Digital Biomarkers and Computational Inference in Smart Neuropsychiatric Healthcare

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Abstract

Digital technologies are increasingly integrated into smart healthcare systems, enabling new forms of data-driven assessment and clinical decision support in neuropsychiatric practice. Digital biomarkers derived from behavioral, cognitive, and physiological signals collected through mobile devices, wearable sensors, and digital platforms provide continuous and ecologically valid indicators of symptom dynamics. At the same time, computational inference methods, including statistical modeling and machine learning, support the integration and interpretation of these heterogeneous data sources within clinical workflows. This paper examines how digital biomarkers and computational inference can be integrated into smart neuropsychiatric healthcare systems to enhance assessment, monitoring, and clinical decision-making. Rather than viewing artificial intelligence as an autonomous diagnostic tool, the analysis conceptualizes it as a set of computational mechanisms that transform raw digital signals into structured clinical insights. A three-component framework is proposed, consisting of biomarker extraction, inferential modeling, and clinical decision support integration. Biomarker extraction identifies clinically relevant digital features from real-world data streams. Inferential modeling synthesizes multimodal biomarkers to characterize symptom profiles and predict risk trajectories. Clinical decision support systems embed these inferences within healthcare workflows to assist clinicians in triage, monitoring, and personalized care planning. By situating digital biomarkers and computational inference within the broader context of smart healthcare infrastructures, this framework clarifies how artificial intelligence contributes to scalable, data-driven, and patient-centered neuropsychiatric assessment. The study highlights practical implications for integrating digital phenotyping into electronic health records, telemedicine platforms, and remote monitoring systems, thereby advancing the development of intelligent and adaptive mental healthcare environments.

Keywords

Digital biomarkers, Computational inference, Smart healthcare, Neuropsychiatric assessment, Clinical decision support

Introduction

Artificial intelligence has become increasingly integrated into neuropsychiatric research and clinical practice through applications in monitoring, prediction, and decision support [1]. As digital technologies are incorporated into mental healthcare, new forms of data emerge through continuous or task-evoked interactions with digital environments, sensors, and computational tasks. These data provide behavioral, cognitive, and physiological indicators that refine the characterization of symptoms and clinical trajectories beyond episodic encounters or patient self-report. Digital phenotyping and digital biomarkers thus enable fine-grained, context-sensitive assessment that complements traditional neuropsychiatric evaluation grounded in interviews, rating scales, and observational judgment [2]. The incorporation of computational methods into assessment expands the evidentiary basis of clinical reasoning and introduces inferential processes that operate at multiple temporal and representational levels.

Digital biomarkers differ from conventional clinical measures in that they are derived from passively or actively collected digital traces, sensor signals, interaction patterns, or cognitive performance metrics captured through digital devices [3]. These biomarkers provide behavioral and physiological correlates of neuropsychiatric symptoms and can be integrated with computational models to support clinical inference [4]. Computational psychiatry extends these capabilities by modeling relationships among symptoms, mechanisms, and outcomes using statistical and machine learning techniques [5]. Together, digital biomarkers and computational inference introduce new representational and analytic forms into neuropsychiatric assessment and enable scalable approaches to individualized mental healthcare.

The growing use of artificial intelligence in neuropsychiatry raises broader questions regarding how assessment is organized and how evidence is constructed and interpreted. Artificial intelligence does not merely automate existing clinical procedures. It participates in constructing intermediate representations that mediate between raw data, symptom profiles, and clinical decisions. These representations influence how symptoms are conceptualized, how disease trajectories are evaluated, and how alternative diagnostic or treatment options are compared. Artificial intelligence therefore contributes to the epistemic processes through which neuropsychiatric knowledge is produced and validated, foregrounding its role in shaping how neuropsychiatric phenomena become computationally legible.

Current scholarship has documented the development of digital biomarkers, the emergence of computational psychiatry, and the growing role of clinical decision support in mental healthcare [6,7]. However, these literatures have largely examined digital biomarkers, computational models, and clinical decision support as separate lines of inquiry. Each domain emphasizes distinct data modalities, computational techniques, and clinical aims. Less attention has been given to how artificial intelligence links these components within a unified assessment process or how these linkages reorganize the evidentiary and inferential architecture of neuropsychiatric evaluation. As a result, the mechanisms through which artificial intelligence contributes to neuropsychiatric assessment remain conceptually fragmented.

