Psychiatric Disorders as Partially Observable Dynamical Systems: A State-Space Framework for Preventive Computational Psychiatry

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Abstract

Psychiatric disorders are traditionally diagnosed through episodic clinical assessment based on interviews, behavioral observation, and patient self-report, providing only intermittent and often subjective evaluations of continuously evolving neurophysiological processes. Recent advances in wearable biosensors, digital phenotyping, electronic health records, and natural language processing have created unprecedented opportunities for continuous monitoring of physiological, behavioral, cognitive, and environmental signals. However, these technologies are typically investigated as isolated predictive tools rather than as complementary observations of a common underlying process.

This paper proposes a novel theoretical framework, termed *Preventive Computational Psychiatry*, that reformulates psychiatric monitoring as a Bayesian state estimation problem over a continuously evolving latent psychiatric state. Within the proposed framework, psychiatric disorders are modeled as partially observable nonlinear dynamical systems whose internal states cannot be measured directly but can be probabilistically inferred through multimodal digital observations. Physiological signals, behavioral patterns, semantic language features, environmental context, medication adherence, and clinical history are integrated into a unified state-space representation that supports continuous estimation of individualized psychiatric trajectories.

The framework further introduces the concept of a *Psychiatric Digital Twin*, representing a patient-specific computational model of normal longitudinal homeostasis. Rather than relying on population-based thresholds or static diagnostic categories, clinical interpretation is based on deviations from each individual's expected physiological trajectory. Artificial intelligence is positioned as a computational approximation to Bayesian inference, enabling multimodal sensor fusion, uncertainty quantification, and explainable clinical decision support while maintaining human oversight in diagnostic and therapeutic decision-making.

Unlike existing approaches focused primarily on classification or prediction, the proposed theory shifts the objective toward continuous estimation of latent psychiatric state trajectories and early identification of state transitions. The paper presents the mathematical formulation, theoretical assumptions, multimodal observation model, validation roadmap, ethical considerations, and explicit research hypotheses required for future prospective clinical evaluation.

By integrating concepts from computational psychiatry, Bayesian estimation, systems theory, digital phenotyping, and explainable artificial intelligence into a unified mathematical framework, this work establishes a foundation for future research on continuous, personalized, and preventive mental healthcare. The proposed framework is intended as a conceptual and computational model that requires prospective longitudinal validation before clinical implementation.

Computational Psychiatry, Preventive Psychiatry, Bayesian State Estimation, State-Space Models, Digital Phenotyping, Wearable Biosensors, Digital Twin, Artificial Intelligence, Explainable AI, Mental Health, Multimodal Sensor Fusion, Longitudinal Monitoring, Clinical Decision Support.

1 Introduction

Mental disorders constitute one of the leading causes of disability worldwide and represent a major public health challenge. Despite significant advances in neuroscience, psychopharmacology, and clinical psychology, psychiatric assessment remains largely dependent on episodic clinical interviews, behavioral observation, and patient self-report. Unlike many other medical specialties, psychiatry lacks continuous objective biomarkers routinely available in clinical practice.

This limitation has important consequences. Clinical deterioration is frequently identified only after symptoms become sufficiently severe to meet diagnostic criteria or require intervention. Consequently, opportunities for earlier therapeutic action may be missed.

Recent technological advances have substantially changed this landscape. Wearable biosensors now provide continuous measurements of physiological variables such as heart rate, heart rate variability (HRV), respiratory rate, skin temperature, physical activity, and sleep architecture. Smartphones generate longitudinal behavioral information through passive digital phenotyping, while conversational Artificial Intelligence (AI) systems enable continuous analysis of natural language, emotional expression, cognitive organization, and self-reported life events.

These developments suggest a fundamental question:

Can psychiatric deterioration be modeled as a continuous latent dynamical process that becomes partially observable through multimodal digital sensing before overt clinical manifestations occur?

