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A Novel Approach to Personalized Personality Assessment with the Attachment-Caregiving Questionnaire: First Evidence in Favor of Interpretation-Oriented Inventory Designs

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Abstract: In clinical psychology and psychiatry, personality is usually assessed using questionnaires developed through factor analysis (FA). Essential domains are identified, which correspond to questions/items defining a (sub)scale, and each question is rigidly assigned to one scale, giving the item the same meaning regardless of how the respondent may interpret it. However, this rigidity might hinder the instrument's assessment capability. We tested this hypothesis using the Attachment-Caregiving Questionnaire (ACQ), a clinical and personality self-report that—through extra-scale information—allows the clinician to infer the possible different meanings that the subjects attribute to the items. Considering four psychotherapy patients, we compared the scoring of their ACQs provided by expert clinicians to the detailed information gained from therapy and the patients. Our results indicated that questions could be interpreted differently—receiving the same score for different (clinically relevant) reasons—potentially impacting personality assessment and clinical decision-making. Moreover, accounting for multiple interpretations requires a specific questionnaire design. Overall, our analysis suggests that a meaning-sensitive, personalized read of a personality self-report may improve profiling and treatment, implying the necessity of more advanced pattern recognition than the one produced by FA or similarly rigid methods, which artificial intelligence may provide. More evidence is required to support these preliminary findings.

Keywords: personality assessment; clinical psychology; psychiatry; artificial intelligence; questionnaire; attachment

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1. Introduction

Clinical psychology and psychiatry recognize the central role personal variables play in the development and maintenance of psychological vulnerabilities and mental disorders [1–3]. Despite being often used without specifications, the term 'personality' refers to a complex concept underpinned by multiple features. Most abstractly, personality can be defined as the unique and (relatively) stable set of an individual's psychological characteristics—in terms of cognition, emotion, and behavior—usually described as traits [2,4–7]. These features are believed to be the product of innate biological factors and acquired knowledge, which confer personality uniqueness and stability.

Coherently, an individual is expected to manifest a recognizable personality (i.e., discernable cognitive, emotional, and behavioral expressions) across various contexts and situations. Nonetheless, subjects with similar traits may express them in different circumstances. Taking two *conscientious* individuals, for example, one could be very careful with their expenditure and neglect to tidy their home. The other, in contrast, may have the highest standards in keeping their living space in order, but pay much less attention to money.

This simple example illustrates how relevant the meaning that the subjects attribute to what they do can be. Therefore, to assess personality correctly, we should reasonably ensure that our instrument is capable of capturing meaning, rather than generic behaviors. Despite this potential issue, the standard validation procedures to develop a questionnaire—typically based on factor analysis (FA) or principal component analysis (PCA) [8–11]—aim to identify a few essential, relatively independent domains corresponding to questions/items that identify a (sub)scale (a questionnaire itself can be considered a scale, possibly consisting of multiple subscales. Here, we refer to the subscales as scales). By doing so, they imply the attribution of a unique, fixed meaning to each item, corresponding to their rigid assignment to one and only one scale (if an item belongs to scale X, it cannot alternatively belong to scale Y). In other words, an item having the same rating ('I strongly agree' on a Likert scale, for instance) from different respondents is given the same interpretation, regardless of what the respondents meant.

1.1. Study Objective and Hypothesis

With this work, we aimed to explore whether allowing the items of a personality inventory to be assigned alternative interpretations could affect the instrument's assessment capability. We hypothesized that different respondents could understand the same item differently, producing a relevant impact on scoring. Consequently, allowing the scorer to interpret items (i.e., to infer what respondents meant by their answers) can significantly impact the assessment and related decision-making. Therefore, an instrument should be designed to capture meaning, rather than binding items to a predefined interpretation. Since the usual questionnaire development procedures imply this rigidity, we should rely on more complex designs and methodologies to provide a more flexible interpretation of data and personalized assessment. We investigated this issue through four case studies and by considering attachment—the evolutionarily preordained mechanism underpinning our innate motivation to seek care from a conspecific. Attachment informs essential aspects of our personality [6,12–20], which we assessed here using the novel Attachment-Caregiving Questionnaire (ACQ) [9,21] (described in detail below).