This paper addresses this gap by examining how digital biomarkers and computational inference support neuropsychiatric assessment. The analysis proposes a computational framework centered on three mechanisms: biomarker extraction, inferential modeling, and clinical decision support. Rather than treating artificial intelligence as a diagnostic instrument, the framework emphasizes its role in restructuring the evidentiary and inferential processes that underlie assessment. This approach contributes to interdisciplinary research on computational psychiatry, digital medicine, and precision mental healthcare by clarifying how artificial intelligence participates in emerging modes of neuropsychiatric knowledge production.

In the context of smart healthcare, the integration of digital biomarkers and computational inference is not limited to research settings but increasingly intersects with clinical infrastructures such as electronic health records, telemedicine platforms, and remote patient monitoring systems. Neuropsychiatric care often involves longitudinal symptom tracking, risk stratification, and coordination across multidisciplinary teams. Embedding computational assessment mechanisms within these infrastructures enables more continuous and data-driven clinical evaluation. Therefore, understanding how digital biomarkers and inferential models operate within healthcare systems is essential for advancing practical and scalable neuropsychiatric services.

Literature review

Digital innovations have generated new pathways for observing and modeling neuropsychiatric conditions. Three strands of scholarship are particularly relevant to understanding how artificial intelligence participates in neuropsychiatric assessment: digital biomarkers and digital phenotyping, computational psychiatry and inferential modeling, and clinical decision support for mental healthcare.

Digital biomarkers and digital phenotyping

Digital biomarkers refer to behavioral, cognitive, and physiological signals derived from digital devices and sensing technologies [8]. These biomarkers provide continuous and fine-grained measurements that complement traditional clinical instruments such as structured interviews and rating scales. Unlike conventional neuropsychiatric tests that rely on discrete points of time and clinician-administered protocols, digital biomarkers generate longitudinal traces that capture variability, context, and dynamics of symptom expression. Digital phenotyping extends this approach by characterizing individual-level patterns across time through data sources such as speech, motor activity, gaze behavior, cognitive tasks, or smartphone interaction [9]. These techniques have been applied to conditions including mood disorders, psychosis, neurodegenerative diseases, and anxiety-spectrum disorders. Digital biomarkers therefore contribute new representational forms to neuropsychiatric inquiry by linking observable signals to symptom clusters, functional impairment, and trajectories of change. They provide data-driven avenues for examining micro-level changes in cognition and affecting as well as macro-level changes in functioning and disease progression.

Two features distinguish digital biomarkers from conventional measures. First, they enable ecological and temporally dense assessment, capturing fluctuations that may not be observable during clinical encounters. This ecological validity allows digital biomarkers to track patterns of behavior and cognition as they unfold within everyday environments rather than within structured testing conditions. Second, they produce computationally tractable signals that can be integrated with machine learning models. Digital biomarkers convert behavior and physiology into numerical and statistical representations that support automated analysis, multimodal fusion, and longitudinal modeling. These properties facilitate the generation of quantitative indicators that support stratification, monitoring, and inference. While the literature demonstrates substantial progress in developing digital biomarkers, current work has focused primarily on data collection, feature extraction, and mapping to symptom measures rather than on how these biomarkers integrate into broader assessment processes. As a result, the role of digital biomarkers in restructuring evidentiary pathways and inferential reasoning within neuropsychiatric assessment remains underexplored.

Computational psychiatry and inferential modeling

Computational psychiatry examines how computational models can represent relationships among symptoms, mechanisms, and outcomes [10]. These models incorporate statistical and machine learning techniques to identify latent structure, generate predictions, and infer mechanistic relationships [11]. Computational psychiatry contributes to neuropsychiatric assessment by formalizing hypotheses regarding symptom expression, disorder heterogeneity, and trajectory patterns. Machine learning models support inference by identifying associations that exceed the resolution of human perception and by generating candidate hypotheses that inform clinical reasoning [12]. In doing so, computational psychiatry shifts attention from categorical diagnostic frameworks toward continuous, multi-dimensional, and dynamic representations of neuropsychiatric conditions.

