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BEYOND THE CLINIC: A NARRATIVE REVIEW OF DIGITAL BIOMARKERS FOR MONITORING PSYCHOTIC DISORDERS IN NATURALISTIC SETTINGS

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ABSTRACT

Psychotic disorders remain a major challenge in psychiatry due to their chronicity and symptom heterogeneity. Digital phenotyping - the passive accumulation of behavioural data via various sensors - offers a pivotal shift toward ecologically valid, continuous monitoring that episodic clinical interviews cannot capture. This review aims to synthesise current literature on digital biomarkers, evaluating their role in predicting disease trajectories and social functioning while addressing inherent methodological and socio-ethical challenges. To achieve this, a comprehensive search of major databases, including PubMed, Scopus, and IEEE Xplore, was conducted to analyse key technological applications and clinical outcomes. We found that smartphones and medical-grade accelerometers remain the predominant tools for data collection, with GPS and mobility metrics serving as main proxies for monitoring symptoms. Simultaneously, next-generation technologies - such as AI-driven home EEG for sleep profiling, AI-driven audiovisual processing of patients' affect and Natural Language Processing - are redefining the boundaries of what can be captured in the patient's daily environment. However, for these technologies to move beyond research pilots, future frameworks must address current methodological fragmentation through standardised reporting protocols. Ultimately, successful clinical implementation requires an evolution of consent models, ensuring that algorithmic precision is deployed within a user-centred architecture that prioritises patient autonomy and the therapeutic relationship.

KEYWORDS

Psychotic Disorders, Schizophrenia, Digital Phenotyping, Wearables, Digital Biomarkers, Passive Sensing

CITATION

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Introduction

The spectrum of psychotic illnesses, among which one can discern schizophrenia, schizoaffective disorder, and related conditions, is clinically defined by a heterogeneous constellation of symptoms. These are typically stratified into three domains: positive symptoms, negative symptoms, and neurocognitive dysfunction. Etymologically rooted in the concept of a "split mind," the term schizophrenia historically describes a disintegration of psychic functions - specifically a dissociation between thought, emotion, and perception. Fundamentally, the psychotic patient is characterised by a severe impairment in reality testing, resulting in a distinct breach between the patient's internal experience and objective reality (Boland et al., 2025).

Despite our better understanding of the possible pathophysiology and the efficacy of antipsychotic drugs, psychotic disorders remain associated with significant functional impairment and a high risk of relapse. Traditional assessments in psychiatry largely rely on episodic clinical interviews, rating scales, and self-reported symptoms. This "snapshot" approach limits the clinician's ability to detect early warning signs of relapse (Hau et al., 2025). The nature of schizophrenia and related psychotic disorders as lifelong illnesses, their heterogeneous presentation, frequent lack of insight and motivation, requires sustained, objective long-term management strategies rather than acute, episodic care alone (Lee & Remington, 2015).

The pressing need for more continuous, objective methods to monitor patients over time, especially given the burden of relapse on individuals and healthcare systems, can be addressed by the development of mHealth. One of their promising sub-branches, digital phenotyping - defined as the "moment-by-moment quantification of the individual-level human phenotype in situ using data from personal digital devices," specifically smartphones and wearables (Benoit et al., 2020; Lane et al., 2023) - has emerged as a promising paradigm to address these limitations. By leveraging passive sensing from smartphones and wearable devices (e.g., GPS, accelerometer, screen usage, heart rate), it may enable continuous behavioural measurement in everyday settings. The feasibility and clinical necessity of integrating mobile health technologies into standard care seems to be solidified by the ubiquitous ownership of smartphones in today's society, and thus, also among patients across the spectrum of psychotic illnesses, from those at clinical high risk to patients with chronic conditions (Hau et al., 2025).