This paper argues that such a reformulation is both mathematically natural and clinically meaningful. Rather than considering psychiatric crises as isolated events, we propose modeling psychiatric disorders as partially observable nonlinear dynamical systems whose latent states evolve continuously over time. Digital sensors provide indirect observations of these hidden states, while Bayesian inference and machine learning estimate their trajectories.

Importantly, this work does not claim that current digital technologies can reliably predict psychiatric crises in clinical practice. Instead, it proposes a theoretical and computational framework that generates explicit, testable hypotheses for future prospective validation.

The proposed framework integrates five complementary concepts:

1. Psychiatric disorders as latent dynamical systems.
2. Multimodal digital observations acquired through wearable sensors, smartphones, conversational AI, environmental monitoring, medication adherence, and electronic health records.
3. Personalized Psychiatric Digital Twins representing each patient's longitudinal physiological baseline.
4. Bayesian state estimation for continuous reconstruction of latent psychiatric trajectories.
5. Explainable clinical decision support designed to assist, rather than replace, psychiatric evaluation.

The central mathematical problem addressed throughout this paper can be formulated as estimating the posterior distribution

$$P(x_t \mid y_{1:t}),$$

where x_t denotes the unobservable latent psychiatric state and $y_{1:t}$ represents the complete sequence of multimodal digital observations collected up to time t.

Within this formulation, wearable devices, conversational language, behavioral data, and clinical information are not viewed as independent predictors but as complementary observations of the same hidden physiological process.

Unlike previous work that focuses primarily on individual digital biomarkers or disorder-specific prediction models, the proposed framework introduces a unified state-space representation capable of integrating heterogeneous information sources into a common mathematical formalism. This representation naturally accommodates uncertainty, missing observations, temporal dynamics, personalization, and explainable inference.

If supported by future prospective longitudinal studies, such a framework may contribute to a transition from reactive psychiatric care toward preventive computational psychiatry, where continuous multimodal monitoring augments clinical decision making through earlier identification of latent physiological destabilization.

The remainder of this paper is organized as follows. Section II reviews recent advances in computational psychiatry, digital phenotyping, wearable biosensors, conversational artificial intelligence, and state-space modeling. Section III formulates psychiatric monitoring as a partially observable dynamical system. Section IV introduces the proposed multimodal observation model. Sections V and VI describe Bayesian state estimation and the Psychiatric Digital Twin framework. Subsequent sections discuss explainable clinical decision support, validation strategies, ethical considerations, limitations, and future research directions.

2 Psychiatric Monitoring as a Partially Observable Dynamical System

The central premise of this work is that psychiatric disorders can be reformulated as partially observable nonlinear dynamical systems.

Unlike conventional psychiatric assessment, which relies on episodic observations obtained during clinical interviews, the proposed framework assumes that the patient's underlying neurophysiological state evolves continuously while remaining only indirectly observable.

This perspective is inspired by state estimation problems commonly encountered in robotics, aerospace engineering, signal processing and computational neuroscience, where the true state of a system cannot be measured directly but must be inferred from noisy observations.

2.1 Latent Psychiatric State

We define the latent psychiatric state as the minimum hidden representation describing the patient's instantaneous neurophysiological, behavioural and cognitive condition.

Formally,

$$x_t \in R^n$$

represents the latent psychiatric state at time t.

Importantly, x_t is not directly measurable using existing clinical technologies.

Instead, clinicians observe indirect manifestations including

- physiological regulation,
- behavioural activity,
- speech,
- emotional expression,
- cognitive organisation,
- medication adherence,
- environmental interaction.

The objective of computational psychiatry is therefore not to observe x_t, but to estimate it.

2.2 State Dynamics

The latent psychiatric state evolves continuously according to

$$x_{t+1} = f(x_t, u_t) + w_t$$

where

- $f(\cdot)$ represents unknown psychiatric dynamics,
- u_t denotes external inputs,
- w_t represents stochastic physiological variability.

