

Research Paper

Digital Psychometrics: An Emerging Paradigm for Psychological Assessment

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ABSTRACT

Advancements in digital technologies are revolutionising psychometric assessment, shifting it from traditional paper-and-pencil methods to advanced multimodal digital evaluations. This review attempts to explore the possibilities and methods of psychometric assessment by integrating data from personal digital devices, online social media activities, passive behavioural sensing, and neurotechnology. The rich source of multimodal information can be further integrated with artificial intelligence, machine learning, computer vision, the Internet of Things (IoT), and immersive techniques such as virtual reality to provide a holistic and context-specific profile of human behaviour and psychological functioning. Such an integrated multimodal data-driven approach provides ways for digital trait mining (DTM) by involving large-scale digital data related to human behaviour in cyberspace, digital devices, and wearable neuro-sensors. The digital footprints deciphered through DTM are capable of providing moment-by-moment quantified patterns of psychosocial behaviour, which can represent the human phenotype in situ within a context to map the digital phenotype of the individual. Digital phenotyping of human behaviour can offer more holistic, contextually sensitive and ecologically valid interpretation of personality and cognitive processes compared to conventional psychometric tools. DTM-based digital phenotyping has the potential for real-time psychological assessment. However, the methodological rigour required for DTM should provide a higher level of data validity, contextual reliability, and measurement invariability. The operational fairness of multimodal data-driven systems is also a critical issue that must be addressed in the context of data security, privacy invasion, and reproducible workflow in digital phenotyping. Another important aspect of DTM is the indispensable role of human expertise in interpreting and comprehending the outcomes. To ensure a higher level of professional ethics, fair use, and wider acceptance of advanced psychometric assessment approach, a balance should be maintained in combining technological innovation with human expertise, having multidisciplinary understandings.

Keywords: *Digital Psychometry, Digital Trait Mining, Digital Phenotyping, Artificial Intelligence, Machine Learning, And Bias Mitigation*

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Over the last three decades, there has been a paradigm shift in the field of psychometric assessment due to rapidly evolving digital and cyber technologies. The emergence of cyber technologies and advancements in digital computational capabilities are significantly transforming psychometric practices by leading them towards sophisticated digitised assessments from conventional paper-and-pencil-based methods. These technological advancements have paved the methodological foundations for an integrated multimodal psychometric assessment by integrating data from different sources. These data sources can be users' social media profiles, content, messages, and likes posted or shared on social media accounts, e-mails, other cyber activities, including web-surfing, blogs, e-shopping, health monitoring applications, wearable sensors, internet-of-things (IoT), and personal digital device usage such as mobile phones. The technology-driven transformation in psychometric assessment based on vast amounts of psychologically and behaviourally relevant data can offer a substantial improvement in the reliability and validity of the assessment system, which is far beyond the conventional approaches. Such multimodal psychometric assessment has shown considerable improvement in the field of teaching and learning (Gan et al., 2022; Hong et al., 2025; Qushem et al., 2021) clinical assessment and mental health examination (Huhn et al., 2022; Peng et al., 2025), consumer behaviour analysis and marketing strategies (Javaid et al., 2021), personnel management (Abdulmalek et al., 2022; Baranyi, 2025; Makovoz & Lysenko, 2024), personnel selection (Antoniadis et al., 2024), organisational effectiveness (Aithal, 2023; Madhavi & Vemaraju, 2026) and so forth. These technologies have the potential to automate the administration, scoring, and interpretation of test scores. However, such advancement requires careful consideration of issues such as developmental appropriateness, cultural considerations, and psychometric validation to ensure the effectiveness and accuracy of the assessments (Neumann et al., 2019).

The purpose of this review is to delineate the upcoming trends in the psychological assessment paradigm and transition from conventional methods to a more sophisticated multimodal digital psychometric framework. This review also sheds light on the emerging trends in digital trait mining (DTM) methodologies by using cyber-behaviour data, social-media behavioural analytics, application of wearable sensors, neurotechnologies, internet-of-things (IoT). The review also emphasised the applicability of computational methodologies for synchronised data integration and synthesis using machine learning and artificial intelligence, multimodal data integration using immersive technologies and behaviourometric approaches such as eye-tracking. Despite several advantages of DTM-based psychometric practices, there are several concerns related to methodological rigour and validation aspects, addressing cultural differences in the assessment, integrity and data privacy of the individual, bias mitigation in the assessment, indispensable human expertise in the assessment and standards of ethical practices.

