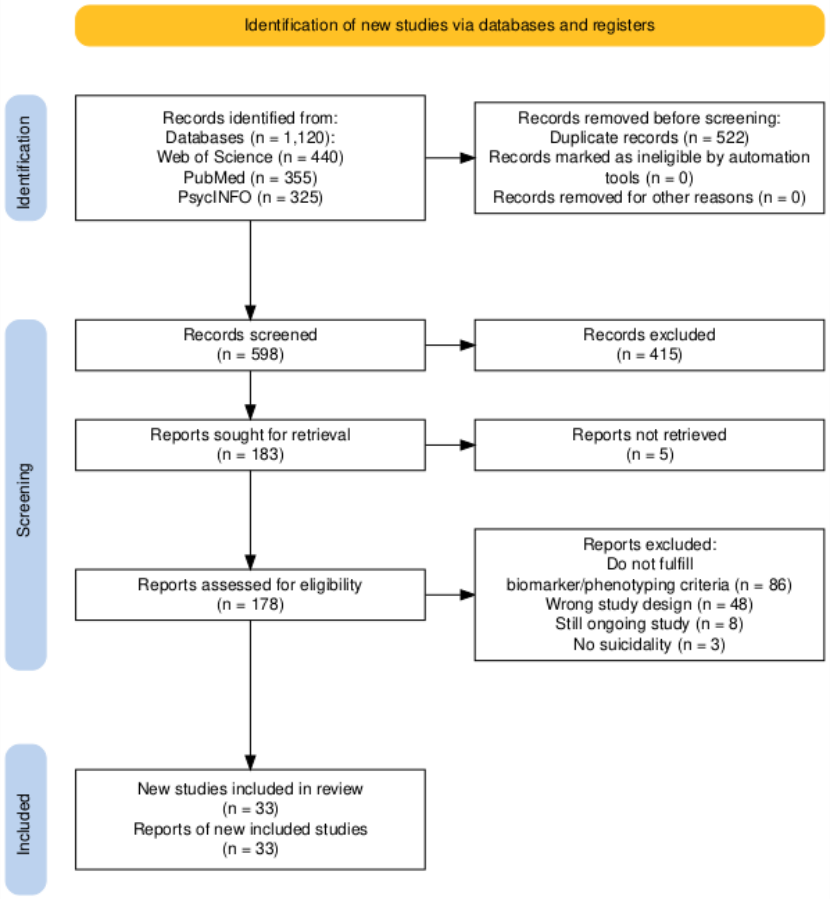
Results

Overview of studies

The database search identified 1120 papers. Following the removal of 522 duplicates, 598 records remained for title and abstract screening. At this stage, 415 studies were excluded, primarily due to a lack of focus on the relationship between digital phenotyping methods and suicidality. Subsequently, full-text screening was conducted on 183 studies, resulting in the exclusion of 150 papers that did not meet the predefined eligibility criteria. Ultimately, 33 studies were included in the final dataset for analysis.

Figure 1

PRISMA Flow Diagram Illustrating the Study Selection Process from Initial Literature Identification to the Final Dataset (Haddaway et al., 2022).



RQ1: Study and intervention characteristics

Across the included studies, the median sample size was 66 participants (*range* = 2-25,987). The mean age of participants was 25.17 years (*SD* = 5.84), and the reported mean ages across studies ranged from 17.58 to 36.11 years. A total of 60.60% of the studies reported providing participants with some form of compensation (*n* = 20). Among studies that reported on ethnicity (*n* = 20), the majority of participants were identified as White (69.19%). In studies that disclosed gender distribution (*n* = 30), the mean proportion of female participants was 66.39% per study (*range* = 13.00-100.00%). A detailed overview of the title and first author of the reviewed studies can be found in Appendix A.

The majority of studies were conducted in the United States (*n* = 24). Only one study, conducted in Brazil, originated from a setting outside of high-income countries. With regard to funding, almost half of the studies (*n* = 15) received at least partial financial support from the

National Institute of Mental Health (USA), while some studies did not disclose any funding sources (n = 5). The mean publication year across studies was 2021 (SD = 2.26). Most studies included clinical samples (n = 23), with additional studies utilising non-clinical (n = 8) and subclinical (n = 1) samples. Furthermore, the majority of studies (n = 26) were conducted in real-world settings.

With regard to study design, the most commonly employed designs were prospective cohort studies (n = 9) and observational longitudinal designs (n = 9), sometimes using intensive longitudinal methods (n = 2). Prospective observational designs (n = 4) and prospective feasibility or pilot study designs (n = 3) were reported in several studies. Cross-sectional approaches, including cross-sectional model validation, secondary data analysis, and retrospective cross-sectional case-control studies (n = 3), were also utilised, however less frequently. Additionally, a smaller number of studies employed comparative case analyses (n = 1), randomised controlled crossover trials (n = 1), micro-randomised trials (n = 1), and qualitative designs such as focus groups (n = 1) and case series studies (n = 1).

Moreover, the most frequent way to measure suicidality was suicidal ideation (n = 29); suicide attempts, suicidal behaviours and depressive symptoms were the only alternative measures used. For the actual assessment, the most common assessment tool was the Columbia-Suicide Severity Rating Scale (CSSRS) (n = 9).

Table 1

Summary of the Key Characteristics of the Reviewed Studies

Reference number	Year	Study design	Country	Sample size	Mean age (*SD*)	Age range	Percentage female	Percentage white	Participant type	Study setting	Privacy mentioned	Incentives
1	2022	Observational longitudinal design	USA	2,238	27.60 (*2.60*)	-	56.80%	58.00%	Non-clinical	Real world	Yes	Yes
2	2016	Case-control study	Ireland	30	41.50 (*12.50*)	-	63.33%	-	Clinical	Laboratory	Yes	No
3	2020	Prospective cohort study	Canada	76	49.00 (*19.75*)	18-65	37.49%	-	Clinical	Real world	No	No
4	2023	Prospective cohort study	USA	106	20.93 (*2.07*)	18-25	81.10%	73.50%	Clinical	Real world	No	Yes
5	2024	Observational longitudinal design	USA	48	14.96 (*1.60*)	12-18	64.60%	77.10%	Clinical	Real world	Yes	Yes
6	2021	Observational longitudinal design	USA	48	14.96 (*1.60*)	12-18	64.60%	77.10%	Clinical	Real world	Yes	Yes
7	2022	Cross-sectional model validation	Brazil	5,699	-	-	-	-	Non-clinical	Laboratory	Yes	No
8	2020	Observational longitudinal design	USA	33	20.40 (*2.40*)	-	84.80%	60.60%	Clinical	Laboratory	No	No
9	2022	Cohort study	USA	147	15.14 (*1.44*)	13-18	69.60%	71.20%	Clinical	Real world	Yes	Yes
10	2022	Cross-sectional secondary data analysis	South Korea	25,987	-	-	45.10%	-	Non-clinical	Real world	No	No
11	2022	Prospective observational study	USA	119	19.87 (*1.75*)	18-26	89.10%	63.90%	Non-clinical	Real world	No	Yes
12	2025	Case series study	USA	186	16.40 (*1.70*)	13-18	79.57%	56.99%	Clinical	Real world	Yes	No
13	2024	Observational longitudinal design	USA	59	21.04 (*2.22*)	-	69.10%	67.60%	Clinical	Real world	No	No

Reference number	Year	Study design	Country	Sample size	Mean age (*SD*)	Age range	Percentage female	Percentage white	Participant type	Study setting	Privacy mentioned	Incentives
14	2020	Prospective cohort study	United Kingdom	66	36.80	18-61	56.25%	-	Clinical	Real world	No	Yes
15	2024	Comparative case analysis	USA	2	33.00 (*4.00)*	29-37	50.00%	100.00%	Clinical	Real world	No	Yes
16	2021	Prospective cohort study	USA	775	27.00 (*1.48)*	-	55.00%	65.16%	Non-clinical	Real world	Yes	Yes
17	2024	Prospective cohort study	USA	27	20.89 (*2.53)*	-	85.18%	59.26%	Clinical	Real world	No	No
18	2016	Prospective cohort study	USA	22	-	20-25	54.55%	-	Non-clinical	Real world	No	Yes
19	2024	Prospective cohort study	Israel	29	14.79 (*1.61)*	12-18	100.00%	-	Clinical	Hospital setting	No	No
20	2024	Randomised controlled crossover	USA	109	25.66 (*4.63)*	-	100.00%	49.00%	Clinical	Real world	No	Yes
21	2024	Prospective observational design	USA	126	22.00	12-69	64.30%	80.20%	Clinical	Hospital setting	Yes	No
22	2021	Prospective cohort study	Switzerland, USA	20	10.90 (*10.20)*	-	-	-	Clinical	Hospital setting	No	Yes
23	2024	Prospective feasibility and pilot study design	USA	20	28.45 (*10.93)*	19-65	80.00%	80.00%	Clinical	Hospital setting	No	Yes
24	2019	Focus groups	United Kingdom	11	23.50 (*3.60)*	18-30	73.33%	-	Non-clinical	Real world	Yes	Yes
25	2021	Retrospective cross-sectional case-control design	USA	246	-	-	-	-	Clinical	Real world	No	No
26	2020	Prospective feasibility and acceptability	USA	83	50.00	24-76	13.00%	63.00%	Sub-clinical	Real world	Yes	Yes
27	2018	Prospective feasibility and pilot study design	France, Spain	5	43.80 (*7.56)*	36-56	60.00%	-	Clinical	Real world	Yes	No