External inputs may include

- medication,
- psychotherapy,
- sleep deprivation,
- stressful life events,
- physical exercise,
- substance use,
- social interaction,
- environmental exposure.

Rather than assuming deterministic behaviour, the proposed framework explicitly models uncertainty through stochastic state evolution.

2.3 Observation Model

The latent psychiatric state generates observable digital measurements through multiple sensing modalities.

The observation process is represented by

$$y_t = h(x_t) + v_t$$

where

$$y_t = \{y^{phys}, y^{beh}, y^{lang}, y^{env}, y^{clin}\}$$

contains

- physiological observations,
- behavioural observations,
- linguistic observations,
- environmental observations,
- clinical observations.

The observation noise

$$v_t$$

captures measurement uncertainty associated with consumer wearables, smartphones and conversational systems.

2.4 Bayesian State Estimation

Because the latent state cannot be measured directly, the clinical objective becomes estimating its posterior probability distribution.

Given the sequence of observations

$$y_{1:t} = \{y_1, \dots, y_t\}$$

the inference problem becomes

$$P(x_t|y_{1:t})$$

This posterior distribution constitutes the mathematical core of the proposed framework.

Different computational methods—including Kalman filters, particle filters, hidden Markov models, variational inference, and deep sequential neural networks—may all be interpreted as alternative approximations to this posterior distribution.

Consequently, the proposed theory is independent of any specific Artificial Intelligence architecture.

2.5 Multimodal Observation Space

Each sensing modality provides complementary information regarding the latent psychiatric state.

Let

$$y_t = [y_t^{phys}, y_t^{beh}, y_t^{lang}, y_t^{env}, y_t^{clin}]$$

where

$$y_t^{phys} = \text{Wearable biosignals,} \tag{1}$$
$$y_t^{beh} = \text{Digital behaviour,} \tag{2}$$
$$y_t^{lang} = \text{Conversational language,} \tag{3}$$
$$y_t^{env} = \text{Environmental context,} \tag{4}$$
$$y_t^{clin} = \text{Clinical records.} \tag{5}$$

The complete observation vector therefore represents a multimodal digital phenotype.

2.6 Observability

Not all components of the latent psychiatric state contribute equally to observable behaviour.

Similarly, not every sensing modality provides equivalent clinical information.

Within the proposed framework, psychiatric observability is defined as the degree to which the latent state can be inferred from the available multimodal observations.

Increasing the diversity and quality of sensing modalities is hypothesized to improve estimation accuracy, provided that new observations contribute information not already contained within the existing observation set.

This concept motivates multimodal sensor fusion rather than reliance upon isolated biomarkers.

2.7 Uncertainty

An essential characteristic of psychiatric inference is that uncertainty can never be completely eliminated.

The framework therefore estimates probability distributions rather than deterministic diagnoses.

Clinical decision support is consequently based upon

- posterior probability,
- confidence intervals,
- temporal evolution,
- uncertainty estimation,
- explanatory evidence.

This probabilistic interpretation is consistent with modern Bayesian approaches to medical decision making and avoids overconfident binary classification of inherently uncertain clinical phenomena.

3 A Unified Multimodal Observation Model

The central hypothesis of the proposed framework is that every digital sensing modality provides an incomplete and noisy observation of the same latent psychiatric state.

Consequently, wearable devices, smartphones, conversational Artificial Intelligence, medication records and electronic health records should not be interpreted as independent prediction systems but as complementary observation channels of a common hidden process.

This unified formulation naturally supports multimodal sensor fusion while providing a probabilistic interpretation of psychiatric monitoring.

3.1 Observation Channels

Let

$$\mathcal{Y} = \{Y^{phys}, Y^{beh}, Y^{lang}, Y^{env}, Y^{clin}\}$$

denote the complete observation space.

Each observation channel measures different aspects of the latent psychiatric state.