We tested our hypothesis by adopting an interpretation approach based on cross-referencing questionnaire data without aiming to present a specific interpretation strategy or guidelines on its implementation, which depends on the considered questionnaire and its theoretical foundation. Nonetheless, since our hypothesis implies an innovative methodology based on the scorer's interpretation of items, below, we provide a statistical background that will help elucidate the novelty of our proposal.

1.2. Statistical Background

Although for simplicity we refer to FA as a representative method informing questionnaire validation, we want to stress that validating a self-report cannot be reduced to FA [22], especially within the framework of item response theory (IRT), which evolved from classical test theory (CTT) [23,24]. When developing a questionnaire, CTT focuses on the entire instrument and assumes that each item contributes equally to the measure, with a score that is the sum of the 'true score' and a random error. On the other hand, IRT focuses on single items and assumes that they can contribute differently to the measure through item parameters such as difficulty, discrimination, and guessing, potentially resulting in better measurements compared to CTT [25,26]. In particular, IRT facilitates the analysis of the items' differential functioning. However, the procedures commonly used for questionnaire development produce 'rigid' groups of items (i.e., not left for interpretation by the scorer). An example concerning attachment assessment is given by the CTT-informed Experiences in Close Relationships (ECR) [27] and its IRT revision, the ECR-R [28]. These two widely used self-reports [29] both consist of two rigid subscales. Coherently with the incompatibility of usual procedures with item interpretation, we suggest artificial intelligence (AI) as a viable solution for validating our questionnaire. Next, we review two classes of statistical methods that touch on assessment rigidity and personalization:

differential item functioning (DIF) and latent class/profile analyses (LCA/LPA) (a latent variable or trait is a variable not directly observed).

1.2.1. Differential Item Functioning Analysis

Given a questionnaire targeted to a population of interest, its objective is to measure some latent traits through its items. DIF indicates the possibility that the population subgroups identified by a difference in a specific characteristic (e.g., age, sex, ethnicity, education, or cultural background), despite having the same level of the latent trait to be measured (e.g., a cognitive ability, a well-being indicator, or a personality trait), differ in the probability of giving the same answer to an item [30,31]. In other terms, DIF presents itself when two subgroups have different conditional probabilities—conditioned to their identifying characteristic—of giving a certain response to an item. Psychometrically, detecting DIF is relevant since such differential functioning can compromise the instrument's validity.

Usually, when comparing two groups for potential DIF, one is labeled as the reference group, and the other as the focus group. Typical cases are when one of the two is larger or potentially advantaged and is considered the reference, while the smaller or potentially disadvantaged is considered the focus. When present, the divergence between the two groups can either be constant (uniform DIF) or vary across the latent trait levels (non-uniform DIF) [30,31].

DIF analysis is particularly relevant in education to detect potential biases in ability scores—and in health care—to detect differences in patient-reported symptoms or outcomes [31–35]. Indeed, the issue that the same test may present a different degree of difficulty first arose when testing the students' performance. A typical example of potential bias/DIF in education may be an item formulated in English (e.g., "*Solve the equation '$1 - x = 2$' for the variable x*") given to a group of native speakers versus a group of non-native speakers. The item may be more difficult to address for non-native speakers. On the other hand, an example in health care may concern the differential way between males and females of reporting their depressive symptoms (e.g., answering the item "*How often do you feel sad?*", which may be more easily rated as high by females than males).

Various methods to analyze DIF are available. The early ones were developed in the context of CTT and considered two groups having different probabilities of giving a correct answer, looking at the proportions of successful respondents in the groups as an indicator of the item difficulty [36]. These proportions were used to build contingency tables and further processed for the DIF analysis, for example, through a chi-square [37] or the Mantel–Haenszel procedure [38]. When the item answer does not have the dichotomous, correct-incorrect form but a polytomous one—as with Likert scales, for example—then a generalized Mantel–Haenszel procedure can be applied [39]. The subsequent development of IRT allowed for direct implementations of DIF analysis using the item parameters or item characteristic curves (ICC), which showed the probability of answering correctly for different latent trait values (e.g., measuring a cognitive ability in groups characterized by age) [40,41]. Several methods have been developed, first addressing dichotomous items and then generalized to polytomous ones, that also consider non-uniform DIF. In particular, the SIBTEST [42,43], which relies on defining an additional latent trait contributing to the DIF, the ordinal logistic regression [44,45], which directly applies logistic regression, and the MIMIC (multiple indicators multiple causes) model, which combines confirmatory factor analysis (CFA) with structural equation modeling (SEM) [46].