The literature on computational inference highlights the importance of intermediate representations. Models translate raw data into probabilistic or structural representations that serve as inputs for clinical judgment. These representations can encode risk, severity, similarity, or expected outcomes, thereby expanding the evidentiary basis on which assessment is performed [13]. Inferential models may estimate latent symptom dimensions, stratify patient subgroups, or predict trajectories under different clinical scenarios. In each case, the model constructs an intermediate layer that mediates between observational data and conceptual constructions used in neuropsychiatry. This layer functions as an epistemic bridge, rendering behavioral and physiological variation computationally tractable and clinically interpretable.

While computational psychiatry has generated insights regarding modeling strategies and mechanistic inference, less attention has been given to how inferential outputs interface with clinical workflow and decision-making. Most modeling efforts emphasize algorithmic performance, interpretability, or mechanistic plausibility, whereas the integration of outputs into assessment practices remains comparatively under-theorized. As a result, the role of computational inference within assessment pipelines remains conceptually under-specified. Clarifying how inferential modeling interacts with clinical judgment, diagnostic deliberation, and resource allocation is therefore critical to understanding how artificial intelligence participates in neuropsychiatric assessment.

Clinical decision support and neuropsychiatric assessment

Clinical decision support systems assist clinicians in evaluating alternatives, weight risks, and selecting courses of action [14]. In neuropsychiatry, decision support encompasses activities such as triage, monitoring, treatment selection, resource allocation, and prognosis estimation. These activities require clinicians to operate under uncertainty, integrate heterogeneous forms of evidence, and anticipate possible clinical trajectories.

Artificial intelligence contributes to these functions by structuring alternatives and generating recommendations based on biomarkers, historical patterns, or predictive modeling [15]. Decision support systems reorganize how information is presented and how clinical reasoning unfolds, particularly in contexts involving complexity or heterogeneity of presentation [16]. Rather than replacing clinical judgment, such systems restructure the informational environment within which judgment is exercised.

The literature on clinical decision support has examined interpretability, workflow integration, clinician acceptance, and translational challenges [17]. These studies highlight how interface design, transparency, and organizational factors influence whether decision support systems are adopted and how their outputs shape clinical practice. However, decision support studies often treat biomarkers and inferential models as upstream components rather than as integral elements of assessment. This separation obscures how artificial intelligence participates in constructing evidence and shaping reasoning before decisions are rendered. When biomarkers and inferential models are conceptualized solely as inputs to decision support, their role in mediating symptom representation, risk stratification, and evidentiary justification becomes less visible.

Advancements in clinical decision support demonstrate the translational potential of artificial intelligence, but they do not fully capture how assessment processes evolve when computational inference and digital biomarkers are incorporated. Existing approaches frequently center on recommendation delivery, policy optimization, or task-specific outcomes. In contrast, the epistemic functions of artificial intelligence, such as organizing evidence, rendering phenomena computationally legible, and generating intermediate hypotheses, remain comparatively under-theorized. Understanding decision support as part of a broader assessment pipeline foregrounds how artificial intelligence participates in structuring the conditions under which clinical reasoning occurs.

Existing scholarship on digital biomarkers, computational psychiatry, and clinical decision support has established foundational insights into how artificial intelligence interacts with neuropsychiatric knowledge and practice. Yet these strands largely examine data, models, and decisions as discrete components rather than as an integrated assessment process. The present study addresses this gap by proposing a computational framework that links biomarker extraction, inferential modeling, and clinical decision support within neuropsychiatric assessment. This framework provides a basis for analyzing how artificial intelligence participates in emerging modes of neuropsychiatric knowledge production.

Computational framework

Artificial intelligence contributes to neuropsychiatric assessment through mechanisms that reconfigure how evidence is generated, represented, and interpreted. Based on developments in digital biomarkers, computational psychiatry, and clinical decision support, three components can be identified as foundational to the computational integration of artificial intelligence into assessment: biomarker extraction, inferential modeling, and clinical decision support. These components structure the pathway through which raw signals become interpretable indicators and subsequently inform clinical reasoning.