The complete observation vector at time t is therefore

$$y_t = \left[y_t^{phys}, y_t^{beh}, y_t^{lang}, y_t^{env}, y_t^{clin}\right]^T.$$

3.2 Physiological Observation Channel

Physiological measurements are acquired continuously through wearable biosensors.

Typical variables include

$$y_t^{phys} = [HR, HRV, RR, Temp, Sleep, Activity].$$

These measurements provide indirect information regarding

- autonomic regulation,
- circadian rhythm,
- physical recovery,
- metabolic activation,
- physiological stress.

Although individually nonspecific, their temporal evolution may reflect changes associated with psychiatric destabilization.

3.3 Behavioural Observation Channel

Digital phenotyping enables continuous measurement of behaviour in natural environments.

Representative behavioural variables include

$$y_t^{beh} = [Mobility, ScreenTime, Calls, Messages, Routine, Exercise].$$

Rather than acting as diagnostic biomarkers, these variables describe longitudinal behavioural trajectories that may reflect changes in functional status.

3.4 Linguistic Observation Channel

Natural language constitutes an important source of cognitive and emotional information.

Within the proposed framework, conversational systems are considered observation instruments capable of transforming free text into structured variables.

Examples include

$$y_t^{lang} = [Sentiment, Coherence, LexicalComplexity, Emotion, Hopelessness, Grandiosity, SleepComplaints].$$

Importantly, these variables are not interpreted in isolation but in conjunction with the remaining observation channels.

3.5 Environmental Observation Channel

Psychiatric stability is influenced by environmental context.

The proposed framework therefore incorporates variables such as

$$y_t^{env} = [Light, Temperature, Weather, Noise, Season, LifeEvents].$$

Environmental information is treated as an external modulating factor acting upon latent psychiatric dynamics rather than as a direct indicator of disease.

3.6 Clinical Observation Channel

Historical clinical information provides long-term context that cannot be inferred from digital sensing alone.

Representative variables include

$$y_t^{clin} = [Diagnosis, Medication, PreviousEpisodes, Hospitalizations, Comorbidities].$$

Unlike continuous sensing modalities, these observations are updated intermittently but provide essential prior information for Bayesian inference.

3.7 Observation Independence

The proposed framework does not assume conditional independence among sensing modalities.

On the contrary, strong correlations are expected between multiple observation channels.

For example, reduced sleep duration may co-occur with increased nocturnal heart rate, decreased heart rate variability, altered language patterns and reduced daily mobility.

Consequently, multimodal inference should explicitly model cross-modal dependencies rather than treating each sensor independently.

3.8 Observation Reliability

Every sensing modality is associated with a different level of uncertainty.

Let

$$R_i$$

denote the reliability of observation channel i.

Reliability depends upon sensor precision, signal quality, sampling frequency and contextual validity.

Rather than assigning fixed confidence values, future implementations may estimate reliability dynamically, allowing the influence of each modality to vary according to data quality.

3.9 Information Fusion

The complete multimodal observation is represented by

$$y_t = \Phi(y_t^{phys}, y_t^{beh}, y_t^{lang}, y_t^{env}, y_t^{clin}),$$

where

$$\Phi(\cdot)$$

denotes a multimodal fusion operator.

The specific implementation of Φ is intentionally left open and may include probabilistic graphical models, cross-attention transformers, graph neural networks or other Bayesian fusion techniques.

This abstraction separates the theoretical formulation from any particular machine learning architecture.

3.10 Interpretation

Within the proposed framework, psychiatric monitoring is no longer interpreted as detecting isolated symptoms.

Instead, it becomes the continuous reconstruction of a hidden dynamical state from heterogeneous observations acquired across multiple sensing modalities.

This formulation naturally accommodates uncertainty, missing observations, asynchronous sampling and future sensor technologies without requiring modification of the underlying mathematical framework.