The methods of today's digital phenotyping consist of three distinct data streams: active data, passive data and metadata. Active data are collected through direct patient engagement with their device. The predominant technique of gathering active data used in digital phenotyping is Ecological Momentary Assessment (EMA), usually in the form of self-report scales, which enables real-time feedback on patients' symptoms within their natural environment, thereby mitigating the retrospective recall bias inherent in traditional clinical interviews and significantly enhancing ecological validity. The other type of collected data in the paradigm of digital phenotyping is passive data, which is collected continuously in the background via embedded sensors (e.g., GPS, accelerometers, call/text logs). This passive monitoring allows for the objective, longitudinal assessment of behavioural biomarkers - including sleep patterns, mobility, and social isolation - without requiring active effort from the patient, thereby reducing burden and capturing the dynamic nature of the illness in real-world (Bladon et al., 2025; Hau et al., 2025). The third stream, metadata, functions as a hybrid of the previous two metrics, quantifying the mechanics of usage - such as the latency in responding to a survey or the learning curve associated with app navigation - serving as a subtle proxy for cognitive functioning (Benoit et al., 2020).

Methodology

A comprehensive literature search was conducted on PubMed, Scopus, Web of Science, PsycINFO, ScienceDirect and IEEE Xplore using the search terms "digital phenotyping", "passive data", "smartphone sensors", "wearables", "smartwatches", combined with "psychosis", "schizophrenia", "first-episode psychosis". In order to identify the development of possibilities of the above-mentioned monitoring devices, the papers from January 2015 to November 2025 were selected. The reason for choosing this timeframe was that the mentioned paper can fill the gap between the previous reviews and the latest available research - it is particularly important considering the rapid technological progress and furthermore the evolution of monitoring devices and their precision. The inclusion criteria were observational studies, controlled or uncontrolled clinical trials and other older systematic reviews; available in full text in the English language. Studies were excluded if they did not use at least one digital biomarker to diagnose patients, monitor their outcomes or influence the delivery of therapeutic intervention for prognostic purposes; they were not human studies; they did not use a wearable, implantable, portable device to measure data; they did not report health outcomes for the study population; they weren't published in the English language between January 2015 to November 2025.

The Types of Used Devices and Sensor Modalities

Based on our analysis of systematic reviews and observational studies published between 2015 and 2025, digital phenotyping in psychotic illnesses relies on a large number of devices. As of 2025, medical-grade accelerometers, which measure movement and sleep, remain the most ubiquitous tool for data collection. There is a rapidly growing number of smartphone usage studies, comparable to the number of studies using accelerometers - interestingly, this trend is observable even before the COVID-19 pandemic. This change may be attributed to the technological advancements in popularly available accelerometers in smartphones, as well as the presence of multiple sensors in these devices, such as light detectors, microphones, and photoplethysmography (PPG) modules, which can provide a more detailed representation of a patient's state (Bladon et al., 2025). In the last few years, the presence of new data processing modalities is also worth mentioning, such as Natural Language Processing (NLP) to detect speech coherence, or the "E-Prevention" system, which integrates an AI analysis of audiovisual captures alongside traditional wearables (Parola et al., 2023; Zaher et al., 2024). These modalities are increasingly viewed as critical for detecting the "neurological soft signs" of schizophrenia that standard activity trackers might miss (Gray et al., 2023). A 2025 systematic review of smartphone applications for schizophrenia analysed 54 articles covering 27 unique monitoring apps (Hau et al., 2025). Their data reveals that GPS is the most frequently utilised sensor modality in app-based monitoring studies, second to phone accelerometers - likely due to its correlation with social withdrawal and life-space mobility, one of the possible markers of relapse. The third type of devices used in the studies, although distinctly less prevalent than smartwatches and accelerometers, were consumer-grade wearables, such as smartwatches and fitness bands. Nevertheless, multiple studies supported their eligibility in the monitoring of psychosis, as a standalone device or in synchronisation with a smartphone (Bladon et al., 2025; Fonseka & Woo, 2022; Hassan et al., 2025; Yang et al., 2025). Contrasting with the widespread use of phones and wearables, "digital pills" represent a highly specialised niche. As of the date of writing this article, the only available medication used in psychotic disorders in the form of a digital pill is aripiprazole. The digital pills are embedded with an ingestible event marker that is activated by stomach fluid and communicates with a sensor patch applied to the patient's skin. Then, the data is accessed and interpreted by a smartphone app (Jan et al., 2023).