The successful implementation of digital psychometric methods depends on addressing usability issues, ensuring the robustness of validation approaches across diverse populations, and ensuring professional training for practitioners to effectively utilise these technologies.

Digital Personality and Psychometric

The ready availability of cyber technologies, such as mobile phones, social media platforms, messaging applications, and e-mail services, has created a digital cyber world in parallel to the real world. Increasing involvement of cyber technologies, social media engagements, internet use, and mobile application reliance in day-to-day activities has considerably changed the real as well as digital world social practices (Yuan et al., 2024). It would not be

hypothetical to consider the cyber-world as part of the holistic environment, having space for all types of human social interactions. Thus, the digital world has become part of a holistic environment that contributes to personality development (Ancis, 2020). Considering this view, there is a need to understand, integrate, and explain cyber social behaviour within the framework of personality theories. A holistic personality framework would provide a better explanation of the digital personality characteristics, psychometric foundations to assess, quantify and explain the cyber behaviour.

By considering the tripartite model of identity, Hammack (2008) mentioned that identity is shaped by an individual's interactions with cultural narratives, personal life stories, and social engagements. Considering Hammack's explanation of identity formation, which includes cognitive, cultural, and social dimensions, the digital world also offers the same modalities for individuals' interactions in cyberspace. By having active social interaction on social media platforms, people can create a space for social engagements, with typical cultural representations in the content and expression style.

Furthermore, contemporary personality theories state that personality is not static. Rather, it is a dynamic construct that is constantly evolving because of social engagements and interactions. Such social engagements also include cyber world interactions as well (McCrae, 2011). Therefore, it may be concluded that for explaining the identity of an individual, the digital dimension of identity should also be given emphasis in addition to the identity aspects associated with real-world interactions. In this context, there are studies reporting that behavioural manifestations in the cyber world are influenced by predominant personality traits and other psychological factors. Personality aspects can determine online interactions and perception of individuals regarding AI agents (such as AI-supported chatbots) and social robots (Staffa et al., 2024). Such inferences indicate the parallel existence of a digital persona.

Thus, based on the recent findings on identity development and personality dynamics in cyber or digital world interactions, there is an emerging need to develop a sound methodological approach for digital psychometrics. A multimodal assessment approach can be developed by combining the principles of psychometric, computational methods based on AI/ ML, computer vision, wearable sensor integration and immersive technologies.

Extracting Personality Traits and Behavioural Markers using Digital Trait Mining

Digital trait mining (DTM) refers to the process of extracting and analysing digital footprints, such as data generated by using social media, mobile applications and other digital devices, to identify and predict personality traits (Hinds & Joinson, 2024; Kosinski et al., 2013; Panfilova & Turdakov, 2024). Digital trait mining (DTM) combines various data sources and analytical techniques to provide broader insights into an individual's personality traits. Unlike conventional psychometric methods, which rely solely on self-reports on questionnaires and behavioural observation methods, digital psychometry uses multimodal data from various digital sources, including cyber behaviour, along with inputs from wearable sensors such as electroencephalography (EEG) (Elosua et al., 2023; Owens, 2020; Rafaeli et al., 2019; Torabi, 2025), heart rate variability (HRV) (Blanck et al., 2019; Owens, 2020; Torabi, 2025); eye-tracking devices (Fu et al., 2024; Guo et al., 2024; Vessoyan et al., 2018); computational approaches such as AI and ML (Wu et al., 2019); and natural language processing (NLP) (Kargarandehkordi et al., 2025).

Related to social media use, studies found that the personality of Facebook users could be inferred from text semantics (Farnadi et al., 2021; Hassanein et al., 2018; Kulkarni et al., 2018; Wang et al., 2020).

Similarly, the analysis of likes on Facebook was found to accurately predict personal attributes, such as sexual orientation, ethnicity, and political views, by using logistic and linear regression models (Kosinski et al., 2013).

Studies have also demonstrated that examining high-level user interests (such as following accounts of other users) on social media platforms can be used to infer psycho-demographic traits (Peters & Matz, 2024; Volkova et al., 2015; Yin et al., 2014).

DTM also encompasses the understanding of users' sentiments by analysing multiple media types such as photos, videos, and textual content (Chandrasekaran et al., 2022; Yadav et al., 2021).