Biomarker extraction

Biomarker extraction involves identifying behavioral, cognitive, or physiological features from digital signals that correlate with neuropsychiatric symptoms or trajectories. Digital biomarkers may be derived from passive sensing, task-based measurement, or device-mediated observation, allowing for continuous and ecologically valid assessment. Extraction processes translate raw signals into quantitative representations that serve as inputs for subsequent inferential operations. These representations can capture temporal patterns, variability, and domain-specific correlates that are not accessible through conventional assessments.

Biomarker extraction contributes to neuropsychiatric assessment by generating structured indicators that augment clinical observation and patient self-report. It converts heterogeneous forms of behavior and physiology into computationally tractable formats, enabling the organization of information across time and context. The extraction process therefore serves as the entry point through which digital signals become integrated into formal assessment practices and provides the representational substrates necessary for computational inference.

Inferential modeling

Inferential modeling links biomarker representations to symptom profiles, mechanisms, or outcomes through computational inference. Machine learning and statistical models identify associations, stratify heterogeneity, and generate probabilistic predictions that support reasoning under uncertainty [18]. Inferential modeling introduces intermediate representations such as risk estimates, cluster structures, similarity metrics, or trajectory predictions. These representations provide clinicians with information that can complement subjective judgment and domain expertise.

The inferential component reframes artificial intelligence as a participant in epistemic processes that govern how evidence is interpreted. Models translate extracted features into clinically meaningful constructs and thereby articulate hypotheses regarding symptom dynamics, disease progression, or treatment response. This function highlights the importance of model outputs not as fixed predictions but as interpretive resources that contribute to assessment by expanding the set of possibilities a clinician may consider.

Clinical decision support

Clinical decision support integrates inferential outputs into clinical workflow by structuring how alternatives are evaluated and how decisions are rendered. Decision support systems organize diagnostic queries, triage determinations, or management strategies by presenting computationally derived information in forms that align with clinical reasoning. These systems operate as translational interfaces between computational inference and clinical applications. The decision support component clarifies the role of artificial intelligence not as an autonomous decision-maker but as a system that mediates information and supports judgment. Through this function, artificial intelligence contributes to assessment by conditioning how clinical decisions are informed by computational evidence.

Clinical decision support therefore completes the progression from digital signal to computational inference to clinical deliberation. It distributes computational guidance within clinical contexts and assists clinicians in navigating uncertainty, weighing options, and coordinating care.

Taking together, biomarker extraction, inferential modeling, and clinical decision support constitute an integrated pathway through which artificial intelligence structures neuropsychiatric assessment. This computational framework highlights the interdependence of representational, inferential, and translational components and clarifies how artificial intelligence contributes to emerging modes of neuropsychiatric knowledge production. The framework emphasizes that data, models, and decisions should not be viewed as isolated stages. Instead, they form a continuous assessment process in which digital signals are transformed into evidence, evidence is organized into inference, and inference is translated into clinical judgment.

Mechanisms of computational assessment

Computational methods contribute to neuropsychiatric assessment through mechanisms that reorganize how evidence is represented, interpreted, and applied. These mechanisms can be understood across four dimensions: representational mechanisms, inferential mechanisms, translational mechanisms, and organizational mechanisms. Each dimension clarifies how artificial intelligence participates in the production and use of knowledge within assessment contexts. Together, they illuminate how computational systems shape the evidentiary and epistemic conditions under which neuropsychiatric reasoning occurs.

Representative mechanisms

Representational mechanisms involve translating behavioral, cognitive, or physiological signals into structured representations that support analysis and interpretation. Digital biomarkers exemplify this representational function by converting sensor-based data streams into quantitative indicators associated with neuropsychiatric symptoms or functional outcomes [19]. These representations provide finer temporal resolution and ecological validity compared to conventional assessments that rely on episodic clinical encounters or retrospective self-report.

Representational mechanisms expand the evidentiary basis on which assessment is performed. Digital biomarkers can encode variability, fluctuations, and contextual dependencies that are difficult to observe through traditional methods. They can also capture behavioral micro-patterns that correlate with symptom trajectories, disease progression, or functional impairment [20]. Through these representational operations, computational systems make neuropsychiatric phenomena available for inference in forms compatible with statistical and machine learning models.