Reference number	Year	Study design	Country	Sample size	Mean age (*SD*)	Age range	Percentage female	Percentage white	Participant type	Study setting	Privacy mentioned	Incentives
28	2021	Prospective within-person observational study	USA	48	14.96 (*1.60)*	12-18	64.60%	77.10%	Clinical	Real world	No	Yes
29	2024	Observational longitudinal cohort	The Netherlands	61	28.00 (*8.60)*	-	74.00%	-	Clinical	Real world	No	No
30	2023	Prospective observational study	USA	53	14.80 (*1.60)*	12-18	64.00%	77.00%	Clinical	Real world	No	Yes
31	2023	Intensive longitudinal prognostic study	USA	102	20.90 (*2.10)*	18-25	81.40%	74.50%	Clinical	Real world	No	Yes
32	2020	Micro-randomized trial	USA	1,565	-	-	55.91%	-	Sub-clinical	Real world	No	Yes
33	2023	Intensive longitudinal methods	USA	2,459	27.60	-	55.10%	52.50%	Non-clinical	Real world	No	Yes

Note: This table provides an overview of the 33 studies included, summarising the reference number, year of publication, study design, country, sample characteristics (size, age, gender, ethnicity, clinical type), study setting, privacy and incentives. Studies were selected based on their investigation of digital phenotyping methods and suicidality. For missing values, a dash (-) was added to the cell. If the standard deviation for the age was not reported the space was left blank. SD = Standard deviation.

An analysis of the clinical populations revealed that 19 of the 23 studies using clinical samples mentioned with specific diagnoses were included in the sample. Here, it was common for studies to include different diagnosis in one sample. Mood disorders, including major depressive disorder, were the most frequently represented diagnostic category (*n* = 15). Followed by anxiety disorders (*n* = 12), post-traumatic stress disorder (*n* = 11) and substance use disorders (*n* = 9). Additionally, attention-deficit/hyperactivity disorder (*n* = 5) and obsessive-compulsive disorder (*n* = 5) were each included, while bipolar disorder (n = 4) and eating disorders (n = 4) were also reported. Less frequently represented diagnoses included suicidal ideation (*n* = 2), behavioural disorders (*n* = 2) psychotic symptoms (*n* = 2), and disruptive behaviour disorders (*n* = 2). Singular mentions were found for agoraphobia (*n* = 1), panic disorder (*n* = 1), anorexia nervosa (*n* = 1), borderline personality disorder (*n* = 1), and adjustment disorders (*n* = 1).

A wide range of data processing and statistical methods was employed across studies. The most common approaches included multilevel modelling techniques (*n* = 18) (multilevel regression models, multilevel logistic models, mixed-effects models) and machine learning/deep learning algorithms (*n* = 7) (random forests, elastic net regression, K-nearest neighbours, conditional generative adversarial networks). Traditional statistical analyses, such as logistic regression (*n* = 3), multiple linear regression (*n* = 1), chi-square tests (*n* = 1), Mann-Whitney U-tests (*n* = 2), and Shapiro-Wilk tests (*n* = 1), were also frequently applied. Principal component analysis (*n* = 2) and principal component analysis (*n* = 2) were used for dimensionality reduction. Furthermore, thematic analysis was commonly utilised for the qualitative evaluation of speech or text data (*n* = 4). Notably, issues of data privacy in the context of digital phenotyping were only explicitly addressed in a smaller number of studies (*n* = 12).

RQ2: Associations & predictive validity of biomarkers

Various biomarkers were assessed across the included studies, each using different devices and measurement methods. The detailed narrative findings of each individual study can be found in Appendix B. Sleep-related parameters were the most commonly investigated biomarker, with 16 studies utilising different devices such as wrist actigraphy (*n* = 9), Fitbit (*n* = 4), and smartphones (*n* = 4). In total, 73.33% of studies found significant associations. Generally, poorer sleep quality and higher fragmented sleep correlated with increased suicidal ideation. Specifically, individuals with higher suicidal ideation often exhibited more disrupted

and irregular sleep. Metrics such as longer sleep onset latency (SOL), increased wake after sleep onset (WASO), and reduced total sleep time were frequently associated with higher next-day suicidal ideation, as were poorer sleep quality and lower efficiency. Remarkably, subjective sleep parameters often proved more consistently predictive of suicidal ideation than objective actigraphy measures, although the latter showed higher adherence. The combination of Ecological Momentary Assessment (EMA) with passive sensor data demonstrated notably high predictive accuracy in one study (AUC = 0.84), far surpassing models based on passive data alone mentioned in the study (AUC = 0.56).

Activity-based biomarkers were assessed in six studies, predominantly through smartphones (n = 8), Fitbit (n = 5), and wrist actigraphy (n = 1), focusing mainly on step counts and smartphone activity. Over half of these studies (63.64%) reported significant associations. Findings on physical activity were mixed: while higher physical activity was linked to fewer depressive symptoms and irregular step count patterns suggested associations with suicidal ideation, one study found no significant difference in overall step counts between suicidal ideation and non-ideation groups. More direct links to suicidality emerged from phone usage, where between-group associations show that smartphone overdependence alone increased the odds of depression by 40.00% (AOR = 1.40), suicidal ideation by 44.00% (AOR = 1.44) and suicidal plans by 21.00% (AOR = 1.21). Furthermore, specific changes in mobility patterns, such as reduced daily travel distance and increased time spent at home, were found to be significant predictors of subsequent increases in depressive symptoms, suggesting they could function as early indicators of clinical deterioration. However, while combining Ecological Momentary Assessment (EMA) with passive data yielded moderate predictive accuracy for suicidal ideation, sensor-based data alone, including some passively collected activity metrics, generally demonstrated lower predictive performance or did not enhance prediction models based solely on mood data.

Extralinguistic features were examined in seven studies using smartphones (n = 5), microphones (n = 3), and the BERTimbau Large (referred to as the Boamente system) (n = 1). These studies primarily assessed emotional tone, word usage, speech prevalence, and speech disfluency, with a high proportion (87.50%) reporting significant associations with suicidality. Key findings indicated that individuals with current or past suicidality exhibited poorer voice quality and significantly more speech disfluencies (e.g., hesitations, errors, with large effect sizes such as *Cohen's d* up to 0.94) compared to controls. Furthermore, decreased speech prevalence showed a strong negative correlation (r = -0.62) with suicide severity. Analysis of

textual content revealed that during episodes of suicidal ideation, communications, particularly with peers, contained significantly more negative emotion words (*OR* = 2.91). Longitudinal analysis also showed that increases in expressed anger and decreases in positive emotion in texts preceded suicide attempts. Notably, a machine learning model, the Boamente system demonstrated high accuracy (*AUC* = 0.95, *Precision* = 0.96) in identifying suicidal ideation from passively gathered text data. While one study did not find significant linguistic associations, the overall evidence points to strong links between altered vocal and textual communication patterns and increased suicidality.

Heart rate was analysed in five studies using devices such as Shimmer3 GSR+ sensors (*n* = 2), Fitbit (*n* = 2), and wrist actigraphy (*n* = 1), measuring resting heart rate, heart rate variability, and mean heart rate. Furthermore, 40.00% of studies found significant associations. The results were mixed, suggesting that heart rate alone is insufficient as a predictive marker; however, lower heart rate variability was linked to higher suicidality.

Movement analysis was explored in two studies using video cameras, focusing on head movement (particularly pitch) and facial expressivity across emotions such as sadness, surprise, and disgust. Both studies reported significant associations. Specifically, lower overall facial expressivity ($r = -0.46$) and diminished expression of specific emotions like sadness ($r = -0.68$), surprise ($r = -0.74$), and disgust ($r = -0.64$) were significantly correlated with increased suicidality, suggesting diminished emotional facial activity may serve as a behavioural marker for suicide risk. Similarly, reduced variability in head movement, especially in pitch (with correlations around $r \approx -0.69$), was negatively associated with suicide severity. This lower dynamic range in head pitch and yaw was predictive of higher suicide risk, pointing to constrained nonverbal behaviour as a relevant indicator of suicidality.

