OPEN ACCESS Freely available online

ISSN: 2378-5756
Journal of Psychiatry

Mini Review

Towards a Deeper Understanding of Respondents to Personality and Clinical Self-Reports through Artificial Intelligence

Marcantonio Gagliardi[1*], Gian Luca Marcialis[2]

[1]Department of Clinical Psychology and Computer Science, University of Greenwich, London, United Kingdom; [2]Department of Electronic and Computer Science Engineering, University of Cagliari, Cagliari, Italy

ABSTRACT

While personality and clinical psychology have started using Artificial Intelligence (AI) to enhance their advancement, classical factor analysis methods remain the standard for self-report development. In our work, relying on the Attachment-Caregiving Questionnaire (ACQ), we suggest a different approach to self-report data analysis that might significantly benefit personality assessment, impacting clinical practice. We can understand respondents more deeply and outline their personality more precisely if we rely on a flexible interpretation of their answers based on contextual information about their history and present life. Despite expert scorers being able to perform this task, AI can be decisive in standardizing and automatizing the procedure, reaching both human accuracy and statistical consistency. Different implementation approaches can be adopted, and we plan to start testing as soon as enough completed ACQs are available. Big data could then be used to optimize item interpretation and improve performance.

Keywords: Personality assessment; Clinical psychology; Psychiatry; Artificial intelligence; Questionnaire; Attachment

INTRODUCTION

The essential role played by personality in the development and maintenance of mental disorders justifies the profound interest of clinical psychologists and psychiatrists in its measurement [1,2]. With this respect, like with every scientific discipline, the performance of clinical psychological and psychiatric methods is linked to the technologies available. In particular, integrating new digital tools in productive ways is becoming increasingly relevant, given the unprecedented developmental rate we are witnessing especially with Artificial Intelligence (AI). Among the AI-based techniques, Machine Learning (ML) is the most widely adopted. Studies have already shown that AI can help us gain new insights into the definition of mental disorders, thereby supporting diagnosis, prevention, and treatment [3,4]. With specific reference to personality, AI-informed chatbots have been employed to infer traits during textual conversations [5]. However, current AI-based methodologies primarily focus on the possibility of accessing large datasets and the ML capacity to analyze them and find new patterns, paying less attention to theoretical development and the potential integration with classical methods such as self-reports in the case of personality assessment. While the data-driven approach can be productive, we believe a more theory-informed and integrated methodology could be even more efficient.

LITERATURE REVIEW

Our study on the self-report assessment of personality used the Attachment-Caregiving Questionnaire (ACQ)-a seven-scale clinical tool that measures the attachment dimensions/traits of disorganization, avoidance, ambivalence, phobicity, depressivity, somaticity, and obsessively to investigate the impact of interpreting items on profiling [6]. Clinician's experts in attachment theory and personality scored the ACQs of four psychotherapy patients before starting treatment, and their profiles were tested against the information gathered in therapy over the following 18 months [7].

Correspondence to: Marcantonio Gagliardi, Department of Clinical Psychology and Computer Science, University of Greenwich, London, United Kingdom, E-mail: m.gagliardi@greenwich.ac.uk

Received: 08-Apr-2024, Manuscript No. JOP-24-25433; **Editor assigned:** 11-Apr-2024 , PreQC No. JOP-24-25433 (PQ); **Reviewed:**25-Apr-2024, QC No JOP-24-25433; Revised: 02-May-2024, Manuscript No. JOP-24-25433 (R); **Published:** 09-May-2024. DOI: 10.35248/2378-5756.24.27.684

Citation: Gagliardi M, Marcialis GL (2024) Towards a Deeper Understanding of Respondents to Personality and Clinical Self-Reports through Artificial Intelligence. J Psychiatry. 27:684.