Finally, when DIF is detected, different actions are taken depending on the case. Typically, with educational questionnaires, DIF represents a bias, and the item is either revised or removed. With health care self-reports, DIF may be expected (e.g., in males vs. females), and the item may help assess the latent trait, leading to keeping the item and treating it differently depending on the group (i.e., scoring it differently), or keeping it but excluding it from scoring.

1.2.2. Latent Class/Profile Analysis

Given a questionnaire addressing a target population, LCA and LPA can be used to identify unobserved subgroups within the population, named 'latent classes' in LCA and 'latent profiles' in LPA [47–50]. Subgroups are built by relying on indicators from the instrument such as item or subscale scores. The primary difference between the two methods is that LCA works on categorical indicators (e.g., yes or no answers), while LPA works on continuous indicators (e.g., 0-to-N scale scores). Specific response patterns in terms of such indicators determine classes/profiles. Respondents are given a probability of belonging to each of them based on their answers and are assigned to the highest probable class/profile.

LCA and LPA are person-centered approaches since they focus on individuals who give similar patterns of responses to the observed variables and cluster them into latent groups based on their shared features (clusters are construct-based) [51,52]. On the other hand, variable-centered approaches (such as factor analysis) focus on relationships between the observed variables. It is worth noting that while LCA and LPA cluster individuals into profiles characterized by latent, unobserved variables, classical clustering methods rely on observed variables, and are therefore non-latent (e.g., k-means and hierarchical methods).

These latent methods are widely used in social, behavioral, and health disciplines. For example, LCA can allow us to identify different types of behavior (e.g., exercising, dieting, drinking, smoking) in a population of interest [53,54]. Similarly, LPA can enable the identification of personality profiles based on continuous trait measures such as the Big Five [7,55–57]. Indeed, "*LPA is recommended to be used for exploring personality and individual differences as a person-centered approach*" ([47], p. 2580). Given the suitability of LPA for personality profiling, we focused on it below.

LPA is an exploratory approach for data analysis based on the SEM framework. Generally, building an LPA model involves the following six stages [47,48]. (1) Selecting the indicators from the questionnaire (e.g., item or subscale scores). (2) Specifying the models to fit, i.e., the number of profiles (N_p) to investigate (according to hypotheses informed by theory and previous studies). (3) Estimating the models, i.e., fitting to the data the models with an increasing number of profiles (usually, until $N_p + 1$). (4) Evaluating the models, selecting the model with the optimal number of profiles according to different criteria. (5) Interpreting the identified latent profiles and labeling them accordingly. (6) Adding covariates to test whether an external variable (e.g., a demographic feature) can predict the membership of an individual to a profile or if an outcome variable differs significantly among profiles. Following these steps, He et al. (2018) [58] applied LPA using the Inventory of Parent and Peer Attachment (IPPA) [59] to identify subgroups of adolescents characterized by specific attachments to parents and peers. Using six indicators, corresponding to the six IPPA subscales scores (three for each of the two attachments), they found four attachment profiles given by combinations between secure/insecure attachment to parent (SePa/InPa) and to peer (SePe/InPe): (P1) InPa-InPe, (P2) SePa-InPe, (P3) InPa-SePe, and (P4) SePa-SePe. The covariate 'gender' was also found to be predictive, with females having a higher probability of being in P3 and P4 than in P1 or P2.