Location data was assessed in one study using smartphone GPS tracking. The study found within-group increases in time spent at home were associated with higher suicidality. No significant between-group effects were reported. Finally, skin conductance, measured through a wearable biosensor, was evaluated in one study using electrodermal activity. Although the uncorrected p-value was 0.05, the result was no longer significant after applying Holm correction, indicating no significant association with suicidality.

Table 2

Overall Associations Between Biomarkers and Suicidality

Biomarker	Samples	Devices	Measurement used	Studies reporting significant associations	Average association
Sleep	16	Wrist actigraphy (9), Smartphone (4), Fitbit (4)	Sleep duration (3) Sleep disruption / variability (3) Wake after sleep onset (2) Sleepiness (1) Sleep onset latency (2) Total sleep time (2) Sleep quality (2) Sleep fragmentation (1)	73.33%	Poorer sleep parameters like more fragmented sleep, shorter sleep duration and poor sleep quality are associated with higher levels of suicidality. Mostly within-group differences were used.
Activity	14	Smartphone (8), Fitbit (5), Wrist actigraphy (1)	Steps (8) Smartphone activity (6)	63.64%	Higher physical activity is associated with lower suicidality; higher smartphone activity is associated with higher suicidality. Mostly within-group differences were used.
Extralinguistic features	9	Smartphone (5), Microphone (3), Bohamente System (1)	Emotional tone (1) Negative words (3) Speech prevalence (1) Disfluency (1) Voice quality (1)	87.50%	Both reduced positive expression and increased negative or disfluent speech patterns are associated with to higher suicidality. Mostly within-group differences were used.
Heart rate	5	Shimmer3 GSR+ (2), Fitbit (2), Wrist Actigraphy (1)	Resting HR (3) HR validity (1) HR mean (1)	40.00%	Mixed, HR alone insufficient; low Heart rate variability is associated with higher suicidality. Mostly between group-differences were used.
Movement analysis	2	Video camera (2)	Head movement (pitch) (1) Facial expressivity (sadness, surprise, disgust) (1)	100.00%	Less facial expression and less variability in head pitch and yaw are associated with higher suicidality. Between-group differences were used.

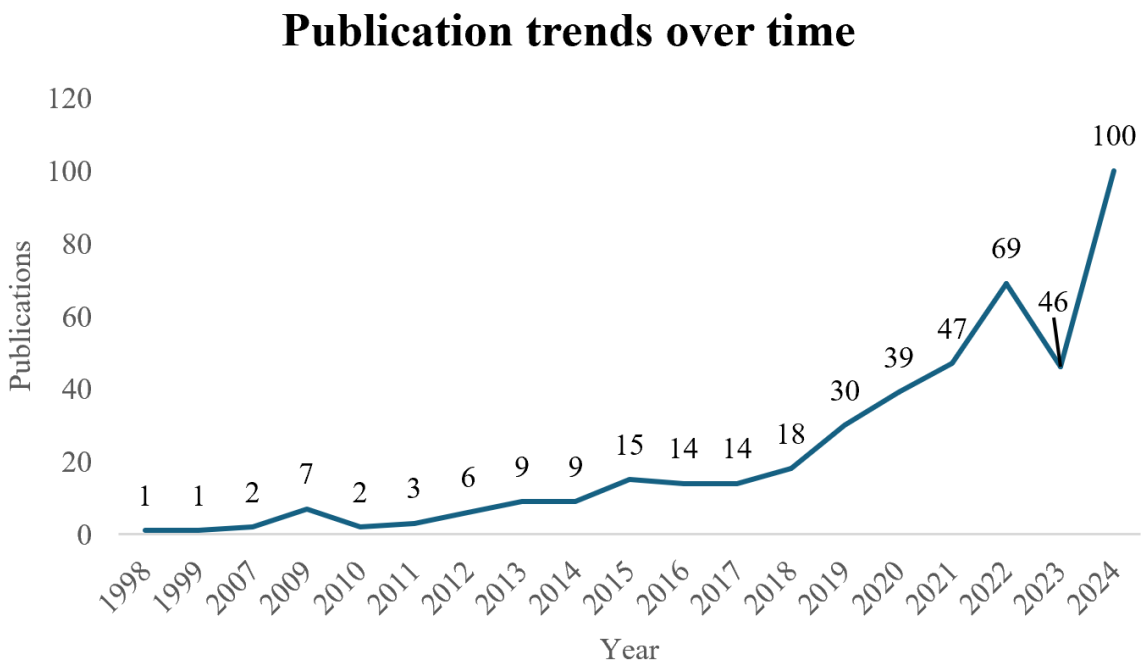
Biomarker	Samples	Devices	Measurement used	Studies reporting significant associations	Average association
Location	1	Smartphone (1)	GPS (1)	100.00%	Positive (within-group); none (between-group). When someone stays more at home than they usually do, suicidality gets higher
Skin conductance	1	Wearable biosensor (1)	Electrodermal activity (1)	0.00%	Non-significant after correction (Between-group differences)

Note. The table summarises findings from the included studies, categorised by biomarker. The number in parentheses next to each specific entry in the "Measurement used" column indicates the number of studies that reported using that particular metric. The "Studies reporting significant associations" column calculates the percentage of studies that found a statistically significant relationship between any of the listed measurements for that biomarker and suicidality. HR = heart rate; GPS = Global Positioning System.

RQ3: Bibliometric analysis of research trends and thematic focuses

Figure 2

Publication Trends Over Time



Note. The bibliometric analysis is based on the total number of search results that the Web of Science database provided for the search string mentioned above in the methods section.

Figure 2 illustrates the trend of annual publications concerning digital phenotyping methods for suicide prediction. The data indicates an initial period of slow emergence from 1998 to approximately 2014, followed by a phase of steady growth beginning around 2015. A significant increase in publication output is apparent after 2018, concluding in the highest annual number of publications recorded in 2024.

Figure 3

Number of Publications per Country

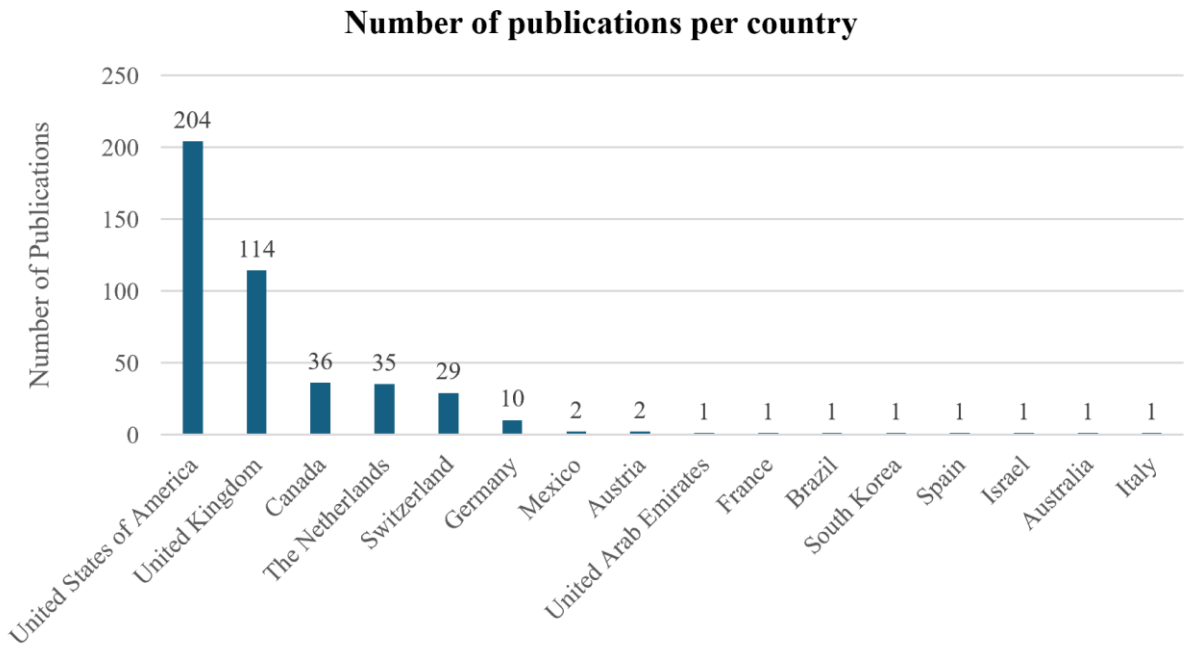


Figure 3 displays the geographical distribution of research output. A strong concentration of publications is evident in a few leading countries, with the United States and the United Kingdom being the most prolific. Following these, a notable decrease in output is observed for other contributing nations. Overall, the data indicate a pronounced geographic skew, with the majority of publications originating from a small number of countries, primarily in North America and Western Europe.