DTM can provide patterns and trends in psychometric assessment that traditional methods might overlook, offering new insights into human behaviour (Rafaeli et al., 2019). It can offer proven advantages by providing insights into various aspects of psychological assessment, such as clinical assessment, by collecting and monitoring data on mood, behaviour, and social interactions through mobile applications (Sverdlov et al., 2021), educational measurement for providing real-time feedback and adapting to individual learning needs, contributing to personalised education programs (Elosua et al., 2023) and a gamified teaching-learning environment, selection and assessment interviews for providing the best fit for job roles based on digital tools (Cubillos & Rienzo, 2023), marketing and consumer behaviour by aiding in understanding and predicting consumer behaviour (Rafaeli et al., 2019).

Sources of Digital Trait Mining

Digital trait mining involves integrating data from multiple sources to enhance the precision and in-depth analysis of psychological attributes and personality traits. It combines sources such as cyber behaviour, social media activities, neurotechnology measures (eye tracking, electroencephalography/event-related potentials, functional magnetic resonance imaging, brain imaging, and transcranial magnetic stimulation), artificial intelligence, machine learning methods, gaming environments, and virtual or augmented reality. Integrating these varied modalities provides richer, more detailed insights into cognitive capabilities and personality attributes of an individual by drawing on both digital behaviour and neurophysiological signals.

Cyber world data and social media

Digital psychometry through digital trait mining involves assessing digital footprints on the cyber world and social media use, such as chats, emojis, posts, likes and text content, to evaluate personality traits. Such information, synthesised using cyber world data, can complement traditional methods efficiently (Grosz, 2026; Kralj Novak et al., 2015; Marengo & Montag, 2020; Montag et al., 2022). Recent studies are focusing on identifying the relationship between personality traits and related social media use. For example, higher extraversion and agreeableness have been found to be linked with a higher frequency of social media platform use. Whereas emotional stability and openness were found to be negatively correlated with social media use frequency in diverse populations (Gil De Zúñiga et al., 2017). A combination of data from different social media sources can provide a high

prediction rate for personality traits. Hybrid machine learning approaches can effectively utilise multi-contextual information from different social media platforms to attain higher precision (Farnadi et al., 2021; R, 2021). Social media use facilitates diverse civic participation and increases the heterogeneity of discussion networks on issues of common concern. The personality traits of extraversion and openness were found to moderate this effect. Thus, personality traits impact social media use dynamics and engagement levels (Dedeoğlu et al., 2019; Kim et al., 2013).

Neurotechnology

Assessments based on neurotechnologies are objective and precise and can mitigate subjective biases. Therefore, these measures are fake-resistant and less prone to impression management by the assessee during the assessment. Thus, the integration of neuroethologies can provide a data-integrity layer against fake and noisy responses in capturing behaviour and emotional states (Rainey & Erden, 2020). For example, brain imaging techniques, such as functional magnetic resonance imaging (fMRI) and electroencephalography (EEG), can provide insights into emotional states and cognitive processes, which in turn can be closely related to certain personality traits (Engemann et al., 2012). The integration of high spatial resolution data from fMRI with temporal neural data obtained by EEG can provide a comprehensive view of the physiological and psychological states of individuals (Luo et al., 2024; Maliske & Kanske, 2022). This integration allows researchers to understand brain networks involved in cognitive processes (Casey et al., 2002; Lei et al., 2010). For example, EEG signals collected in real time, in response to specific stimuli, can reveal the personality dimensions of extraversion and introversion by detecting the neural patterns associated with different traits (Bhardwaj et al., 2021).

Artificial Intelligence and Machine Learning Integration

Artificial Intelligence (AI) and Machine Learning (ML) can facilitate the synthesis of multimodal data obtained from various sources, such as cyber technology and social media use, neurotechnology and psychological assessment tools, into comprehensive personality and cognitive profiles. These computational models of AI and ML can use algorithms to correlate data from various sources with established personality metrics, thereby enhancing predictive accuracy (Tay et al., 2020). The integration of multimodal data using AI and ML is fundamental to developing a robust personality assessment system that effectively accounts for diverse input modalities (Bleidorn & Hopwood, 2018). By using algorithms to classify individuals into various personality types, AI can enhance the reliability and accuracy of assessments compared to traditional psychometric methods (Fountzilas et al., 2025). AI technologies can adapt assessment approaches and modalities in a tailored manner to match an individual's psychological characteristics (Lainjo, 2024). AI-enabled adaptive and interactive features can ensure increased user engagement in the assessment and improve measurement precision (Lainjo, 2024). Utilising an AI-based approach for DTM can also address cultural and ethnic differences and provide a more nuanced understanding of cultural variations.