Since the interpretation of the model results strongly depends on the number of selected latent profiles, evaluating the models is a critical step of the analysis. Coherently, the evaluation is usually based on multiple criteria. (1) Model fit/enumeration indices (e.g., AIC (Akaike information criteria), BIC (Bayesian information criteria), and SABIC (sample size-adjusted BIC). (2) Model parsimony (i.e., the least number of profiles possible). In this regard, profiles corresponding to a small proportion of the sample (e.g., less than 5%) are usually excluded [60]. (3) Theory and studies. (4) Functional interpretation (i.e., the model should have practical use) [61].

2. Methods and Materials

This study relied on four clinical cases concerning patients who completed the ACQ before starting therapy. They received treatment from one of the first three authors and gave informed consent to use the questionnaire data and therapy material for research purposes. The ACQ received ethics approval first from the University of Sheffield (Ref. 032300), and then from the University of Greenwich (Ref. 21.5.7.14). A copy of the instrument is included in the Supplementary Materials.

Below, we present a summary of the cases (cf. 2.1), a detailed description of the ACQ (cf. 2.2), and the procedure we followed for the case analysis (cf. 2.3).

2.1. Participants

The participants in this study were four patients who asked for assistance in reducing the distress arising from their life circumstances (as described below). All were treated for 18 months with weekly sessions—long enough to collect detailed clinical information and formulate an accurate case. What follows is a synopsis of their clinical cases at the beginning of therapy (names are fictional).

2.1.1. Case Study 1—Harry

Harry is a 40-year-old nurse who loves his job, sports, and traveling. He is a friendly man and is extremely helpful to the people he takes care of as well as to his friends and his brother. At the moment of starting therapy, Harry was not in a relationship, but he sought help to address the conflictual dynamics with his ex-partner. Since Harry was a child, his parents' arguments and neglect of his needs have triggered great anger in him. Reflecting on these circumstances, Harry used to say to himself that one should choose their partner very carefully. However, looking at his last relationship, he reports many instances of feeling sidelined by his ex and unimportant. Harry used to protest, but her job, friends, and many interests always seemed to come before him. Not even when he asked her to marry him and create their own family could he catch her attention. Despite being aware of his dissatisfaction, Harry kept following the same patterns until she finally left him for another man.

2.1.2. Case Study 2—Erika

Erika—a 28-year-old nightclub bartender who lives with her mother—has been feeling depressed for over six months, experiencing a loss of hope in the future, her abilities, and the people around her, from whom she is constantly disappointed. She believes she has made poor choices that have led her to her current failure. When Erika was eight, her parents separated, and her father left. A few years later, she reached out to him, who became a part of her life again. Now, her bond with her father seems stronger. Erika admires him, and he sometimes reciprocates by praising her skills and perfectionism. However, she views herself as flawed, incapable of maintaining friendships, yearning for recognition that never comes, and appearing as a loser in comparison with others. Working overnight, Erika spends her free daylight hours in her room, haunted by a profound sense of loneliness. She interacts with only a few people including her parents and the man with whom she has an intermittent relationship. Her romantic relationships do not last long.

2.1.3. Case Study 3—Jordan

Jordan is 24 years old as he approaches the conclusion of his university studies and works part-time at an accountant's office. Lately, he has seen an increase in the obsessions that were already present since adolescence, during which he was diagnosed with obsessive-compulsive disorder (OCD). Jordan recounts a childhood poor of parental affection and characterized by precise and rigid family rules. He was particularly struck by an episode at the age of 16 when—after informing his mother he had kissed the young girl he was dating—his mother blamed him for committing a grave act that required not only confession, but also to undertake a path of 'true' redemption. She accused him of severely hurting her by not preparing her to face the fact he was growing up and forbade him to keep seeing the girl. During the last months, Jordan has returned home in the evening and incessantly dwelled on what happened at work. He experiences intrusive thoughts about not completing all tasks correctly and feels compelled to retrace, in his mind, every step taken throughout the workday. He is also distressed at the thought that his inattentiveness might have harmed a colleague.