Figure 4

The Authors with 10 or More Publications

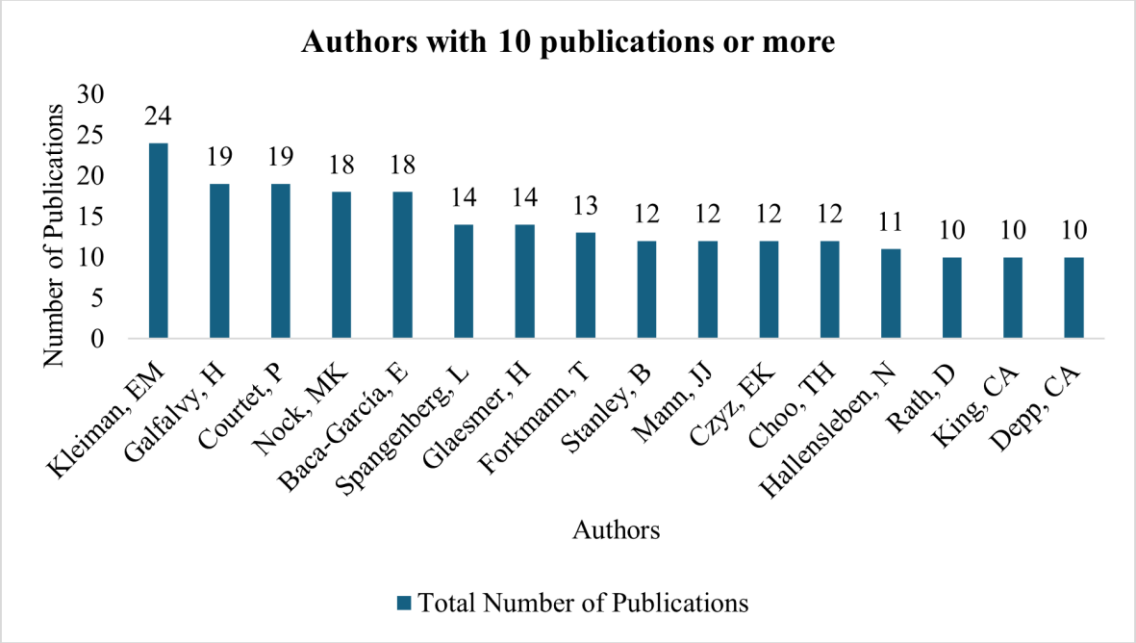


Figure 4 demonstrates the distribution of publications at the author level. The data reveal a skewed productivity pattern, where a small group of authors has contributed a disproportionately large number of publications. A few researchers are identified at the highest level of productivity, followed by a tiered decrease in output among other authors who meet the analysis threshold. This indicates that a relatively small number of investigators account for a substantial portion of the research in this field.

Figure 5

The 10 Most Frequent Journals

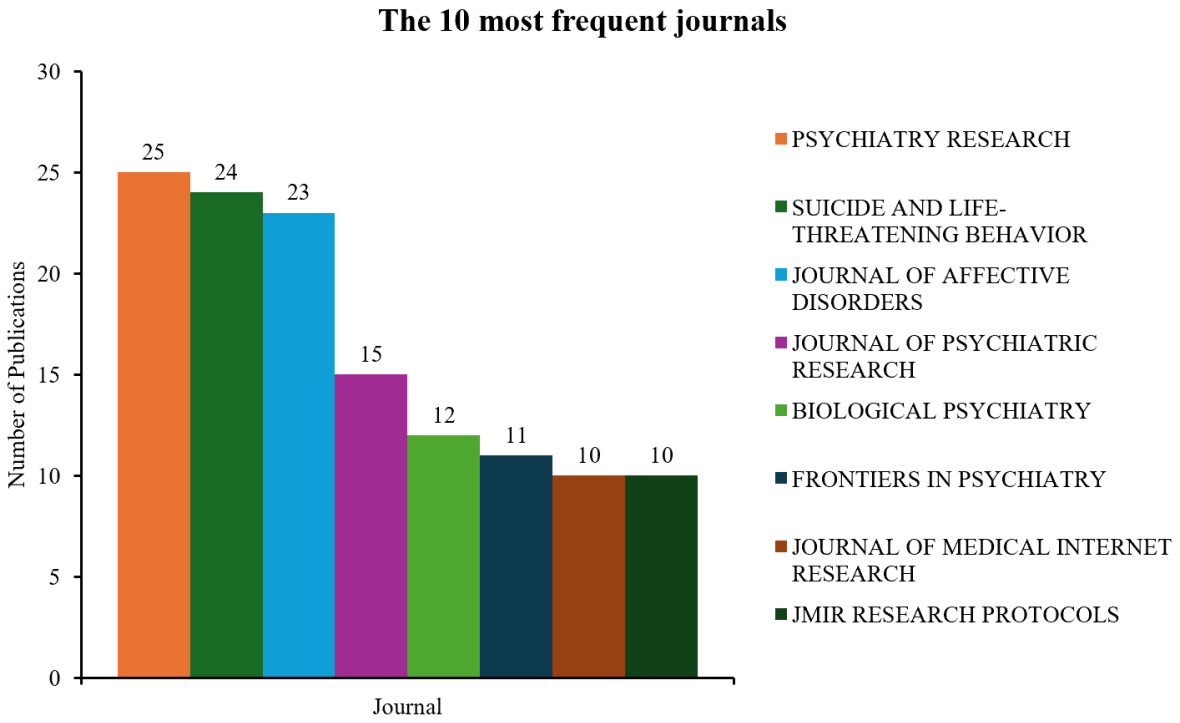


Figure 5 presents the leading journals publishing on digital phenotyping methods for the prediction of suicidality. The distribution shows a concentration of articles within a few prominent journals, primarily those focused on general psychiatry and suicidology. A secondary group of specialty and digital-health oriented journals also contribute notably to the field, although the show fewer publications than the leading outlets.

Figure 6

The 25 Most Common Keywords

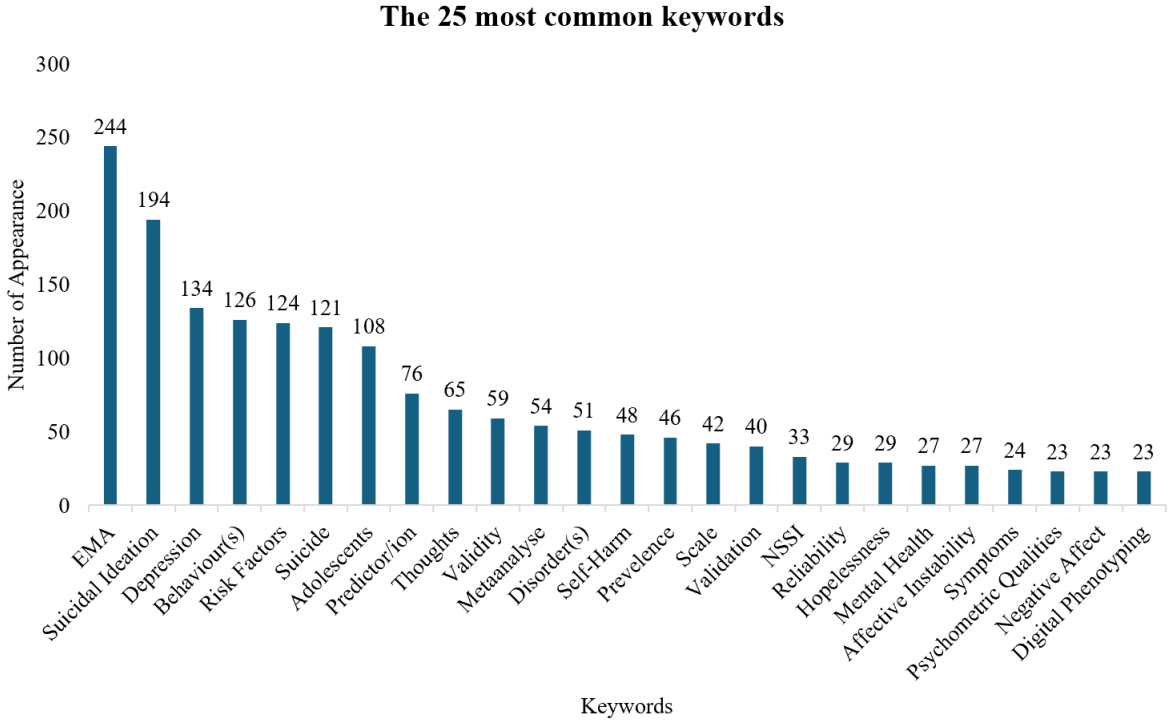


Figure 6 displays the most frequently occurring author keywords. A small number of keywords, such as "EMA (Ecological Momentary Assessment)," "suicidal ideation," and "depression," appear with high frequency, indicating central research themes. Following these, keyword frequency decreases, revealing clusters related to broader clinical phenomena (e.g., "suicide," "adolescents") and methodological aspects (e.g., "risk factors," "behaviour(s)"). The distribution shows a tapering off into mid-range and lower-frequency terms, some of which represent measurement concepts and specific cognitive-affective constructs, alongside emerging research terms.