Representation also plays an epistemic role. The way data is structured influences how symptoms are conceptualized and compared. For example, time-series representations emphasize dynamics across time, cluster-based representations emphasize population heterogeneity, and task-based measures emphasize cognitive profiles. These formats shape how clinicians interpret symptoms and how computational models extract relationships [21]. Representational mechanisms therefore serve as foundational components of computational assessment, enabling the translation of raw signals into clinically relevant forms and providing substrates for subsequent inferential modeling.

Inferential mechanisms

Inferential mechanisms link representational structures to hypotheses, symptom constructs, or predicted outcomes through computational modeling. Machine learning and statistical models support inference by estimating relationships among variables, identifying patterns, and generating probabilistic predictions that inform clinical reasoning under uncertainty. Inferential mechanisms operate by mapping digital biomarkers to symptom constructs, clinical subtypes, or expected trajectories, thereby expanding the analytical capacity of assessment.

Inferential outputs function as intermediate epistemic artifacts. These outputs may express risk, similarity, severity, or stratification and can be used to inform decisions regarding monitoring, triage, or treatment planning. The inferential component transforms artificial intelligence from an assistive instrument into a participant in reasoning processes that shape how evidence is evaluated. Computational psychiatry research emphasizes that inferential models enable structured hypothesis formation and the exploration of alternative explanatory scenarios [22]. These capacities extend assessment beyond descriptive categorization toward analytic processes that support interpretation, prediction, and scenario evaluation.

Inference also introduces methodological considerations. Decisions regarding model selection, feature representation, hyperparameter tuning, and uncertainty quantification influence how inferential outputs are interpreted in clinical contexts [23]. These considerations highlight that inferential mechanisms are not purely technical operations but epistemic decisions regarding how evidence should be encoded and understood. Despite these complexities, inferential mechanisms provide a means for integrating digital biomarkers into structured assessment processes and for supporting reasoning in neuropsychiatric contexts.

Translational mechanisms

Translational mechanisms connect computational inference to clinical application. These mechanisms operate by embedding computational outputs within workflows, interfaces, and decision pathways that structure clinical reasoning. Clinical decision support systems exemplify translational functions by presenting computational information in formats that align with clinical objectives and temporal constraints. Translational mechanisms clarify how inferential outputs are interpreted and how they contribute to decisions regarding monitoring, referral, or further evaluation.

Translational mechanisms emphasize alignment rather than substitution. Artificial intelligence does not replace clinical judgment. It conditions how judgment is exercised by structuring the informational environment in which decisions occur. Through translational mechanisms, computational inference contributes to assessment by guiding how options are evaluated, how evidence is prioritized, and how uncertainty is managed. These mechanisms highlight the importance of workflow integration, interpretive compatibility, and interface design for the effective incorporation of artificial intelligence into neuropsychiatric contexts.

Translational mechanisms therefore illustrate how computational outputs move from representational and inferential domains into clinical reasoning. They also clarify the epistemic implications of integrating artificial intelligence into assessment, since translational practices shape not only what decisions are made but how clinical deliberation itself unfolds.

Organizational mechanisms

Organizational mechanisms coordinate cognitive, informational, and collaborative activities within neuropsychiatric assessment. Artificial intelligence participates in organizational mechanisms by structuring how information is prioritized, how tasks are allocated, and how resources are managed across clinical environments [24]. These mechanisms operate broadly and systematically at institutional and workflow levels, influencing assessment pipelines and interdisciplinary collaboration [25].

Organizational mechanisms reveal that artificial intelligence functions not only as a computational tool but also as a system that structures clinical and epistemic environments. By coordinating information flows and structuring collaboration, artificial intelligence supports the operational dimensions of assessment and reinforces its role in emerging models of neuropsychiatric practice. Organizational mechanisms therefore contribute to the integration of digital biomarkers and computational inference into clinical settings and clarify how artificial intelligence supports assessment at the system level [26]. They illustrate the importance of considering artificial intelligence in relation to clinical organization, profession-specific roles, and institutional priorities rather than solely as a technical artifact or analytical instrument.