2.1.4. Case Study 4—Beth

Beth is a data scientist aged 35. She sought psychological support for managing a period of particular stress. Her boyfriend was away most of the time for work. She was working on an important project and under a lot of pressure from her boss. Additionally, her parents were becoming particularly demanding, asking for her support with family matters. One year through therapy, it started to become clear that Beth's childhood experiences had a relevant impact on how she tended to feel and think. In particular, she reported how her mother used to push her toward being a professional dancer—an activity everybody would admire. She has present in her mind the endless hours of training with her team and how disappointed her mother was when she did not perform as expected. She gradually managed to distance herself from professional dancing and pursue a career as a data scientist, landing in a top software company. Nonetheless, she realizes how hard it can be for her to be herself without disappointing the expectations of others and take life easier. Even with her friends, she always tries to be the 'perfect' one and pays a lot of attention to every comment on her.

2.2. Measures

The Attachment-Caregiving Questionnaire

Our study relied on the ACQ [9,21], a novel personality and clinical inventory. The instrument is informed by attachment-personality theory (APT) [6,62], which, besides the three classical attachment dimensions of *disorganization*, *avoidance*, and *ambivalence* [63,64], measures an additional four—*phobicity*, *depressivity*, *somaticity*, and *obsessivity*—similarly assessed by the 'personal meaning' questionnaires [65–67]. These seven attachment-related traits can be described as follows [6,18,62,68]:

(1) Disorganization (Dis). The disorganized is particularly sensitive to the possible threat coming from their caregiver. This dimension is related to experiencing a frightening/frightened caregiver and some form of trauma. As a result, the disorganized tends to overactivate their defensive system.

(2) Avoidance (Av). The avoidant is particularly sensitive to the caregiver's inclination to provide emotional support, which they expect to be deficient. As a result, the avoidant tends to deactivate their attachment system and dismiss attachment-related matters.

(3) Ambivalence (Am). The ambivalent is particularly sensitive to the caregiver's availability, which they expect to be inconsistent. As a result, the ambivalent tends to hyperactivate their attachment system and be preoccupied about their relationship, producing more frequent and intense requests for care.

(4) Phobicity (P). The phobic is particularly sensitive to the dichotomy of 'being close to the reference figure to receive protection' and 'being free to explore'. The need for protection corresponds to perceiving the world as dangerous and being vulnerable to separation anxiety. As a result, the phobic tends to focus on their physiological expressions as a signal of danger to their health, overlooking alternative explanations, especially relational ones.

(5) Depressivity (D). The depressive is particularly sensitive to having their value recognized by their reference figure, and is therefore oriented toward reaching some evident achievements. Perceiving the lack of recognition causes an underlying sense of defeat and irremediable loss, corresponding to inherent solitude. As a result, the depressive tends to attribute the meaning of loss to life events, particularly concerning their relationships, and systematically rely on themselves.

(6) Somaticity (S). The somatic is particularly sensitive to their reference figure's confirmation in order to define themselves, primarily their sensations and emotions. The sense of uncertainty about oneself—rooted in being unsure about the interpretation of one's somatic state—leads to relying on external references and being approved by others to define one's own thoughts and feelings. As a result, the somatic tends to follow expectations and comply with social standards.

(7) Obsessivity (O). The obsessive is particularly sensitive to appearing as a good person—primarily to their reference figure—by strictly abiding by a given set of rules. Respecting this code, which distinguishes between right and wrong, determines one's intrinsic nature, and is therefore essential. Rules can be more or less abstract, from general principles to specific ways to operate in particular domains. As a result, the obsessive tends to control their actions with respect to the domains involved by their rules.

The ACQ measures these dimensions in adulthood, serving two functions. (1) Personality profiling. Given the relevant role played by attachment in structuring personality [6,12–20], the ACQ aims to provide a seven-dimensional personality profile (each dimension represents an attachment-related trait). (2) Clinical assessment. Given the link between attachment and psychopathology [6,15,68–72] including the most common psychological conditions such as anxiety, mood, eating, and obsessive disorders; the ACQ also aims to be a clinical tool. Coherently, the instrument has been shown to be capable of detecting psychological vulnerabilities, with specific dimensions correlated to expected groups of symptoms in a sample of patients in psychotherapy [21]. Overall, the ACQ works as a personality inventory and a clinical test that evaluates the patient's attachment-related vulnerabilities to mental disorders.