Discussion

This paper combines a scoping review with a bibliometric analysis. The primary objective is to map the characteristics of the current research and intervention landscape concerning the associations between and the predictive validity of digital phenotyping methods for suicidal ideation, suicide attempts, and completed suicides. The findings indicate that the field is rapidly growing but remains methodologically narrow, geographically skewed, and dominated by a small number of contributors. Most studies focus on sleep, activity, and language features, with predictive models appearing promising primarily when combining

passive data with self-report measures. Notably, studies report the most significant associations for the biomarkers sleep, with 16 studies that utilising the biomarker and 73.33% showing significant associations, and extralinguistic features, with 9 studies utilising the biomarker and 87.50% showing significant associations. In these cases, sleep duration, sleep disruption, emotional tone, negative words, and speech disfluency showed the strongest associations.

First research question

The findings of the first research question indicate that the average participant is White, female, 25 years old and is currently diagnosed with a mood disorder. Furthermore, the average study uses a real-world and observational design with suicidal ideation to measure suicidality and utilises multilevel regression, rarely addressing privacy. Additionally, there is an overfocus on affective disorders (depression and anxiety) while disorders that have a high suicide risk, for example schizophrenia and substance use disorders are underexplored (Miller et al., 1991; Pompili et al., 2007; Olfson et al., 2021).

These findings indicate dominant patterns in existing literature, but also systematic blind spots. Firstly, a lack of diversity often appears in scientific research and is also frequent in digital health research (Coss et al., 2023; Ghai et al., 2023). Studies often suffer from WEIRD (Western, Educated, Industrialized, Rich, Democratic) sampling biases (Lillas & Marchel, 2015; Newson et al., 2020). These biases limit generalisability, particularly for suicide risk detection in marginalised groups (Centers for disease control and prevention, 2025), therefore contradicting the precision medicine paradigm, which aims for personalised risk prediction (Boulos & Blond, 2016). The results are not representative of global suicidality. The predominant focus fails to capture suicide risk patterns observed in non-Western, rural, or predominantly male populations (World Health Organization, 2021). Consequently, these findings cannot be generalised to high-risk populations in countries such as non-western countries.

Secondly, studies with real-world and observational longitudinal designs dominate the literature, amid a persistent shortage of experimental research. Because these designs are non-experimental, they offer limited scope to establish direct causality, therefore more experimental designs are needed. Although it is impossible to randomise participants to “have” or “not have” a physiological marker, future studies could randomise the use of biomarker-guided interventions. For example, in a sleep-marker study, all participants would wear a sleep-tracking device, but only a randomly selected subgroup would receive a brief cognitive-behavioural intervention

whenever significant sleep disturbances are detected. The remaining participants would continue with standard monitoring. By comparing suicide-related outcomes between these two groups, future studies could assess whether biomarker-triggered interventions reduce suicidality more effectively than usual care. Similar randomised designs could be applied to extralinguistic features or ecological momentary assessments, using real-time feedback or therapeutic prompts as experimental conditions.

Furthermore, the prevalent use of suicidal ideation as the primary outcome measure (n = 29) in suicide risk assessment is problematic. A major meta-analysis by Franklin et al. (2016) showed that suicidal ideation alone has limited predictive power, as many individuals who think about suicide do not go on to attempt it. Ideation-to-action models help explain this by emphasising that different factors contribute to the development of suicidal thoughts versus the progression to suicidal behaviour. One such factor is suicide ambivalence, the coexistence of a wish to live and a wish to die. Höller et al. (2024) found that ambivalence is a sufficient predictor for attempted suicides in a high-risk clinical sample. These findings highlight the importance of including dynamic and motivational factors such as ambivalence in suicide risk assessment, rather than focusing solely on suicidal ideation.

Thirdly, fewer than half of the reviewed studies (n = 12) explicitly discuss privacy, a common issue in digital mental health (Lustgarten et al., 2020; Surani et al., 2023). This oversight decreases user trust and casts doubt on the ethical integrity of passive sensing applications, especially this absence inhibits clinicians and hospitals to utilise digital tools in fear of legal issues related to data privacy (Yadav et al., 2023). To advance clinical translation, future work must embed privacy-by-design principles (Van Rest et al., 2014) and user perspectives. Privacy-by-design means embedding data protection into the system architecture from the outset, not as an afterthought (Barth et al., 2022). This includes strategies like local data processing on devices instead of cloud-based storage, differential privacy techniques, and offering users meaningful control over what data is collected and shared. Additionally, incorporating user perspectives means involving patients and clinicians in the development process to ensure tools align with real-world expectations for transparency, security, and consent.

Second research question

The objective of the second research question was to identify associations of digital phenotyping methods across populations, diagnoses, and contexts. The findings suggest that biomarkers are typically measured using smartphones and wearables, usually focusing on sleep-

related parameters, physical activity, or language and speech features. Overall, the findings demonstrate that multiple digital biomarkers are significantly associated with suicidal ideation, depressive symptoms and suicidal behaviour, while showing moderate to high predictive accuracy, particularly when combined with ecological momentary assessments (EMAs). Models integrating EMA self-reports and passive data streams achieved the strongest discrimination (sleep parameters: *AUC* up to 0.84). However, this reliance on EMA is problematic as it introduces significant participant burden, which can lead to inconsistent engagement and lower long-term adherence (Stone et al., 2022). Consequently, the high predictive accuracy observed in research settings may not be sustainable or generalizable in real-world clinical applications where such intensive monitoring is less feasible.

These findings, particularly the significant associations of digital biomarkers with suicidal outcomes and the improved predictive accuracy of models combining active and passive data for within-group differences, align with precision-medicine frameworks by emphasising the need for individualised, context-sensitive monitoring approaches that account for the dynamic and multifactorial nature of suicide risk. This is particularly crucial as the transition from suicidal ideation to an attempt can be extremely rapid, a time limit often too short for detection by periodic EMA prompts (Bryan & Rudd, 2016). In these moments of acute risk, continuous passive sensing is therefore essential, as it may capture subtle, immediate changes in behaviour that precede an attempt without relying on delayed user reports.

The significant results on within-group biomarker associations like subjective sleep disturbances, speech disfluency, and emotional word use emerged as especially strong predictors for suicidality. These results also reinforce theoretical models linking suicide risk to dysregulated affective, physiological, and behavioural patterns, including disrupted sleep, autonomic dysregulation, diminished facial expressivity, and speech abnormalities (Ferrer et al., 2020; Rüesch et al., 2022; Rogante et al., 2024). Notably, the results support theories that view emotional dysregulation and neurovegetative symptoms as proximal signals of suicidality (Keilp et al., 2017). However, the findings do not suggest universal or causal mechanisms; for example, poor sleep may both contribute to and result from suicidality. Future research should therefore focus on establishing directionality using methods suited for intensive observational data, such as cross-lagged analysis, which can help clarify whether these biomarkers are precursors to or consequences of suicidality. To truly examine causal relationships, micro-randomised trials could be used, where participants are repeatedly randomised to receive or not receive an intervention based on changes in a specific biomarker. However, the ethical and practical feasibility

of manipulating certain biomarkers, such as sleep or affective states, remains a critical challenge that future research must carefully address, for example, by targeting modifiable behavioural patterns with low-risk interventions such as sleep hygiene prompts or mood-regulation strategies delivered during periods of elevated risk.

Moreover, publication bias may have inflated positive results, particularly in domains like voice and movement where null findings in this review were rare (Franklin et al., 2016; Nair, 2019). These areas are relatively new and technically complex, and given the rapid growth of the field, the dominance of a few prolific research groups, and the concentration of publications in high-influence journals, there may be stronger incentives to publish novel, significant findings over null results. Furthermore, the results of studies solely using passive data technologies do not confirm the predictive validity of these technologies alone, which generally show low to moderate performance. For example, the study with the reference number 31 showed an *AUC* of 0.56 for passive sensing alone and an *AUC* of 0.84 for combining EMA and passive sensing. This challenges earlier claims that passive data alone could serve as scalable, low-burden tools for early detection of suicidality.