Gaming and Immersive Technologies

Immersive gaming environments providing interactive context through augmented and virtual reality can be potentially used for studying behavioural traits under controlled and ecologically comparable conditions. Gaming platforms offer an efficient approach for simulating real-life conditions. These technologies can be used for revealing different aspects of personality dynamics under different social conditions, including decision-making, risk-taking, and social interactions (Mcbain et al., 2022). A dynamic and immersive

gaming environment improves cognitive and emotional engagement and creates a stronger sense of presence and enjoyment (Bender & Sung, 2021; Gupta et al., 2020; Pajić et al., 2025).

Additionally, VR integration with neuropsychological measures can play an indispensable role in several research areas, including therapeutic applications (Alvari et al., 2024; Colloca et al., 2020; Ishaque et al., 2020; Rah & Chen, 2025), educational planning (Oyelere et al., 2020; Udeozor et al., 2023), marketing research (Balasubramanian et al., 2022; Cowan & Ketron, 2019; Radianti et al., 2019), consumer behaviour (Shafer et al., 2018; Vlahovic et al., 2021), defense applications (Ahir et al., 2019; Shafer et al., 2018), organisational behaviour (Pierce & Aguinis, 1997), clinical interventions (Dellazizzo et al., 2020; Du et al., 2025; Zhou, 2024), and behavioural modifications (Klein Schaarsberg et al., 2022; Zhang et al., 2025).

Balancing the Need for Human Elements in the Technology-Enabled Psychological Assessment

Technology can offer efficient, fast, data-driven, and more accurate insights into human behaviour. However, human involvement remains crucial for interpreting finer behavioural cues, emotional expressions, contextualising individual experiences, and exercising professional judgment. Therefore, a balance between technology-enabled psychological assessment and the human element is crucial to ensure clear explanations, nuanced interpretations, empathy, cultural sensitivity, and adherence to professional ethics. Expert human integration with technology-driven psychometric assessment is needed for risk mitigation related to misdiagnosis, loss of rapport and trust, ethical concerns, privacy, and the informed consent of the individual. Human expertise is required for personalised feedback, cultural sensitivity, and adaptive responses that technology alone cannot replicate. Some of the key considerations for human-technology integration in digital psychometric assessment are as follows:

Multidisciplinary Approaches

The integrated use of different technologies for psychological assessment requires knowledge and technical understanding of various underlying disciplines, and hence, calls for a multidisciplinary and transdisciplinary approach for the testing paradigm development. Such an approach may include in-depth knowledge of various fields not just limited to psychology, but including neurology, psychiatry, sociology, linguistics, computer science, electronics and data communication, statistics and mathematical modelling, and culture and anthropology. Therefore, psychometricians must play a pivotal role, with professional oversight, in ensuring that sound expertise in measuring the psychological constructs and preserving the human aspect of psychological expertise and understanding (Elosua et al., 2023).

Patient-Centred Models

The integration of evidence-based medicine with psychological assessment offers a hybrid model that is more client-centred. By incorporating patient preferences into decision-making and using methods that explicitly integrate assessment data, such as Bayesian techniques, assessment becomes more personalised. This approach promotes collaboration between technology, psychometry and clinicians, ensuring that the human element in psychological care is not overshadowed by technological advancements (Youngstrom, 2012).

Human-Machine Interaction

The synergy between AI and human interaction in providing interventions, such as mental healthcare, should be strategically managed. AI can enhance patient care through innovative detection and treatment strategies while maintaining patient privacy and data security. The ethical use of AI in psychological interventions requires a dynamic balance between automation and human interaction to ensure personalised, high-quality care (Jeyaraman et al., 2023; Nashwan & Abujaber, 2023).

User-centred Design

In the development of AI applications for healthcare, educational evaluation, recruitment and placement, and forensic-psychological evaluations, etc., ensuring ecological validity and considering human aspects are critical. By focusing on user-centred design, usability, and acceptance of AI tools in clinical practice can be improved (Asan & Choudhury, 2021).

Technology and Well-being in Organisations

The use of AI in organisational settings should balance technological and human agencies, particularly when addressing mental well-being. This can involve redefining practices and using AI to assist rather than replace human interactions in fostering mental health. The synergy between technology and organisational practices highlights the role of human agents in maintaining meaningful connections and understanding in the workplace (Dutta & Mishra, 2023).