The results demonstrated that different respondents could refer to qualitatively different experiences relevant to their profiles when answering a given item. In other words, a question could receive the same high score say an eight, on a 0-to-10 scale for clinically different reasons. Considering attachment-related traits, an item concerning, for example, the sense of guilt such as "Not respecting my rules would be unacceptable to me" could be assigned to the obsessive or somatic scale. In the former case, the respondent would convey the concern of causing harm by failing to respect their rules. In the latter, they would express the worry of not adhering to some expected social standard. The two attributions correspond to the clinically relevant activation of two different motivational systems caregiving in the obsessive case and affiliation in the somatic one and can be connected to the differentiation between deontological and altruistic guilt [8,9].

The attachment case clarifies that differential interpretation can not only impact personality assessment-e.g., attributing an item to the obsessive or somatic scale but also clinical evaluation and treatment since each trait can be related to specific psychological vulnerabilities, e.g.-obsessive-compulsive or social anxiety symptoms. Therefore, our study provided the first evidence that allowing the generation of alternative interpretations from a self-report can significantly affect personality assessment and clinical operation.

The innovative methodology for self-report analysis we propose produces flexible scales–where items can be moved from their default-scale to another according to how they are interpreted by the scorer in the context of the whole questionnaire. While this flexibility overcomes the limitations of classical Factor Analysis (FA), which produces rigid scales, it introduces two requirements to allow for item interpretation: (1) including contextual information in the self-report; and (2) being able to extract meaningful patterns. The first condition requires a theory informed design-i.e., building a framework of items coherent with a specific reference theory. On the other hand, the second condition requires having scorers with expert knowledge of the theory and the ability to identify the numerous possible patterns of answers respondents can produce.

The ACQ meets the first condition by design. It is informed by attachment theory and includes extra-scale information about the respondent's present and past, providing the substrate for interpreting unidentified items. However, scorers need to be experts in attachment theory to meet the second condition and produce a profile by extracting data correctly. It is worth noting that in principle-the same rationale can be applied to any other personality inventory. Even if a self-report was originally not underpinned by any theoretical framework like those inspired by the Five Factor Model (FFM), it could be extended by including coherent additional information that is functional to redirect items to different scales [10]. In this case, an item such as "I see myself as someone who... does a thorough job"-from the FFM-informed Big Five Inventory (BFI), could be interpreted as a sign of agreeableness rather than conscientiousness, for example [11].

Despite the evident advantage, flexibility comes at a cost. Training a scorer to interpret a self-report (as well as the interpretation process itself) is time-consuming. However as our work suggests technology can now help us overcome this issue. The same questionnaire structure that allows human scorers to identify meaningful patterns of answers and produce corresponding profiles can also allow AI/ML models to learn those patterns from a sufficient number of scored questionnaires. As we further suggest, decision trees and neural networks could, for example, be used to perform this task. Moreover, ML-based models can be specifically designed to integrate a 'whole' vision of the ACQ answers and the one given by specific subsets of answers for any of the personality dimensions explored, according to the multi-head and multi-branch design approaches adopted in other contexts, such as digital manipulation detection (deepfakes) and physics-informed problems [12-15].

As a result, the innovative methodology implemented by the ACQ allows us to conjugate the flexibility of human interpretation driven by expert knowledge with the standardization and reliability of a machine trained over a large number of cases.

DISCUSSION AND CONCLUSION

Technology and AI in particular is about to radically change how we approach personality assessment in clinical psychology and psychiatry. Data-driven techniques based on the analysis of large datasets can lead us to discover hidden information and formulate more accurate profiles, improving diagnosis and treatment and even the definition of mental conditions. Nonetheless, we believe a more theory-informed approach to the application of AI would allow us to integrate it into consolidated tools such as self-reports providing even more advantages. This is the case of personality inventories used by clinical psychologists and psychiatrists to profile patients and support their professional duties.

Relying on attachment theory and the ACQ, our study demonstrated that different respondents can connect clinically different experiences to the same item, and grasping what they mean by their answers can significantly affect profiling and clinical practice. As a consequence, item interpretation becomes essential, and even though it can be performed by expert scorers the natural evolution of the process is developing AI/ML models instead. By learning from a sufficiently large dataset of scored questionnaires, a trained artificial profiler can ensure the same flexibility as a human but, at the same time, provide the standardized and reliable results expected by a machine.