Furthermore, not all biomarkers appear equally valid or developed. Specifically, behavioural indicators derived from sleep, speech, and smartphone activity emerged as the most promising predictors in the reviewed literature. For instance, subjective sleep parameters like total sleep time showed strong correlations with next-day ideation ($r = 0.58$), while decreased speech prevalence was similarly linked to higher suicide severity ($r = -0.62$). Additionally, speech disfluencies showed large effect sizes in identifying at-risk individuals (e.g., speech errors, *Cohen's d* = 0.94), and patterns of smartphone overdependence increased the odds of suicidal ideation significantly (*Adjusted Odds Ratio* = 1.44).

Notably, these findings highlight that some passive biomarkers can achieve significant predictive value without being combined with EMA data. This strong performance of behavioural indicators contrasts with physiological measures like skin conductance, which showed no association, and heart rate variability, which offered only modest or inconsistent results on its own. The key conclusion, therefore, is that digital traces of core clinical phenomena, such as social withdrawal, anhedonia, and psychomotor changes, may be more direct and robust proxies for suicide risk than the more generalised stress responses captured by peripheral physiology.

Third research question

The third research question aimed to chart the evolution of digital phenotyping and digital biomarker research in suicidality by identifying trends, key contributors, and dominant themes. The bibliometric analysis shows a marked rise in publications since 2018, likely due to the expansion of sensor-rich smartphones and wearables, advances in machine learning for behavioural data analysis, and increased attention to mental health driven by awareness and funding initiatives (Mance, 2022; Wall et al., 2023; European Commission, 2025). Most articles appear in psychiatric and suicidology journals and frequently use terms like "suicidal ideation," "depression," and "ecological momentary assessment (EMA)," reflecting shared focus and conceptual grounding.

Although the field is rapidly growing, its research remains concentrated within a few geographic (primarily the US and UK) and institutional centres, which are often led by small, productive research teams. While such specialisation can drive progress, this high degree of centralisation is problematic. It likely originates from early access to major funding (e.g., NIH, Wellcome Trust), established research infrastructures, and suitable patient populations (Kliegr et al., 2019; Woelbert et al., 2020). The clustering of publications within a few influential journals then reinforces this concentration; by determining which studies gain prominence, these journals help create a feedback loop that directs prestige and future resources towards the same established groups. As a result, voices from low- and middle-income regions, non-Western contexts, and culturally diverse populations, where suicide rates may be high, but research capacity is lower, are underrepresented (World Health Organisation, 2021). When a small set of authors and journals dominate, prevailing views on suicidality may go unchallenged, narrowing perspectives and hindering global innovation.

Limitations

The generalisability of the findings is subject to several crucial limitations. Firstly, the search strategy was restricted to English-language publications issued after the year 1998 and was performed on only three databases. The subsequent bibliometric analysis was narrowly focused, drawing exclusively from the Web of Science database. Therefore, relevant publications outside these language, time, and database parameters were not included. Secondly, a single reviewer conducted the screening and assessment of all identified studies. This methodology introduces a risk of subjective bias and blocks any analysis of inter-rater reliability. A third limitation is the exclusion of grey literature, such as working papers, and

non-academic reports. In a field undergoing rapid change, this exclusion criteria may mean that crucial developing insights contained within unpublished works were not captured in this review.

Recommendations for future research

To ensure findings are truly generalisable, future investigations must significantly broaden participant diversity beyond the young, Western samples that are typical of so-called WEIRD studies, a well-documented limitation in psychological research. This requires targeted community partnerships, culturally adapted materials, international collaborations, and strategies to overcome participation barriers, thereby ensuring more globally representative data. Methodologically, studies should adopt robust multimodal designs. When collecting passive data over long periods, researchers should prioritise methods that capture diverse behavioural indicators without relying on active participant input. This could include leveraging wearable sensor technologies for physiological and activity data, analysing digital footprints from consented online interactions, and utilising environmental sensors to understand contextual influences. Ecological momentary assessments (EMA) can still provide valuable real-time self-reported data to complement passive streams, but their use should be highly strategic. A promising method is a stepwise approach, where passive data provides continuous, low-burden monitoring, and EMA is deployed only during critical periods identified by changes in that passive data, for example a decline in social interaction or sleep quality. This targeted use minimises participant burden while capturing crucial contextual information when it is most needed. This integrated approach, with a strong emphasis on scalable passive data collection, will therefore yield more comprehensive and ecologically valid insights into behaviour across diverse populations and contexts.

Moreover, the ability to collect continuous, unobtrusive passive data presents a profound, although still developing, potential for predicting suicidality. By identifying subtle, real-time deviations from an individual's typical behavioural patterns or significant shifts in indicators derived from passive streams, these methods could offer essential early warning signs of escalating suicidal ideation or distress. Such insights could proactively inform clinicians about periods of heightened risk, facilitating timely outreach and targeted support, and potentially shifting the paradigm from a reactive crisis management to an initiative-taking prevention.

Finally, policy and ethical frameworks must advance with technological innovation. This necessitates developing clear guidelines for privacy, employing privacy-enhancing technologies, and establishing dynamic and clear informed consent processes, especially for suicide risk contexts. Multi-stakeholder collaborations involving researchers, clinicians, ethicists, regulators, and individuals with lived experience are crucial. These collaborations should aim to create robust standards for data security, algorithmic transparency, and user autonomy. This will ensure that digital mental health innovations are ethically stable, scientifically rigorous, and genuinely user-cantered, for example, through the inclusion of co-design practices.

Conclusion

This review mapped the evolving landscape of digital phenotyping for suicidality, revealing a field of dualities: one of rapid technological advancement but nascent scientific maturity. Behavioural biomarkers from passive data demonstrate strong potential as reliable indicators, supported by consistent findings across multiple studies. However, a few limitations persists. This is because the findings emerge from a research base that remains methodologically narrow, geographically concentrated in high-income nations, and often overlooks crucial ethical issues like data privacy.

Consequently, while the potential for standalone clinical application is on the horizon, it is not yet a reality. For these tools to become effective and equitable, future work must shift focus from pure technological novelty towards building trustworthy foundations through globally representative samples, methodological rigour, and robust privacy-by-design principles.

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Appendix

Appendix A

Table 3

Summary of Reviewed Studies

Reference number	First author	Year	Title
1	Horwitz	2022	Utilising daily mood diaries and wearable sensor data to predict depression and suicidal ideation among medical interns
2	Sikander	2016	Predicting Risk of Suicide Using Resting State Heart Rate
3	Bertrand	2020	Suicidal ideation and insomnia in bipolar disorders
4	Jiang	2023	Acceptability and feasibility of ecological momentary assessment with augmentation of passive sensor data in young adults at high risk for suicide.
5	Patel	2024	Anhedonia Links Sleep Problems and Suicidal Thoughts: An Intensive Longitudinal Study in High-Risk Adolescents.
6	Kearns	2021	Sleep problems and suicidal thoughts and behaviors among youth: An examination of global factors, methodology, and mechanisms
7	Diniz	2022	Boamente: A Natural Language Processing-Based Digital Phenotyping Tool for Smart Monitoring of Suicidal Ideation

Reference number	First author	Year	Title
8	Glenn	2020	Can Text Messages Identify Suicide Risk in Real Time? A Within-Subjects Pilot Examination of Temporally Sensitive Markers of Suicide Risk.
9	Nugent	2022	Adolescents hospitalised for suicidality: biomarkers, social and affective predictors: a cohort study
10	Kim	2022	Combined Effects of Smartphone Overdependence and Stress on Depression and Suicide-Related Behaviors among High School Students
11	Burke	2022	Sleep irregularity and nonsuicidal self-injurious urges and behaviors
12	Auerbach	2025	Using Smartphone GPS Data to Detect the Risk of Adolescent Suicidal Thoughts and Behaviors
13	Porter	2024	Daily sleepiness magnifies the relation between same-day passive and active suicide ideation
14	Haines-Delmont	2020	Testing Suicide Risk Prediction Algorithms Using Phone Measurements With Patients in Acute Mental Health Settings: Feasibility Study
15	Jacobucci	2024	Examining Passively Collected Smartphone-Based Data in the Days Prior to Psychiatric Hospitalization for a Suicidal Crisis: Comparative Case Analysis
16	Adler	2021	Identifying Mobile Sensing Indicators of Stress-Resilience