4 The Inverse Problem of Psychiatry

The formulation presented in previous sections naturally recasts psychiatric monitoring as an inverse problem.

In most areas of medicine, the internal physiological state can be directly or indirectly measured through laboratory tests, medical imaging or electrophysiological recordings.

In psychiatry, however, the underlying neurobiological state remains largely inaccessible during routine clinical practice.

Instead, clinicians observe a collection of indirect, heterogeneous and noisy manifestations generated by the hidden psychiatric state.

Consequently, psychiatric assessment may be formulated as an inverse estimation problem in which the objective is to reconstruct the latent state from multimodal observations.

4.1 Forward Model

Assume the patient's latent psychiatric state evolves according to

$$x_{t+1} = f(x_t, u_t) + w_t$$

The observable variables are generated through

$$y_t = h(x_t) + v_t.$$

The pair

$$(f, h)$$

defines the forward physiological model.

If these functions were completely known, prediction would be straightforward.

Unfortunately, neither function is directly observable.

4.2 Inverse Estimation

The computational objective therefore becomes estimating

$$\hat{x}_t = \arg\max P(x_t | y_{1:t}).$$

Rather than estimating disease labels, the framework estimates the most probable latent physiological configuration consistent with all available observations.

Diagnosis, risk estimation and clinical interpretation are then derived from the estimated latent state rather than directly from the observations themselves.

4.3 Ill-Posedness

Inverse problems are frequently ill posed.

Different latent states may generate similar observable behaviour, while incomplete observations introduce additional ambiguity.

Consequently,

multiple psychiatric states may explain identical behavioural patterns.

This uncertainty motivates Bayesian inference, where the solution is represented by a posterior probability distribution instead of a single deterministic estimate.

4.4 Regularization Through Prior Knowledge

Clinical information provides essential constraints for solving the inverse problem.

Prior information includes

- previous diagnoses,
- medication,
- age,
- family history,
- previous episodes,
- baseline physiological profile.

These priors reduce uncertainty and improve estimation of the latent state.

4.5 Sequential Bayesian Updating

As new observations become available, the posterior distribution is recursively updated.

Prediction step

$$P(x_t|y_{1:t-1})$$

Correction step

$$P(x_t|y_{1:t})$$

This recursive estimation naturally supports continuous monitoring without requiring episodic reassessment.

4.6 Clinical Interpretation

Within the proposed framework,

psychiatric diagnosis is no longer viewed as a static classification problem.

Instead,

it becomes a continuous probabilistic estimation problem in which confidence evolves as additional physiological, behavioural and linguistic information becomes available.

This interpretation naturally accommodates uncertainty, missing observations and changing patient conditions.

4.7 Research Implications

Formulating psychiatry as an inverse problem produces several important consequences.

First,

it separates physiological modelling from machine learning implementation.

Second,

it allows different estimation algorithms to be compared within the same mathematical framework.

Third,

it naturally integrates future sensing technologies without modifying the underlying theoretical formulation.

Finally,

it establishes a direct connection between computational psychiatry, Bayesian estimation, information theory and systems engineering.

5 Latent Psychiatric State Trajectories

The formulation developed in the previous sections implies that psychiatric disorders should not be interpreted as static diagnostic categories but as continuous trajectories evolving within a latent physiological state space.

Traditional psychiatric assessment observes isolated points in time. By contrast, continuous multimodal sensing enables the reconstruction of an individual's temporal trajectory through the hidden state space.

Consequently, the primary objective is no longer diagnosis but trajectory estimation.

5.1 Latent State Space

Let

$$\mathcal{X} \subset R^n$$

denote the latent psychiatric state space.

Each point represents one possible neurophysiological configuration of the individual.

The patient's evolution is described by the continuous trajectory

$$\Gamma = \{x(t) : t \in [0, T]\}\,.$$

Different psychiatric conditions correspond not to isolated locations but to characteristic families of trajectories.