Following usual practice, the ACQ was realized by drawing on the extant literature, but, in this case, items were grouped in seven 'default scales' according to their expected interpretation and not through a standard statistical method such as FA. Each default scale was linked to a specific dimension—with 16 items for disorganization, 18 for avoidance, 15 for ambivalence, and 19 for phobicity, depressivity, somaticity, and obsessivity. However, the ACQ items can be moved, and its scales are flexible. More specifically, when analyzing a completed questionnaire, the scorer can interpret items and reallocate them to a different scale, aiming to match what the respondents meant by their answers. For example, the scorer can move a default ambivalent item to the depressive scale (if they believe that the respondent gave that item a depressive meaning). This feature is enabled by including extra-scale information that allows the scorer to interpret answers by cross-referencing data. Overall, the ACQ consists of three sections: (1) contextual data, (2) current attachment state (default scales), and (3) childhood caregiving experiences (Table 1).

Table 1. ACQ structure. The ACQ is structured into three sections: (1) contextual data, (2) attachment (default scales), and (3) caregiving, gathering information on the subject's context, current attachment state, and childhood caregiving experiences, respectively. The relevance and range of these data allow for interpreting the default scale items by cross-referencing information.

ACQ Section		Subsection		Items	Description
1	Contextual Data	A	Personal Information	23	Data on the subject's context–current life environment and clinically relevant information.
		B	General Condition	20	
		C	Specific Issues	17	
2	Attachment	A	Introduction	3	Current attachment state. Default scales for seven attachment-related personality traits.
		B	Attachment	125	
3	Caregiving	A	Introduction	1	Childhood caregiving experiences with the two most relevant attachment figures and in the family in general.
		B	Family	17	
		C	Introduction	4	
		D	Maternal Figure	83	
		E	Introduction	4	
		F	Paternal Figure	83	
		G	Additional Information	14	
				394	

In conclusion, the ACQ design allows a scorer (e.g., a clinician) to build a comprehensive picture of the subject's state and attribute meaning to the items accordingly. In contrast to standard self-reports, this questionnaire is not intended to undergo the usual validation procedures such as those informed by FA. Indeed, its objective of implementing flexible scales would be inconsistent with procedures that imply rigid item allocations. Nonetheless, the ACQ validity is supported by the clinical analysis of more than 200 completed questionnaires and the connection found between dimensions and specific groups of symptoms (somaticity and dysfunctional eating, for example) [21]. As discussed below (cf. 4), we suggest AI as a formal method to validate the ACQ. As soon as sufficient data are available, we will train a machine learning model to mimic the scorer's performance and provide a novel form of validation based on advanced pattern recognition. If successful, this procedure will enable the personalization of clinical interpretation—since the machine will operate as a human expert scorer—while ensuring the standardization provided by a mathematical model.

2.3. Procedure

The study relied on assessing the patients' personality through the ACQ, aiming to test the instrument's potential to improve personality assessment by interpreting unclear answers (i.e., those potentially not belonging to their default scale because the respondent might have read them differently) (cf. 2.2.1). Patients completed the ACQ, but to ensure that treatment was not influenced by what they had reported, the outcomes remained undisclosed to them and their therapist. After 18 months, the knowledge gained in therapy was used to test the ACQ interpretation. More specifically, the study followed the four-stage design outlined below (S1–S4) (Figure 1).