Reference number	First author	Year	Title
17	Ladis	2024	Emerging Adults With a Suicide Attempt History Text More Emotionally With Peers than Family Members
18	Tseng	2016	Assessing Mental Health Issues on College Campuses: Preliminary Findings from a Pilot Study
19	Ratzon	2024	Sleep measures as a predictor of suicidal ideation among high-risk adolescents.
20	Knol	2024	Smartphone keyboard dynamics predict affect in suicidal ideation
21	Karas	2024	Smartphone Screen Time Characteristics in People With Suicidal Thoughts: Retrospective Observational Data Analysis Study.
22	Galatzer-Levy	2021	Validation of Visual and Auditory Digital Markers of Suicidality in Acutely Suicidal Psychiatric Inpatients: Proof-of-Concept Study.
23	Rizvi	2024	Using Biosensor Devices and Ecological Momentary Assessment to Measure Emotion Regulation Processes: Pilot Observational Study With Dialectical Behavior Therapy.
24	Rooksby	2019	Student Perspectives on Digital Phenotyping the Acceptability of Using Smartphone Data to Assess Mental Health
25	Stasak	2021	Read speech voice quality and disfluency in individuals with recent suicidal ideation or suicide attempt

Reference number	First author	Year	Title
26	Betthauser	2020	Mobile App for Mental Health Monitoring and Clinical Outreach in Veterans: Mixed Methods Feasibility and Acceptability Study
27	Berrouiguet	2018	Combining Continuous Smartphone Native Sensors Data Capture and Unsupervised Data Mining Techniques for Behavioral Changes Detection: A Case Series of the Evidence-Based Behavior (eB2) Study
28	Glenn	2021	Sleep problems predict next-day suicidal thinking among adolescents: A multimodal real-time monitoring study following discharge from acute psychiatric care
29	Kivelä	2024	Sleep, hopelessness, and suicidal ideation: An ecological momentary assessment and actigraphy study
30	Kearns	2023	Agreement between actigraphy and sleep diaries: A 28-day real-time monitoring study among suicidal adolescents following acute psychiatric care.
31	Czyz	2023	Ecological Momentary Assessments and Passive Sensing in the Prediction of Short-Term Suicidal Ideation in Young Adults.
32	NeCamp	2020	Assessing Real-Time Moderation for Developing Adaptive Mobile Health Interventions for Medical Interns: Micro-Randomized Trial
33	Horwitz	2023	Using machine learning with intensive longitudinal data to predict depression and

Reference number	First author	Year	Title
			suicidal ideation among medical interns over time.

Note. This table provides an overview of the 33 studies included finally, summarising the reference number, first author, year of publication, and study title. Studies were selected based on their investigation of digital phenotyping methods and suicidality.

Appendix B

Table 4

Individual Findings of the Studies Between Biomarkers and Suicidality Measures

Reference number	Biomarker	Device	Suicidality measurement	Sensor modality	Association	Narrative description of findings
1	Sleep (duration)	Fitbit	Suicidal ideation (past 2 weeks)	Active & Passive	No association	No significant difference in sleep duration between suicidal ideation and no suicidal ideation groups.
1	Activity (steps)	Fitbit	Suicidal ideation (past 2 weeks)	Active & passive	No association	No significant difference in steps between suicidal ideation and no suicidal ideation groups.
2	Resting heart rate	Shimmer3 GSR+	Suicidal ideation (past three months)	Passive only	No association	Mean heartrate does not distinguish between patients and healthy controls.
2	Heart rate variability	Shimmer3 GSR+	Suicidal ideation (past three months)	Passive only	Negative	Reduced heart rate variability (SDRR) is associated with higher suicidal ideation.
3	Sleep (disrupted)	Wrist actigraphy	Suicidal ideation (current)	Active & passive	Positive	The individuals with the higher suicidal ideation showed more disrupted sleep.
4	Activity (steps)	Fitbit	Suicidal ideation	Active & passive	No association tested	Wearable sensor monitoring was feasible and acceptable among high-risk young adults, with moderate adherence rates (Fitbit: 53.60%) over two months. Prior-day suicidal ideation was linked to lower Fitbit adherence the following day.
5	Sleep (disrupted)	Wrist actigraphy	Suicidal ideation (same day)	Active & passive	Positive	Within-group differences: more sleep problems can be linked to more suicidal ideation.
6	Sleep (sleep onset latency)	Wrist actigraphy	Suicidal ideation (same day)	Active & passive	Positive	Fewer minutes awake after sleep onset predicted higher next-day suicidal ideation.
7	Extralinguistic features	Boamente system	Suicidal ideation	Passive only	Positive	The BERTimbau Large model identified suicidal ideation from passively gathered text data, (*AUC* - 0.95, *Precision* - 0.96, *Recall* - 0.95).
8	Extralinguistic features	Smartphone	Suicidal ideation, Suicide attempt	Passive only	Negative	Increases in anger and drops in positive emotion over two weeks preceded suicide attempts. *Correlation* of 0.39 based on t-value.

Reference number	Biomarker	Device	Suicidality measurement	Sensor modality	Association	Narrative description of findings
9	Extralinguistic features	Smartphone	Suicidal thoughts, suicidal behaviours	Passive only	No association	No significant association between linguistic features and suicidality, but sufficient possibilities for feasibility.
10	Activity (smartphone)	Smartphone	Depressive symptoms	Passive only	Positive	Smartphone overdependence alone increased the odds of depression by 40% (*Adjusted odds ratio* (*AOR)* = 1.40), suicidal ideation by 44.00% (*AOR* = 1.44) and suicidal plans by 21.00% (*AOR* = 1.21).
11	Sleep (irregularity)	Wrist actigraphy	NSSI	Active & passive	Negative	Sleep irregularity (measured via sleep regularity index) is significantly associated with increased NSSI urges, independent of other sleep parameters and affective states.
12	Location	Smartphone	Suicidal ideation	Passive only	Positive	Higher homestay than usual was linked to twice the odds of suicidal events the following week (*OR* = 1.99, *95% CI* = 1.15-3.45). Entropy and distance travelled were not significant. Predictive accuracy of the homestay model was modest (*AUC* - 0.64, *95% CI*: 0.50-0.78).
13	Sleep (sleepiness)	Smartphone	Suicidal ideation (past 2 weeks)	Passive only	Positive	Moderate between-group variability in sleepiness (*ICC* = -0.46) and suicidal ideation (SI) characteristics, with the highest stability observed for SI duration (*ICC* = 0.68) and intensity (*ICC* = - 0.66). Notably, sleepiness moderated the relationship between passive and active SI, such that higher daily sleepiness amplified the association with both the severity and likelihood of active SI.
14	Sleep (time in bed)	Fitbit, Smartphone	Suicidal ideation, Suicidal behaviour, Suicide attempt	Active & passive	Negative	Principal component analysis identified sleep quality features (sleep efficiency and time in bed) as key contributors to suicide risk. The K-nearest neighbours model significantly outperformed baseline classifiers, including majority guess, random forest, support vector machine, and logistic regression (*F* - 10.70, *p* - .009; *F* = 17.60, *p* = .003). Overall, poorer sleep quality, reflected by less efficient and shorter sleep, was associated with increased suicidality.
14	Activity (steps)	Fitbit, Smartphone	Suicidal ideation, Suicidal behaviour, Suicide attempt	Active & passive	Negative	The same model used as above. Here, less activity (steps) was related to more suicidality.
14	Activity (smartphone)	Smartphone	Suicidal ideation, Suicidal behaviour, Suicide attempt	Active & passive	Positive	The same model used as above. Here, more phone activity was related to more suicidality.