While the study suggests AI to be more suitable than classical FA to develop personality inventories, this hypothesis still needs to be tested by implementing adequate ML models. Such implementations will be our next task, for which we have already collected a dataset of over 700 completed ACQs. We will start testing the suggested decision trees and standard neural networks to expand progressively toward more complex solutions. This approach must be carefully driven by the relationships among the whole set of questions and the individual (or subset of) questions to allow the system to correlate the answers with the most likely attachment dimension. We hypothesize that models such as decision trees and neural networks, coupled with multi-head or multi-branch design paradigms, could play a relevant role in the coming generation of computer-aided profile and diagnosis support systems.

Finally, we can envision the following step where the contextual data necessary to interpret the questionnaire items will be external to the self-report and retrieved by interrogating the internet–social media, for example, instead of being included in the questionnaire. This solution may involve using Large Language Models (LLMs) and the ability to prompt them adequately, merging a data-driven approach with a theory-informed retrieval.

ACKNOWLEDGMENT

This study was not funded and not preregistered. The authors want to thank the Institute for Lifecourse Development (ILD), University of Greenwich, London, UK, for the collaboration in producing this work.

CONFLICT OF INTEREST

The authors declare that they have no financial or non-financial conflicts of interest related to the subject matter or materials discussed in this manuscript.

REFERENCES

1. Beck AT, Davis DD, Freeman A. Cognitive therapy of personality disorders. Guilford Publications. 2015.
2. Wright AG, Hopwood CJ. Integrating and distinguishing personality and psychopathology. J Pers. 2022;90(1):5-19.
3. Luccioni AS, Rogers A. Mind your Language (Model): Fact-Checking LLMs and their Role in NLP Research and Practice. arXiv preprint arXiv:2308.07120. 2023.
4. Bzdok D, Meyer-Lindenberg A. Machine learning for precision psychiatry: Opportunities and challenges. Biol Psychiatry Cogn Neurosci Neuroimaging. 2018;3(3):223-230.
5. Fan J, Sun T, Liu J, Zhao T, Zhang B, Chen Z, et al. How well can an AI chatbot infer personality? Examining psychometric properties of machine-inferred personality scores. J Appl Psychol. 2023;108(8): 1277.
6. Gagliardi M. The role of developmental caregiving programming in modulating our affiliation tendency and the vulnerability to social anxiety and eating disorders. Front Psychol. 2024;14:1259415.
7. Gagliardi M. How our caregivers shape who we are: The seven dimensions of attachment at the core of personality. Front Psychol. 2021;12:657628.
8. Gagliardi M, Bonadeni M, Billai S, Marcialis GL. A novel approach to personalized personality assessment with the Attachment-Caregiving Questionnaire (ACQ): First evidence in favor of ai-oriented inventory designs. arXiv preprint arXiv:2403.08823. 2024.
9. Mancini F, Gangemi A. Deontological guilt and obsessive compulsive disorder. J. Behav Ther Exp Psychiatry. 2015;49:157-63.
10. McCrae RR, Costa PT. Personality in adulthood: A five-factor theory perspective. Guilford Press. 2003.
11. John OP, Srivastava S. The Big-Five trait taxonomy: History, measurement, and theoretical perspectives. Guilford Press. 1999;102-138.
12. Concas S, Perelli G, Marcialis GL, Puglisi G. Tensor-based deepfake detection in scaled and compressed images. IEEE International Conference on Image Processing (ICIP) 2022.
13. Wang H, Li L, Cui Y, Wang N, Shen F, Wei T. MBSNN: A multi-branch scalable neural network for resource-constrained IoT devices. Journal of Systems Architecture. 2023;142:102931.
14. Zhang H, Shao J, Salakhutdinov R. Deep neural networks with multi-branch architectures are intrinsically less non-convex. In the 22nd International Conference on Artificial Intelligence and Statistics. 2019.
15. Zou Z, Karniadakis GE. L-HYDRA: Multi-head physics-informed neural networks. arXiv preprint arXiv:2301.02152. 2023.