Digital Biomarkers in Detection of Negative Symptoms

The currently available research demonstrates more data supporting the usage of passive sensing modalities, particularly GPS and accelerometry in monitoring the negative symptoms of schizophrenia compared to positive symptoms. A 2025 observational study reported that 10 out of 12 passive sensor features showed significant associations with negative symptoms (Yang et al., 2025).

The core of the digital phenotype of negative symptoms lies in the quantification of avolition and anhedonia through mobility metrics. As negative symptoms worsen, patients exhibit a diminishing in their living space, characterised by reduced community integration and increased sedentary behaviour). This trait was empirically consistent with an active and passive data gathered by MindLAMP app (Ranjan et al., 2022). It demonstrated that "home-time" - the cumulative duration spent at the primary residence serves as a robust, longitudinal proxy for social withdrawal and motivational deficits. One of their main findings was that mood, sleep and psychotic symptoms were more severe at home. This variability of reports in different settings highlights a pressing need for personalised intervention, tailored to the unique environmental sensitivities of each patient.

Furthermore, this social isolation also has cognitive implications. Greater amount of home time was significantly associated with poorer performance on the Faux Pas Recognition Test, a standard measure of theory of mind and social cognition at baseline and at 6-month follow-up (Das et al., 2025). Critically, subsequent partial correlation analyses demonstrated that when other characteristics as symptom severity, prescribed dose of medicine and status of employment, were introduced as covariates, the aforementioned direct association between home-time and social cognitive performance was statistically non-significant. Thus, further study is needed to conclude whether the digital mobility metrics are largely mediated or moderated by negative symptoms.

Beyond spatial metrics, the measurement of sleep dysregulation serves as an important marker in the trajectory of psychotic illness, frequently emerging as a harbinger of the prodromal phase and a reliable predictor of acute decompensation. A critical precedent was established for the clinical validity of mobile sensors, demonstrating that the continuous data harvest through smartphone accelerometers, augmented by intermittent active Ecological Momentary Assessments (EMA) thrice a week, can serve as accurate surrogates for standardised in-clinic assessments like the Pittsburgh Sleep Quality Inventory (PSQI) (Staples et al., 2017). It highlighted the superior efficacy of a multimodal approach in monitoring patients with schizophrenia; while active ecological momentary assessment alone showed strong correlation with clinical ratings (85% classification agreement between PSQI scores and data from EMA), the integration of passive accelerometer data with active self-reports significantly enhanced predictive precision of predicted PSQI scores. (mean average error = 0.75). However, this investigation also brought to the forefront the methodological challenge of missing data by explicitly addressing gaps in the raw sensor stream - an artifact frequently ignored in broader literature.

However, accelerometers are not the only modality of tracking sleep in patients with schizophrenia and affective psychoses. Their distinct polysomnographic signatures, characterised by prolonged sleep onset latency, fragmented continuity, significant reduction of slow-wave activity (SWA), and, recently, also specific deficits in sleep spindles, demonstrate a significant correlation with both positive and negative symptoms (Chouinard et al., 2004; Manoach et al., 2014). Thus, the 2024 study tried to apply these findings to determine if nightly EEG monitoring by consumer-grade devices in domestic circumstances, integrated with deep learning and real-time processing, is feasible. This architecture achieved a reported classification accuracy of 99.94% in detecting schizophrenia-related abnormalities on standard datasets (Paraschiv et al., 2024). Other similar studies also achieved great accuracy, varying from 84,42% to 99,02% (Jindal et al., 2022; Khare et al., 2023). Moreover, passive metrics such as bedtimes and sleep duration can be effectively synthesised with ecological momentary assessment (EMA) to forecast clinical acuity (measured as BPRS scores) in post-discharge populations (Ben-Zeev et al., 2017). This finding validates the utility of sleep architecture not merely as an isolated health metric but as a dynamic variable essential for broader symptom prediction algorithms. At the same time, while patients exhibit a strong willingness to adopt consumer-grade wearables and dedicated sleep tracking platforms due to their efficacy, the motivational deficits inherent to negative symptoms render passive sensing a far more sustainable modality for longitudinal passive data gathering than active logging. In a similar trial, initial compliance was robust - with active diary completion rates averaging approximately 90% - statistical analysis revealed a significant inverse correlation between negative symptoms and protocol compliance ($\rho \approx$ - 0.40 to - 0.49) (Meyer et al., 2018). This suggests that the very symptoms of the disorder the technology aims to monitor (specifically avolition) may actively hinder the user's ability to engage with self-reporting tasks.