5.2 Healthy Homeostatic Region

Rather than assuming a single healthy point, we define a homeostatic manifold

$$\Omega \subset \mathcal{X}$$

containing the range of latent states compatible with the individual's normal physiological regulation.

Normal variability therefore satisfies

$$x(t) \in \Omega.$$

The geometry of

$$\Omega$$

is patient-specific and evolves throughout life.

5.3 Trajectory Drift

Psychiatric deterioration is represented as gradual departure from the homeostatic manifold.

The deviation is quantified by

$$D(t) = d\left(x(t), \Omega\right),$$

where

$$d(\cdot, \cdot)$$

denotes an appropriate distance metric.

Importantly,

the framework estimates deviations from the individual's own baseline rather than population averages.

5.4 Trajectory Velocity

The rate of physiological change is often more informative than the current state.

Therefore,

the first temporal derivative

$$v(t) = \frac{dx(t)}{dt}$$

describes the instantaneous velocity through the latent state space.

Rapid changes may indicate increasing instability despite relatively small deviations from baseline.

5.5 Trajectory Acceleration

Likewise,

the second derivative

$$a(t) = \frac{d^2x(t)}{dt^2}$$

captures acceleration of physiological change.

Persistent acceleration may indicate progressive destabilization before clinical symptoms become evident.

5.6 Trajectory Curvature

Complex psychiatric evolution rarely follows linear paths.

The curvature

$$\kappa(t)$$

of the latent trajectory provides additional information regarding abrupt changes in system dynamics.

Future work may investigate whether increased curvature precedes clinically significant transitions.

5.7 Trajectory Uncertainty

Because the latent state cannot be observed directly,

the estimated trajectory is represented by a probability distribution

$$P(\Gamma|Y).$$

The framework therefore estimates confidence regions rather than deterministic trajectories.

5.8 Clinical Interpretation

Within the proposed framework,

psychiatric assessment shifts from assigning categorical diagnoses toward estimating

- current latent state,
- trajectory direction,
- velocity,
- acceleration,
- uncertainty,
- distance from personalized homeostasis.

These quantities provide richer longitudinal information than isolated diagnostic labels and may better support preventive clinical decision-making.

5.9 Research Hypothesis

The framework generates the following testable hypothesis.

Hypothesis H6.

Patients approaching clinically significant psychiatric deterioration exhibit measurable changes in latent trajectory geometry before overt clinical manifestations become observable.

Prospective longitudinal studies are required to evaluate this hypothesis.

6 The Principle of Latent Psychiatric Continuity

The theoretical framework proposed in this paper is based upon the following fundamental principle.

Principle of Latent Psychiatric Continuity

The neurophysiological processes underlying psychiatric disorders evolve continuously through time, whereas clinical assessment observes only discrete and noisy manifestations of those processes.

Consequently, psychiatric diagnosis should be interpreted as a sampling process performed over a continuously evolving latent dynamical system.

The objective of computational psychiatry is therefore not to identify isolated pathological events, but to reconstruct the continuous evolution of the hidden state from incomplete multimodal observations.

This principle provides the conceptual foundation of the proposed framework.

7 Formal Scope of the Theory

The framework proposed in this paper is intended as a computational theory describing how latent psychiatric states may be estimated from continuous multimodal observations.

It does not propose a new psychiatric nosology, nor does it replace existing diagnostic criteria such as the DSM or ICD. Instead, it introduces a complementary computational layer that models the temporal evolution of psychiatric function.

Accordingly, the theory is based on the following assumptions.

1. Psychiatric function evolves continuously through time.
2. Only indirect observations of this process are available.
3. These observations are noisy, incomplete and heterogeneous.
4. Sequential probabilistic inference can estimate latent state trajectories from such observations.
5. Clinical interpretation remains the responsibility of qualified healthcare professionals.

Within this scope, the proposed framework should be understood as a computational model intended to support clinical reasoning rather than replace it.