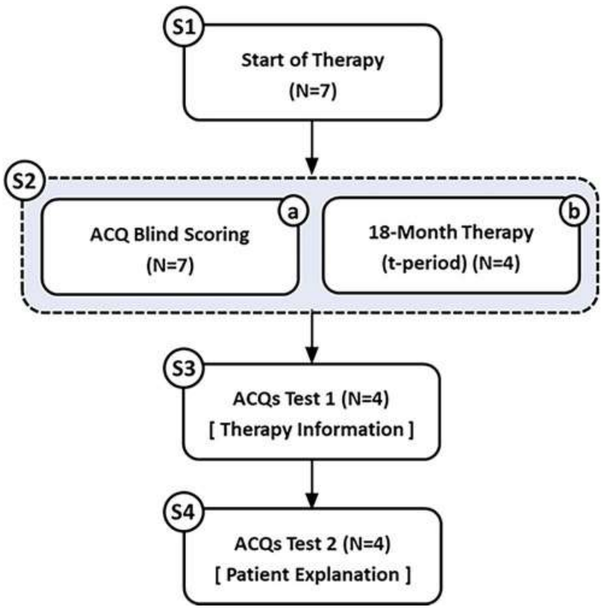

Figure 1. Study design. The study was designed in four stages (S1–S4). (S1) It started with seven participants consisting of the patients who began therapy in the same two-week period and agreed to participate. (S2) These patients completed the ACQ—whose scores were not disclosed to the therapists (S2a). After 18 months (t-period), four patients were still in treatment and continued the study (S2b). Their ACQs presented two primary interpretation issues—on the ambivalent and obsessive (default) scales—which were tested against the (S3) therapy information and (S4) patients' explanations of their answers.

(S1) Start of therapy. Recruitment took place during a two-week time frame. The initial participants were the seven patients who started therapy with one of the first three authors in that time frame and agreed to participate. Based on the authors' clinical experience, an 18-month standard treatment (t-period) was estimated to be necessary (and reasonably sufficient) to explore the attachment-related traits most relevant to the patient. As a result, this condition was considered essential for inclusion in the post-treatment stages of the study.

(S2a) ACQ blind scoring. Starting therapy, the seven participants completed the ACQ, generating a personality profile on the seven attachment dimensions of disorganization, avoidance, ambivalence, phobicity, depressivity, somaticity, and obsessivity (cf. 2.2.1). Each self-report was scored by the two authors who did not treat the respondent. The scoring was carried out independently (97% inter-rater agreement) and later discussed to agree on a final 'blind' profile (i.e., not informed by clinical knowledge of the patient). Therapists had no access to their patients' questionnaires for the first 18 months.

(S2b) 18-month therapy (t-period). Therapists conducted therapy following cognitive-evolutionary principles [6,68,73,74] with a focus on the patient's relationships, cognitive structures, and motivational dynamics, using the therapeutic relationship as an active therapeutic tool [75–77]. Attention was given to the attachment-related traits most relevant to the patient, aiming to clarify them in the light of critical events. After the t-period, four patients had attended regularly and could enter the following stages of the study. The other three were excluded—one had completed treatment after a little over a year, and two had attended inconsistently.

(S3) ACQ scoring test 1. At this point, the therapists provided a detailed written profile of their patients guided by their session notes, without any knowledge of the patients' ACQs. The authors then used theses material to test the initial ACQ blind interpretation against the information gained in treatment, focusing on specific answers underpinned by possible alternative meanings.

(S4) ACQ scoring test 2. Finally, therapists explicitly invited the four patients to elaborate in writing on their Am1–Am4 and Ob1–Ob4 answers to test the ACQ interpretation against the patients' explanations. Patients all received the same hints for each item (i.e., "What motivated you to answer with this score?", "What were your thoughts?", "What were your feelings?", and "Had you one or more specific episodes in mind?").

3. Results

We report the results of our analysis following the four stages outlined above.

(S1) Start of therapy. Seven patients started therapy, but only four—Harry, Erika, Jordan, and Beth—attended 18 months of treatment regularly and completed the study.

(S2a) ACQ blind scoring. On the ACQ, Harry and Erika reported high scores on the ambivalent scale—significant concerns about rejection and abandonment. Jordan and Beth scored high on the obsessive one—a marked propensity to abide by given rules and worry about doing the right thing. Such features are recognized to be typical of ambivalence and obsessivity, respectively [6,28,71,78]. However, the scorers deemed two patients gave several items of these scales a non-default meaning (i.e., despite belonging to the ambivalent/obsessive scale, they were read by the respondent as an item of another scale). This was the case for items Am1–Am4 and Ob1–Ob4 (Table 2), whose ratings by the four patients are reported below (Table 3).

Harry's and Erika's means were comparably high on the ACQ ambivalent items (8.75 vs. 8.5), and similarly, Jordan's and Beth's means on the ACQ obsessive items (9.00 vs. 8.75). As a result, these items alone would make it difficult to detect a possible difference between the patients' ambivalence and obsessivity levels. Nonetheless, a non-default meaning attribution—in this case, not ambivalent or obsessive—was enabled by the possibility given by the ACQ to consider information from other parts of the questionnaire.