Discussion

The computational integration of artificial intelligence into neuropsychiatric assessment has conceptual, clinical, and translational implications. The framework developed in this study clarifies how digital biomarkers and computational inference contribute to emerging evidentiary forms that support assessment. These developments highlight the need to reconsider how evidence is produced, represented, and interpreted within neuropsychiatric contexts. Computational assessment operates not only as a technical innovation but also as a shift in the epistemic and organizational foundations of neuropsychiatric practice.

First, the analysis indicates that computational assessment expands the representational space of neuropsychiatry. Digital biomarkers provide granular and ecologically valid indicators that capture symptom fluctuations and behavioral dynamics that may elude episodic clinical encounters. By translating continuous behavioral and physiological signals into structured representations, digital biomarkers supplement subjective symptom descriptions and shift assessment toward measurement-based models. This shift aligns with broader movements toward precision mental healthcare but also raises questions regarding the interpretive alignment between computational representations and clinical reasoning. Representational expansion prompts further examination of how measurement-based approaches interface with diagnostic categories, symptom constructs, and multimodal evidence. It also prompts examination of how clinicians evaluate the relevance of digitally derived indicators in relation to traditional clinical judgments.

Second, computational inference introduces new forms of analytic and epistemic mediation. Inferential outputs such as risk estimates, similarity structures, or trajectory predictions support reasoning under uncertainty and contribute to hypothesis formation [27]. These inferential mechanisms differ from conventional assessment approaches in that they formalize relationships among symptoms, biomarkers, and outcomes. Inferential models enable structured exploration of heterogeneity, variability, and alternative scenarios, supporting analytic engagement with the complexity of neuropsychiatric conditions. The integration of inferential outputs into assessment suggests that artificial intelligence participates in knowledge production rather than merely automating tasks. This perspective situates computational psychiatry as a bridge between data-driven representation and clinical interpretation and underscores the importance of understanding models as epistemic artifacts that both inform and shape interpretation.

Third, translational mechanisms emphasize that the value of computational assessment depends on alignment with clinical workflow and decision-making practices. Clinical decision support systems have demonstrated potential to facilitate triage, monitoring, and evaluation in contexts characterized by complexity and heterogeneity. However, translational challenges remain. These challenges include interpretability, trust, workflow integration, and compatibility with existing normative and institutional structures. Translational success requires consideration of how clinicians engage computational outputs, how uncertainty is managed, and how artificial intelligence complements rather than substitutes clinical judgment. Attention must also be given to temporal and contextual factors that govern clinical decision-making, since translational alignment is contingent on clinical priorities, resource constraints, and professional norms.

Fourth, the organizational dimension underscores that artificial intelligence functions not only at the level of analysis but also at the level of coordination. Organizational mechanisms shape how information flows within clinical environments, how tasks are distributed across actors, and how interdisciplinary collaboration unfolds. These mechanisms highlight the infrastructural character of computational assessment and suggest that its impact extends beyond algorithmic performance to the organization of clinical and epistemic environments. Understanding computational assessment as a system-level development foregrounds the importance of institutional arrangements, workflow design, and interprofessional roles in determining how artificial intelligence is integrated into practice.

Finally, computational assessment introduces methodological considerations regarding evidence standards, validation strategies, and normative frameworks. Digital biomarkers and computational models challenge traditional boundaries between observational, mechanistic, and inferential evidence in neuropsychiatry [28]. The question is not whether artificial intelligence can replicate existing assessment practices but how it reshapes the conditions under which assessment is conducted. Future research must therefore examine how computational assessment interacts with diagnostic nosologies, symptom constructs, and emerging models of disease heterogeneity [29]. These methodological considerations suggest that computational assessment may require revised evidentiary frameworks capable of integrating data-driven signals, mechanistic hypotheses, and clinical interpretation within a unified assessment process.

Conclusion

Artificial intelligence introduces computational methods into neuropsychiatric assessment by generating digital biomarkers, supporting inferential modeling, and structuring clinical decision processes. The analysis presented in this paper conceptualizes these contributions as components of a computational assessment pathway in which representation, inference, translation, and coordination function as interdependent mechanisms. This perspective clarifies how artificial intelligence participates in neuropsychiatric knowledge production and reshapes the evidentiary and interpretive conditions of assessment. The framework highlights that computational assessment is not limited to algorithmic prediction or task automation but involves transformations in how symptoms, trajectories, and outcomes are rendered clinically legible.