Another innovative technology, promising integrated support and monitoring state of patient with psychotic disorders is e-Prevention. One of its most interesting features is a detection method of a blunted affect by extraction and analysis of facial Action Units (AUs) from video captures (Zlatintsi et al., 2022). By quantifying the reduced motor variability of facial muscle movements and excerpts from the spontaneous speech and correlating them with other, more typical physiology-measuring modalities, such as heart rate, sleep rates and accelerometry, the system provided a continuous metric of emotional flattening that correlated with standard clinical assessments, moving beyond simple mobility tracking to capture complex emotional behavioural markers. More research on this technology, its limitations and opinions of both patients and healthcare providers is needed; if its practical applicability is successful, it would offer a standardised, reproducible metric, eliminating inter-rater variability and observer bias.

Digital Biomarkers in Detection of Positive Symptoms

While passive mobility tracking (GPS/accelerometry) is predominantly sensitive to negative symptoms (e.g., avolition), current literature provides compelling evidence that passive sensing modalities can also effectively isolate the digital biomarkers of positive symptoms. Research indicates that weekly summaries of everyday interactions with smartphones, such as duration of conversation, number of incoming calls, and screen unlocks, are inversely related to symptom severity; as the illness progresses, the entropy (disorder) of a patient's routine typically increases - that suggests such gathering of data may be successfully used in the prediction of relapse (Adler et al., 2020; Bladon et al., 2025). Another study used NLP models to measure semantic coherence (how logically connected sentences are) and syntactic complexity in the transcripts provided in Danish, German and Chinese languages (Parola et al., 2023). Automatic linguistic analysis could reliably detect the disorganised speech patterns characteristic of positive symptomatology, although they were not the same in all of the examined languages. The only marker applicable to all of them was the reduced ability to organise text into coherent parts. Another study used NLP to analyse 60,009 posts from the Reddit schizophrenia message board and other non-mental health related subreddits. The measured detection accuracy of the algorithm finding posts linked to the disorder was 96% - one of the significant metrics was the use of words conveying negative emotions and "they, them, theirs, and themselves" pronouns (Plank & Zlomuzica, 2024). A similar study analysing tweets from 671 users who self-disclosed their condition in their Twitter bio found an 88% accuracy of schizophrenia detection by NLP analysis of their content (Birnbaum et al., 2017). Moreover, digital social behaviour in individuals at clinical high risk for psychosis has been linked with the risk of conversion to psychosis. For example, lower reciprocity in text messaging predicted increased probability of transition to full psychosis over follow-up (Kuhney et al., 2025). The presence of multiple studies successfully correlating positive symptoms in NLP-analysed speech or text and smartphone activity raises questions about the applicability of their findings in routine clinical practice, which would require patients' informed consent for gathering data that may contain intimate details of their lives. At the same time, in an observational study using wrist wearables, the authors found a positive correlation of heart rate measures with positive symptoms - likely reflecting the heightened autonomic arousal state associated with paranoia and hallucinations (Yang et al., 2025). Another study suggests that positive symptomatology manifests in passive data through signatures of hyperactivity and chaos - specifically, elevated heart rate and high-entropy mobility patterns - contrasting sharply with the sedentary profile of negative symptoms (Adler et al., 2020).