References

[B+20] Bjorn Bjornsson et al. Digital twins to personalize medicine. *Genome Medicine*, 2020.

[CA+20] Jorge Corral-Acero et al. The digital twin to enable the vision of precision cardiology. *European Heart Journal*, 2020.

[F+17] Joseph C. Franklin et al. Risk factors for suicidal thoughts and behaviors. *Psychological Bulletin*, 2017.

[GBBV16] Iria Grande, Michael Berk, Boris Birmaher, and Eduard Vieta. Bipolar disorder. *The Lancet*, 2016.

[GJ07] Frederick K. Goodwin and Kay Redfield Jamison. *Manic-Depressive Illness*. Oxford University Press, 2007.

[H+19] Kit Huckvale et al. Assessment of the data sharing and privacy practices of smartphone apps for depression and smoking cessation. *JAMA Network Open*, 2019.

[HMF16] Quentin J. M. Huys, Tiago V. Maia, and Michael J. Frank. Computational psychiatry as a bridge from neuroscience to clinical applications. *Nature Neuroscience*, 2016.

[Ins17] Thomas R. Insel. Digital phenotyping: Technology for a new science of behavior. *JAMA*, 2017.

[K+18] Hyun Kim et al. Heart rate variability and psychiatric disorders. *Psychiatry Investigation*, 2018.

[Kal60] Rudolf E. Kalman. *A New Approach to Linear Filtering and Prediction Problems*. 1960.

[LL17] Scott M. Lundberg and Su-In Lee. A unified approach to interpreting model predictions. *NeurIPS*, 2017.

[M+23] Michael Moor et al. Foundation models for generalist medical artificial intelligence. *Nature*, 2023.

[May79] Peter S. Maybeck. *Stochastic Models, Estimation and Control*. Academic Press, 1979.

[MDFD12] P. Read Montague, Raymond J. Dolan, Karl J. Friston, and Peter Dayan. Computational psychiatry. *Trends in Cognitive Sciences*, 2012.

[OR16] Jukka-Pekka Onnela and Sarah L. Rauch. Harnessing smartphone-based digital phenotyping to enhance behavioral and mental health. *Neuropsychopharmacology*, 2016.

[Rud19] Cynthia Rudin. Stop explaining black box machine learning models for high stakes decisions. *Nature Machine Intelligence*, 2019.

[S+12] Marten Scheffer et al. Anticipating critical transitions. *Science*, 2012.

[S+18] Erik Smets et al. Large-scale wearable data reveal digital phenotypes for mental health. *EPJ Data Science*, 2018.

[S+23] Karan Singhal et al. Large language models encode clinical knowledge. *Nature*, 2023.

[Sch09] Marten Scheffer. *Critical Transitions in Nature and Society*. Princeton University Press, 2009.

[SG17] Fred Shaffer and J. P. Ginsberg. An overview of heart rate variability metrics and norms. *Frontiers in Public Health*, 2017.

[Sha48] Claude E. Shannon. A mathematical theory of communication. *Bell System Technical Journal*, 1948.

[TKLO16] John Torous, Michael V. Kiang, Jack Lorme, and Jukka-Pekka Onnela. New tools for new research in psychiatry: A scalable and customizable platform to empower data driven smartphone research. *JMIR Mental Health*, 2016.

[TWBC21] John Torous, Hannah Wisniewski, Benjamin Bird, and Elizabeth Carpenter. Creating a digital health smartphone app and digital phenotyping platform. *NPJ Digital Medicine*, 2021.

[V+18] Eduard Vieta et al. Bipolar disorders. *Nature Reviews Disease Primers*, 2018.

[W+24] Xiao Wang et al. Computational psychiatry: Current progress and future directions. *Nature Reviews Psychology*, 2024.

[Wor22] World Health Organization. *World Mental Health Report*. WHO, 2022.