Reliability and Validity in Digital Trait Mining

Traditional assessment methods, such as paper-and-pencil tests, often lack context-dependent evaluation and are more susceptible to subjective bias. Whereas a multi-layered data integration approach in DTM offers the added advantages of various data collection modalities. However, the accuracy and validity of psychometric assessments, based on digital footprints, are indisputably a major concern. Despite initial research showing advantages over traditional methods of psychological assessment, more exhaustive validation studies are required to establish reliability and generalisability across different populations and contexts. Digital trait mapping, a closely related concept to the personality trait identification in the conventional psychometric approach, involves the systematic identification and analysis of personality traits using digital data. This process makes use of various digital sources to create a comprehensive map of an individual's personality characteristics and quantify personality traits. It also enables the system to capture real-time changes in behaviour and psychological states (Montag & Rumpf, 2021; Schmand, 2019), adding a step ahead for higher ecological validity.

Data from cyber-behaviour provides a more ecologically valid contextual source, whereas the neurotechnologies provide insights into the brain's functional and structural aspects, which are crucial for understanding the underlying neurological conditions and psychological health (Bigler, 2024). In contrast to neurotechnologies, psychometric tools offer structured and validated measures of psychological constructs. Modern psychometric techniques, such as item response theory (IRT) and computerised adaptive testing (CAT), enhance the precision and reliability of these assessments (Harrison et al., 2017). Psychometric assessments quantify different psychological constructs and individual differences and generally serve as a crucial aspect for psychological evaluation, planning intervention, and ensuring efficient mitigation of the psychological issues.

Biases and Their Mitigation in DTM-based Psychometry

The integration of DTM-based technology-driven assessments into psychometric assessments can introduce biases that may affect the accuracy and fairness of results. Identifying and mitigating these biases involves several strategies grounded in psychometric theory and related technological applications. First of all, it is important to evaluate the psychometric properties of digital assessments. This includes assessing the validity, reliability, and engagement, as well as the influence of device variability (e.g. differences in hardware and software) on the test results (Passell et al., 2019). Technological assessments must account for differences in devices, as they can affect measures such as reaction time, which could introduce inconsistencies (Passell et al., 2019, 2021).

Additionally, modern psychometric frameworks, such as IRT, can be used to detect whether assessment tools behave differently across groups through methods such as differential item functioning (DIF). This approach aids in identifying biases that could be specific to certain subgroups, such as those related to language or cultural background (Bilder & Reise, 2018). Furthermore, adaptive testing algorithms can increase the efficiency of assessments by minimising bias by tailoring the test to the individual's responses (Bilder & Reise, 2018).

Bias in machine learning (ML) models, often used in technology-driven psychological assessments, can be addressed by ensuring that data handling, model development, and performance evaluations are conducted with careful consideration of bias minimisation strategies (Sreerama & Krishnamoorthy, 2022).

To facilitate the transition from traditional methods to technology-driven psychological assessments, efforts should be made to maintain compatibility and comparability with existing validated measures while integrating new technological tools as a complementary mechanism to the traditional methods. This can be achieved by creating a global repository for item-level data, allowing modern psychometric analyses to refine current methods and developing new assessment strategies (Bilder & Reise, 2018).

Strategies to mitigate biases in multimodal systems include data balancing and adversarial learning, which can help in developing fairer model outputs (Yan et al., 2020). It is essential to consider these biases to ensure equitable assessment outcomes with specific emphasis on cultural variations, ethnicity, gender, geographical conditions, political orientations, religious differences, and beliefs. Some of the potential sources of bias in DTM-based psychological assessment are given below:

Cultural Variations and Ethnicity

Psychometric assessments often struggle to generalise across diverse cultural and ethnic groups because of inherent biases in the data and algorithms used. Often, these models are trained on datasets that predominantly reflect certain cultural norms, leading to systematic biases when applied to diverse populations (Liu, 2024; Principi et al., 2021). Addressing such challenges can include technical strategies of data augmentation and debiasing, ant colony optimisation for diversified representation in training datasets and adapting models to account for cultural sensitivity (Foka et al., 2025; Jankowsky et al., 2020).

Gender Bias

Gender bias in digital psychometric assessments occurs when the algorithms yield different outcomes solely based on variation across gender, but not due to any systematic variation attributable to the variable of interest. This form of bias manifests as differential functioning

of machine learning models. As a result, the predictions or score levels vary across the genders, even when the underlying traits are equivalent. It may also appear as differential predictive accuracy between genders due to biased data or algorithm training (Tay et al., 2022). Gender bias may result due to biased training of datasets, lack of sufficient gender variability, choice of algorithmic design, differential feature weighing or transformation in the algorithms, gender biased data sources, and gender stereotyping in data encoding.