The framework developed here contributes to ongoing research in computational psychiatry, digital medicine, and precision mental healthcare. By examining the roles of digital biomarkers and computational inference, the analysis highlights the epistemic and translational dimensions of computational assessment. These dimensions include the production of structured representations, the articulation of inferential hypotheses, and the alignment of computational outputs with clinical reasoning. Rather than treating artificial intelligence as an autonomous diagnostic instrument, the framework emphasizes its role in generating intermediate representations that support clinical reasoning and decision-making. This focus underscores the importance of alignment between computational outputs and clinical practice and suggests that the value of artificial intelligence depends on compatibility with existing norms, workflows, and interpretive strategies in neuropsychiatry.

Future research may extend this framework in several directions. Empirical studies could examine how computational assessment performs in real-world clinical settings and how clinicians interpret inferential outputs during decision processes. Translational research may explore workflow integration, user interaction, and interoperability with existing clinical systems. Conceptual work may investigate how computational assessment interacts with diagnostic nosologies, symptom constructs, and emerging models of disease heterogeneity. These avenues would clarify how computational approaches contribute to precision neuropsychiatry and how artificial intelligence integrates into the evolving landscape of mental healthcare. In addition, attention to methodological and institutional considerations would support the development of validation frameworks, implementation strategies, and organizational infrastructures. These would enable computational assessments to operate reliably and interpretably within diverse clinical environments.

Taking together, the analysis presented in this study demonstrates that computational assessment operates at multiple levels of neuropsychiatric practice. It also demonstrates that artificial intelligence contributes to assessment not solely through prediction but through the restructuring of evidence, interpretation, and decision-making. Understanding these contributions is essential for conceptualizing the role of artificial intelligence in future models of neuropsychiatric care and for guiding the responsible development of computational methods within clinical contexts.

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Conflict of Interest

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References

[1] Torous, J., Onnela, J. P., Keshavan, M. (2017) New dimensions and new tools to realize the potential of RDoC: digital phenotyping via smartphones and connected devices. *Translational Psychiatry*, 7(3), e1053-e1053.

[2] Torous, J., Ledley, K. T., Gorban, C., Strudwick, G., Schwarz, J., Choudhary, S., Kochhar, S. (2025) Accelerating digital mental health: the society of digital psychiatry's three-pronged road map for education, digital navigators, and AI. *JMIR Mental Health*, 12(1), e84501.

[3] Oudin, A., Maatoug, R., Bourla, A., Ferreri, F., Bonnot, O., Millet, B., Adrien, V. (2023) Digital phenotyping: data-driven psychiatry to redefine mental health. *Journal of Medical Internet Research*, 25, e44502.

[4] McGinnis, E. W., Cherian, J., McGinnis, R. S. (2024) The state of digital biomarkers in mental health. *Digital Biomarkers*, 8(1), 210-217.

[5] Davidson, B. I. (2022) The crossroads of digital phenotyping. *General Hospital Psychiatry*, 74, 126-132.

[6] Parziale, A., Mascalzoni, D. (2022) Digital biomarkers in psychiatric research: data protection qualifications in a complex ecosystem. *Frontiers in Psychiatry*, 13, 873392.

[7] Friston, K. (2023) Computational psychiatry: from synapses to sentience. *Molecular Psychiatry*, 28(1), 256-268.

[8] Castro Martínez, J. C., Santamaría-García, H. (2023) Understanding mental health through computers: an introduction to computational psychiatry. *Frontiers in Psychiatry*, 14, 1092471.

[9] Hitchcock, P. F., Fried, E. I., Frank, M. J. (2022) Computational psychiatry needs time and context. *Annual Review of Psychology*, 73, 243-270.

[10] Spadaro, B., Martin-Key, N. A., Bahn, S. (2021) Building the digital mental health ecosystem: opportunities and challenges for mobile health innovators. *Journal of Medical Internet Research*, 23(10), e27507.

[11] Lee, K., Lee, T. C., Yefimova, M., Kumar, S., Puga, F., Azuero, A., Dionne-Odom, J. N. (2023) Using digital phenotyping to understand health-related outcomes: a scoping review. *International Journal of Medical Informatics*, 174, 105061.