Methodological Challenges

Despite promising outcomes of a vast majority of currently available literature, they also reveal substantial and recurrent problems. One of them is methodological and reporting heterogeneity. While accelerometers and smartphones are commonly used, there is significant divergence in how features are derived, data quality is assessed, thresholds are applied, and analytic strategies (e.g., machine learning, time-series) are implemented. (Bladon et al., 2025). Furthermore, across studies using machine learning, there are marked inconsistencies in preprocessing methods, algorithms, and performance metrics. Often, the data collected by smartphones does not match the symptom ratings given by doctors, leading to weak statistical connections. This disagreement is largely due to a difference in timing. Smartphones collect data continuously - every day or even every minute - whereas clinicians typically assess patients only once a month based on memory, which creates a resolution gap (Benoit et al., 2020; Bladon et al., 2025). When researchers try to average out weeks of detailed, daily smartphone data to match a single monthly clinic visit, they lose the fine details of how symptoms fluctuate day-to-day. Consequently, this averaging process can smooth over important changes in motivation or pleasure, making the digital technology appear less effective than it actually is, simply because it is being compared to a much less detailed standard. Moreover, these inconsistencies hamper comparability across studies and limit the translation of digital phenotyping into routine clinical practice. Some of the reviewed literature attempted to address this problem and develop appropriate protocols, such as: HOPE-S for collecting digital phenotypes to predict readmission and relapse; m-RESIST for patients with treatment-resistant schizophrenia that uniquely includes the caregivers in its loop, by allowing them to receive alerts and participate in the therapeutic process; the Hummingbird Protocol monitoring adherence to digital medicine system; E-CHR framework for digital recruitment patients with clinically high risk in the general population by remote monitoring, and "just-in-time" interventions to prevent the transition to psychosis (Abdul Rashid et al., 2021; Alonso-Solís et al., 2018; Fowler et al., 2019; Reilly et al., 2019). Moreover, the duration of analysed studies could be broadly categorised into short-term cross-sectional snapshots lasting one to two weeks, and long monitoring protocols, extending from several months to over a year. These two types of study length have significant implications; while short-term windows may capture immediate symptom fluctuations, they lack the capacity to detect gradual behavioural adaptations to macro-stressors.

Apart from typical digital biomarkers, the digital pills have a different set of challenges in their successful implementation. One of its main drawbacks, reported in numerous studies, are skin irritation events (SIE) due to the prolonged contact of the sensor patch with the skin. Multiple versions of such patches were developed, that partially addressed this problem – for the most recently developed patch, RW2, the SIE appeared in 9,2% of the patients, significantly lower than in DW5 (14,2%) and RP4 (18,1%) version (Jan et al., 2023). Nevertheless, the studies confirm heightened patient compliance to the treatment compared to the non-digital medicine (Hadzi Boskovic et al., 2023).

Socio-Ethical Challenges

Beyond methodological challenges, important socio-ethical considerations complicate clinical implementation. Privacy, data security, informed consent, and potential exacerbation of paranoia in individuals with psychosis must be carefully navigated.

The long-term acceptability of smartphone-based monitoring has been demonstrated across several studies. A feasibility trial showed that sustained monitoring over six months was well tolerated (Eisner et al., 2019). Participants completed 65% app assessments, with 78% completing ≥33% assessments. This is reinforced by reports indicating high levels of acceptability for relapse monitoring applications (Ben-Zeev et al., 2017; Eisner et al., 2019; Gumley et al., 2022). However, other studies also highlight the importance of user-centred design and personalisation to optimise engagement. Another qualitative analysis inquired into the impressions of recently-diagnosed young adults using an app not only monitoring their health, but also providing insight into their own patterns, and developing strategies to maintain remission (Terp et al., 2018). Patients perceiving the resources as closely aligned and relevant to their needs reported higher engagement than those who didn't. These findings align with patients' remarks on an application used in another study (Del Piccolo et al., 2025). After its course a substantial group of patients appreciated its predictability that facilitated initial familiarisation, others found the repetitiveness of questions monotonous and couldn't find clear benefits of the app. The strongest motivators for the participants were: the possibility to further schizophrenia-related research and give back the received support to the community, and a sense of helping others. Another motivators were the assessments with the scientists, perceived as an opportunity to self-reflect. These insights inform future implementation strategies, emphasising the need for flexible systems tailored to patient needs and a complementary role of digital psychiatry to the care provided by physicians in real life.