Reference number	Biomarker	Device	Suicidality measurement	Sensor modality	Association	Narrative description of findings
15	Activity (smartphone)	Smartphone	Suicidal ideation	Active & passive	No association tested	EMA compliance dropped before hospitalization, while passive data showed increased phone use (especially social activity) and captured crisis triggers like pain and loneliness missed by self-report.
16	Activity (steps)	Fitbit	Depressive symptoms	Passive only	Negative	Higher physical activity was linked to fewer depressive symptoms (β = -0.16, p < .01). Skew in step count during the internship was negatively associated with both resilience and stress sensitivity (β = -0.16, p < .01), suggesting that irregular activity patterns may reflect lower psychological stability. These effects remained significant after controlling for age and sex.
16	Sleep (time in bed)	Fitbit	Depressive symptoms	Active & passive	Positive	Longer time in bed and higher variability in sleep during the internship were associated with higher stress sensitivity, with mean seconds in bed showing a positive association (β = 0.17, p < .001). Similarly, both the average duration (β = 0.18, p < .001) and skew (β = 0.16, p < .001) of sleep were positively linked to stress resilience. All results remained significant after adjusting for age and sex.
16	Heart rate	Fitbit	Depressive symptoms	Active & passive	Negative	Lower heart rate, measured both at baseline and during the internship, was significantly associated with higher stress resilience. Effects remained robust after controlling for age and sex.
17	Extralinguistic features	Smartphone	Suicidal ideation (past 2 weeks), Suicide attempt	Passive only	Positive	During episodes of suicidal ideation, texts with peers contained significantly more negative emotion words compared to texts with family, with an odds ratio of 2.91 (p < .001). The frequency of negative words in peer chats was positively associated with suicidal ideation.
18	Sleep (time)	Smartphone	Suicidal ideation	Passive only	No association	No direct association between sleep and suicidal ideation, but passive sensor data and self-assessment data show consistency.
19	Sleep (sleep onset latency)	Wrist actigraphy	Suicidal ideation	Passive only	Positive	Longer sleep onset latency significantly predicted next-day suicidal ideation, with each additional minute increasing the odds by 5.00% (OR = 1.05, p = .04). This positive association, though modest, indicates that delayed sleep initiation may be a proximal risk factor for suicide-related thoughts. The effect was identified using a mixed-effects model.
20	Activity (smartphone)	Smartphone	Anhedonia	Passive only	Negative	Less phone movement while typing was associated with increased anhedonia (β = -0.12, p = .00030)

Reference number	Biomarker	Device	Suicidality measurement	Sensor modality	Association	Narrative description of findings
20	Activity (smartphone)	Smartphone	Irritability	Passive only	Positive	More keyboard presses linked to more irritability and social dysfunction, however relation to suicidality is indirect.
21	Activity (smartphone)	Smartphone	Suicidal thinking	Passive only	No association	Daily smartphone screen-on time and usage patterns were stable over time and did not significantly differ by operating system or across weeks. But the findings support the feasibility of using passively collected phone logs to study screen time in individuals with suicidal ideation
22	Extralinguistic features	Smartphone	Suicidal ideation	Passive only	Negative	Decreased speech prevalence was significantly associated with higher suicide severity, with a strong negative correlation ($r = 0.62$) and a regression coefficient of $\beta = -0.68$ (*Adjusted* $r^2 = 0.37$). Individuals who spoke less had higher suicidal ideation.
22	Facial expressivity	Video analysis	Suicidal ideation	Passive only	Negative	Lower facial expressivity, both overall ($r = -0.46$) and emotion-specific (sadness: $r = -0.68$; surprise: $r = -0.74$; disgust: $r = -0.64$), was significantly associated with increased suicidality. Diminished emotional facial activity may serve as a behavioural marker for suicide risk.
22	Head movement	Video analysis	Suicidal ideation	Passive only	Negative	Reduced variability in head movement, particularly pitch ($r \approx -0.69$), was negatively associated with suicide severity. Lower dynamic range in head pitch and yaw was predictive of higher suicide risk, pointing to constrained nonverbal behaviour as a relevant indicator.
23	Skin conductance	Wearable biosensor	Suicidal ideation	Passive only	No association	No association between skin conductance and suicidal ideation. After Holm correction the results were unsignificant.
24	Extralinguistic features	Microphone	Suicidal ideation, Suicide attempt	Passive only	Positive	Significant vocal feature differences were observed between suicidal and control groups, with medium to large effect sizes (e.g., *Cohen's d* = 0.60-0.84) for GRBASI dimensions like grade, roughness, and strain. More problematic vocal features were associated with higher levels of suicidal ideation and attempts.
24	Speech disfluency	Microphone	Suicidal ideation, Suicide attempt	Passive only	Positive	Suicidal individuals showed markedly more speech disfluencies compared to controls, including hesitations (*Cohen's d* = 0.50/.86), *errors* = 0.81/0.94), and *uncorrected errors* = 0.82/0.87). These findings support disfluency as a behavioural marker of suicidality, with large and consistent effect sizes.
25	Extralinguistic features	Microphone	Suicidal ideation, Suicide attempt	Passive only	Positive	Psychiatric inpatients with recent suicidal ideation or attempts exhibited 4-6× poorer voice quality and 2-4× more speech disfluencies compared to healthy controls.

Reference number	Biomarker	Device	Suicidality measurement	Sensor modality	Association	Narrative description of findings
						These features enabled automatic classification of suicidality history with up to 80.00% accuracy.
26	Extralinguistic features	Smartphone	Suicidal ideation	Active & passive	No association provided	Passive and active data from the Cogito Companion app were feasible and acceptable for monitoring mental health in veterans. While active use declined, passive data still enabled clinicians to detect risk indicators and provide outreach.
27	Activity (steps)	Smartphone	Depression	Passive only	No clear association	Smartphone sensor data, processed with unsupervised change-point detection, could identify changes in mobility patterns among depressive outpatients. These changes may serve as early indicators of behavioural or clinical deterioration, potentially supporting relapse prevention and suicide risk monitoring.
28	Sleep (quality & onset latency)	Wrist actigraphy	Suicidal ideation	Active & passive	Positive	Longer sleep onset latency ($\beta = 0.06$, $p = .002$) and better perceived sleep quality ($\beta = 0.07$, $p < .001$) were both positively associated with higher suicidal ideation, while less total sleep time was linked to increased ideation ($\beta = -0.05$, $p = .010$). These associations were consistent across most models, suggesting that both difficulties falling asleep and better subjective sleep quality relate to higher suicide risk.
29	Sleep (efficiency, time, onset latency, awake after onset)	Wrist actigraphy	Suicidal ideation	Active & passive	Positive	Subjective sleep parameters, including sleep efficiency ($r = 0.51$, $p = .001$), total sleep time ($r = 0.58$, $p = .006$), sleep onset latency ($r = 0.57$, $p = .005$), and wake after sleep onset ($r = 0.44$, $p < .001$), were positively associated with next-day suicidal ideation. Subjective sleep assessments were more consistently predictive of suicidal ideation than objective actigraphy measures, with only the fragmentation index showing a significant objective link.
30	Sleep (duration)	Wrist actigraphy	Suicidal ideation	Active & passive	No association provided	In high-risk adolescents recently discharged from psychiatric care for suicide risk, wrist actigraphy and sleep diaries showed high adherence to actigraphy and moderate agreement between both methods, particularly for Total Sleep Time ($r = 0.85$). Agreement was weaker for other sleep metrics, for example WASO.
31	Resting heart rate	Wrist actigraphy	Suicidal ideation	Active & passive	No clear association	Sensor-based resting heart rate data alone showed poor prediction of suicidal ideation.
31	Activity (steps)	Wrist actigraphy	Suicidal ideation	Active & passive	No clear association	Sensor-based steps data alone showed poor prediction of suicidal ideation.

Reference number	Biomarker	Device	Suicidality measurement	Sensor modality	Association	Narrative description of findings
31	Sleep (duration)	Wrist actigraphy	Suicidal ideation	Active & passive	No clear association	Passive-only sleep features performed poorly
32	Activity (steps)	Smartphone	Depressive symptoms	Active & passive	Negative	Activity notifications similarly showed a negative moderation effect (*estimate* = -0.03, p = .01), increasing step counts when baseline activity was low but reducing steps when baseline activity was already high.
32	Sleep (duration)	Smartphone	Depressive symptoms	Active & passive	Negative	Sleep notifications had a differential effect depending on prior sleep levels: they increased sleep duration when prior sleep was low but decreased it when prior sleep was already high, with a significant negative moderation effect (*estimate* = -0.08, p < .001).
33	Sleep (duration)	Fitbit	Suicidal ideation	Active & passive	No association	Passive sensing data with sleep metrics, did not enhance suicidal ideation prediction; elastic net regression models based solely on mood data outperformed those incorporating passive features.
33	Activity (steps)	Fitbit	Suicidal ideation	Active & passive	No association	Step count data from passive sensing introduced noise and decreased model accuracy, with mood-only models yielding better predictions of suicidal ideation.
33	Resting heart rate	Fitbit	Suicidal ideation	Active & passive	No association	Inclusion of passive heart rate data in random forest models reduced prediction accuracy for suicidal ideation (*AUC* dropped from 0.73 to 0.69, indicating no meaningful predictive value from heart rate measurements.

Note. Each row represents a specific finding from an individual study, indicated by the reference number in the first column. The "Association" column describes the direction of the reported relationship: a "Positive" association indicates that an increase in the biomarker measure was associated with an increase in suicidality, whereas a "Negative" association indicates that a decrease in the biomarker measure was associated with an increase in suicidality. A dash (-) was added when the study did not provide a clear association. The narrative description of findings summarises the key findings of the association between the individual bio marker and the suicidality measurement. WASO = Wakefulness After Sleep Onset; SDRR = standard deviation of R-R intervals; AUC = Area Under the Curve; OR = Odds ratio; ICC = Intraclass correlation.