[12] Zarate, D., Stavropoulos, V., Ball, M., de Sena Collier, G., Jacobson, N. C. (2022) Exploring the digital footprint of depression: a PRISMA systematic literature review of the empirical evidence. *BMC Psychiatry*, 22(1), 421.

[13] Marsch, L. A. (2021) Digital health data-driven approaches to understand human behavior. *Neuropsychopharmacology*, 46(1), 191-196.

[14] Singh, O. P. (2023) Artificial intelligence in the era of ChatGPT - opportunities and challenges in mental health care. *Indian Journal of Psychiatry*, 65(3), 297-298.

[15] Wu, H., Li, M. D. (2025) Digital psychiatry: concepts, framework, and implications. *Frontiers in Psychiatry*, 16, 1572444.

[16] Alsalloum, G., Dalibalta, S., Hadijat, Y. (2025) Harnessing digital health interventions to address the heterogeneity of depression: a systematic review. *Frontiers in Digital Health*, 7, 1654745.

[17] Singhal, S., Cooke, D. L., Villareal, R. I., Stoddard, J. J., Lin, C. T., Dempsey, A. G. (2024) Machine learning for mental health: applications, challenges, and the clinician's role. *Current Psychiatry Reports*, 26(12), 694-702.

[18] Muñoz, J. M., Borbón, D., Bezerra, A. M. (2024) Computational psychiatry and digital phenotyping: ethical and neurorights implications. *Developments in Neuroethics and Bioethics*, 7, 49-63.

[19] Alfalahi, H., Dias, S. B., Khandoker, A. H., Chaudhuri, K. R., Hadjileontiadis, L. J. (2023) A scoping review of neurodegenerative

manifestations in explainable digital phenotyping. *NPJ Parkinson's Disease*, 9(1), 49.

[20] Paquin, V., Ferrari, M., Sekhon, H., Rej, S. (2023) Time to think "meta": a critical viewpoint on the risks and benefits of virtual worlds for mental health. *JMIR Serious Games*, 11, e43388.

[21] D'Alfonso, S., Coghlan, S., Schmidt, S., Mangelsdorf, S. (2025) Ethical dimensions of digital phenotyping within the context of mental healthcare. *Journal of Technology in Behavioral Science*, 10(1), 132-147.

[22] Shaw, A. D., Sumner, R. L., Berndt, L. C. (2025) Predictive coding and neurocomputational psychiatry: a mechanistic framework for understanding mental disorders. *Frontiers in Psychiatry*, 16, 1713833.

[23] Tun, H. M., Rahman, H. A., Naing, L., Malik, O. A. (2025) Trust in artificial intelligence-based clinical decision support systems among health care workers: systematic review. *Journal of Medical Internet Research*, 27, e69678.

[24] Machleid, F., Michnevich, T., Huang, L., Schröder-Frerkes, L., Wiegmann, C., Muffel, T., Kaminski, J. (2024) Remote measurement based care (RMBC) interventions for mental health - Protocol of a systematic review and meta-analysis. *Plos one*, 19(2), e0297929.

[25] Borsboom, D. (2017) A network theory of mental disorders. *World Psychiatry*, 16(1), 5-13.

[26] Smith, R., Badcock, P., Friston, K. J. (2021) Recent advances in the application of predictive coding and active inference models within clinical neuroscience. *Psychiatry and Clinical Neurosciences*, 75(1), 3-13.

[27] Tse, G., Lee, Q., Chou, O. H. I., Chung, C. T., Lee, S., Chan, J. S. K., Zhou, J. (2024) Healthcare big data in Hong Kong: development and implementation of artificial intelligence-enhanced predictive models for risk stratification. *Current Problems in Cardiology*, 49(1), 102168.

[28] Onnela, J. P. (2021) Opportunities and challenges in the collection and analysis of digital phenotyping data. *Neuropsychopharmacology*, 46(1), 45-54.

[29] Bzdok, D., Meyer-Lindenberg, A. (2018) Machine learning for precision psychiatry: opportunities and challenges. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, 3(3), 223-230.