On the other hand, three participants of study from 2018 reported heightened fear of surveillance; these privacy concerns intensified in the absence of a well-established patient-clinician relationship (Terp et al., 2018). Another study observed that approximately 20% of participants experienced distinct distress regarding the automated monitoring, despite the short duration of the protocol (Ben-Zeev et al., 2017). Aforementioned findings underscore that the passive nature of data collection does not automatically circumvent the characteristic paranoia or surveillance anxiety found in schizophrenia. However, observations suggest that this resistance is not static; rather, the "surveillance concern" tends to decrease as patients become acclimated to the digital ecosystem and solidify their trust in the supervising healthcare providers, indicating that acceptability is a dynamic trait that evolves with sustained exposure and developing feelings of security in the therapeutic relationship. A study conducted in 2025 concerning the applicability of smartphone-based assessment in patients after first-time psychosis seem to be in line with these findings (Del Piccolo et al., 2025). Although its participants generally demonstrated confidence in the integrity of data handling within both experimental and clinical environments, the anxieties regarding data governance, its access, and the contextual parameters of shared information persisted.

These recurring anxieties over handling the patients' data cannot be ignored or diminished. The possible presence of paranoia and cognitive deficits raises questions about obtaining valid informed consent in digital phenotyping. A 2021 descriptive review cautions that traditional 'broad consent' models are insufficient for passive sensing, as they fail to convey the risks of algorithmic processing due to its possible repurposing or de-anonymisation (Chivilgina et al., 2021). Instead, recent frameworks advocate for dynamic consent - a flexible model allowing users to toggle specific data streams on or off - and the use of simplified visual protocols to ensure comprehension of the consent forms (Arnautovska et al., 2025; Martinez-Martin et al., 2021). Crucially, in a 2017 review across multiple studies (FOCUS, CrossCheck) it was observed that consent is not a one-time event but a relational process (Ben-Zeev et al., 2017). The authors suggested that "technical" consent (signing a form) was less important than "relational" consent (trusting the clinician). When patients understood who was watching (a nurse vs. "the government"), consent was maintained; when this was ambiguous, patients withdrew.

Future study designs must integrate transparency protocols to mitigate these specific fears. Simultaneously, the regulatory landscape requires dynamic adaptation; ethical guidelines must undergo continuous revision to match the rapid development and application of technology in psychiatric practice. Given the hyper-sensitive nature of psychiatric data, the ethical stakes are particularly high; the potential for privacy breaches poses severe risks, as unauthorised exposure threatens not only patient confidentiality but also exacerbates the vulnerability to social stigmatisation and structural discrimination (Gooding, 2019).

Conclusions

The integration of digital phenotyping into the management of psychotic disorders represents a pivotal paradigm shift, moving psychiatric assessment from episodic, clinic-based snapshots to continuous, ecologically valid monitoring. As this review has demonstrated, the ubiquity of smartphones and consumer-grade wearables provides an unprecedented capacity to capture the "lived experience" of schizophrenia and schizoaffective disorders through objective, passive data streams. The evidence currently supports the utility of accelerometry and GPS mobility patterns as robust proxies for negative symptoms, offering clinicians a tangible metric for avolition and social withdrawal. Simultaneously, emerging modalities - ranging from Natural Language Processing of speech for positive symptoms to AI-driven home EEG for sleep architecture - are expanding the frontiers of what can be monitored in naturalistic settings. However, the translation of these innovative technologies from research pilots to routine clinical care is currently hindered by significant methodological fragmentation. The "resolution gap" between high-frequency digital signals and sporadic clinical ratings remains a critical barrier, often obscuring the true predictive power of the digital phenotype. Future research should focus on developing standardised measurement frameworks, conducting multicenter validation trials, and integrating digital tools into clinical care pathways. Addressing these barriers will be critical to realising the full potential of digital psychiatry in schizophrenia. Furthermore, the successful implementation of these tools is not merely a technological challenge but a socio-ethical one. While feasibility studies indicate high tolerability, patient engagement is heavily contingent upon user-centred design and the strength of the therapeutic alliance. The inherent vulnerability of this population to paranoia and surveillance anxiety necessitates a departure from traditional "broad consent" models toward "dynamic consent" frameworks that prioritise patient autonomy and transparency. Ultimately, for digital phenotyping to achieve its potential as a personalised intervention tool, it must be deployed not as a replacement for human care, but as a supportive technology that aligns algorithmic precision with the complex, longitudinal reality of the patient's life.

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