Geographical Conditions

Digital psychometric assessments are vulnerable to biases due to environmental, cultural, and socioeconomic variations across different geographical regions and conditions. Tools developed and validated in specific geo-cultural conditions often fail to maintain their validity and reliability when applied in other geographical contexts. Possibly, this can happen because of insufficient underlying data and assumptions to reflect upon local realities. Variations in the geographical conditions can challenge the generalizability of digital psychometric tools across diverse populations (Jarva et al., 2023; McGaffin et al., 2026).

To mitigate geographical bias, the localisation of digital psychometric models is critical. This involves adapting algorithms to reflect region-specific characteristics, such as environmental context, language, cultural norms, and other geo-cultural conditions (McGaffin et al., 2026).

Political Orientations and Religious Differences

Political and religious biases emerge when digital psychometry tools inadvertently favour certain ideologies due to skewed data representations. The biased training data can embed disproportionate favour for certain political or religious perspectives into the model behaviour. These trained models with biased data would result in biased and inaccurate assessments (Liu, 2024).

Computer algorithms and source or training data sets must be scrutinised for possibilities of biases introduced through differential perspectives on cultural and religious orientation. Neutrality in the databases and AI model training should be ensured for fair assessment.

Biases Mitigation Strategies in DTM-based Psychometry

Several statistical and machine learning-based bias mitigation techniques exist, ranging from preprocessing, in-processing, and post-processing approaches. Each of these approaches is tailored to address specific sources and manifestations of bias (Wan et al., 2023; Xu et al., 2022).

Preprocessing methods focus on the data before model training. This includes balancing datasets by augmenting underrepresented groups, removing or correcting biased samples, and reweighting data points to reduce representation disparities. These interventions aim to create a fairer training dataset so that downstream models learn less biased associations (Leavy et al., 2020; Siddique et al., 2023).

In-processing techniques intervene during model training to directly incorporate fairness considerations into the learning process. This involves modifying loss functions to penalise biased outcomes, adversarial training to correct unfair correlations, or refining the latent feature matrix to be invariant towards sensitive attributes, such as gender or ethnicity (Wan et al., 2023; Xu et al., 2022).

Post-processing methods adjust model outputs after training to rectify biases in predictions. These techniques include threshold adjustments, calibration, and re-ranking of predicted outcomes to ensure comparability (parity) across sensitive groups. These methods are particularly useful when retraining models is impractical or when fairness requires continuous correction through a feedback loop from model deployment (Caton & Haas, 2024; Pagano et al., 2023).

Effectively mitigating bias requires context-specific customisation. This customisation is required due to variations in the cultural norms, availability of the domain-specific database, differential societal fairness standards and differences in societal views on various demographic strata. Employing appropriate bias correction mechanisms in DTM-based psychometrics, such as equalised odds or demographic parity, can improve the assessment fairness (Pagano et al., 2023; Siddique et al., 2023).

CONCLUSION

Technology-driven DTM-based psychometric assessment represents a transformative advancement in psychometric practices. This transformation enables more precise, comprehensive, and dynamic evaluations of personality traits and cognitive functions. By combining multimodal data sources, including cyber behaviour, social media activity, neurotechnologies, AI/ ML, and immersive gaming environments, digital psychometry transcends the limitations of traditional psychometric methods. This fusion facilitates continuous, real-time psychological interpretation in naturalistic settings, enhances the ecological validity of the assessment, and bridges conventional practices such as self-reports with objective biological and behavioural measures. DTM-based approaches bridge the gap in traditional psychometric practices. Instead of replacing the conventional approach, it offers a promising avenue for technological comparability and compatibility in a broader context, with complementarity of the advanced psychometric approaches in a more holistic context.

However, the successful integration of various technologies in DTM requires careful attention to psychometric validation, usability, and cultural sensitivity. Addressing biases inherent in data and algorithms, particularly those related to gender, culture, geography, and political or religious orientations, is critical to ensuring fairness and accuracy across diverse populations. Moreover, human expertise plays an indispensable role in interpreting complex data, contextualising assessments, and maintaining ethical standards. Overall, the convergence of digital phenotyping, neuroimaging, AI-driven analytics, and traditional psychometric methods into DTM-based psychometry and digital trait mining holds significant potential for revolutionising psychological assessments. This integrated framework has the potential to offer more individualised, unbiased, and valid insights into human behaviour, personality dynamics and cognitive processes.

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Conflict of Interest

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