Table 2. Eight ACQ items. (a) The upper part of the table shows four items from the ACQ ambivalent scale that concern worrying about rejection and abandonment. (b) The lower part of the table presents four items from the ACQ obsessive scale that concern the tendency to follow rules and the worry of doing the right thing.

(a)	**Four items from the ACQ ambivalent scale**
Am1	In a relationship, the idea of being left by my partner hardly enters my mind.
Am2	In a relationship, I'm confident my partner would never leave me.
Am3	In a relationship, I think of what I'd do if my partner left me.
Am4	In a relationship, I wonder whether my partner really cares about me.
(b)	**Four items from the ACQ obsessive scale**
Ob1	Not respecting my rules would be unacceptable to me.
Ob2	Moral issues—what is right or wrong—are at the heart of my thoughts.
Ob3	Always doing the right thing is essential.
Ob4	The slightest doubt that I have done something wrong can make me feel terrible anguish.

Table 3. Sample ACQ scores. (a) The first two patients—Harry and Erika—scored similarly on items Am1–Am4, characterizing ambivalence (Table 2) (Am1 and Am2 indicate reversed scores). (b) The other two—Jordan and Beth—gave similar ratings to items Ob1–Ob4, inherent to obsessivity.

(a)	(1) Harry	(2) Erika	(b)	(3) Jordan	(4) Beth
Am1	8	10	Ob1	9	10
Am2	9	7	Ob2	9	9
Am3	8	8	Ob3	8	9
Am4	10	9	Ob4	10	7
Mean	8.75	8.50	Mean	9.00	8.75

First, the two pairs of patients differed on other scales. In particular, Erika's predominant scale was depressivity, and Beth's was somaticity. Moreover, other items suggested possible non-standard interpretations of Am1–Am4 from Erika and Ob1–Ob4 from Beth. Erika was previously diagnosed with depression and reported depressive experiences during childhood in relation to her mother (e.g., not having the chance to spend time with her mother, missing her mother, and longing to be recognized by her mother as valuable). Beth reported feeling significantly under pressure due to others' expectations of her and the experience of a typical somatic childhood with both parents (e.g., high admiration for the parents and marked dependence on the parents' approval). Finally, Erika's and Beth's life histories emerging from their questionnaires were inconsistent with the high ambivalent and obsessive manifestations suggested by the default scales.

On these grounds, while Harry's and Jordan's ACQ scores appeared to be driven by their ambivalence and obsessivity, respectively, Erika's ambivalent answers were recognized to be underpinned by her depressivity, and Beth's obsessive answers by her somaticity (Table 4). In other words, the ACQ included enough data to deem it more probable that Erika and Beth attributed Am1–Am4 and Ob1–Ob4 depressive and somatic meanings, respectively.

(S2b) 18-month therapy (t-period). The 18 months of therapy planned for the study allowed the therapists to formulate a reliable evaluation of the patients' attachment-related personality traits. In particular, two clinically relevant themes related to Am1–Am4 and Ob1–Ob4 emerged in therapy: (T1) A sense of loneliness—expressed by worries about being rejected and abandoned—crucial to the first two patients (Harry and Erika). (T2) The tendency to follow (some) rules, characterizing the other two (Jordan and Beth).

(1) Harry's ambivalent attitude was clear early on in treatment. His anger and worry about being disregarded and left alone were central to the interpretation of his life events. The therapist recognized a prevalent ambivalent trait characterized by marked protest toward his reference figures. (2) On the other hand, Erika had sought help for her depressed mood. She seemed to have never overcome the loss of her father, although she could reconnect with him after some time. Her sense of solitude and the impossibility

of feeling valued by her significant others dominated her experience. (3) Jordan had a history of OCD. He focused on following the rules that made him feel like a good person. Obsessivity was clearly his primary trait. (4) In contrast, Beth focused on how she appeared to others and found it extremely hard to express her true self. She felt oppressed by others' expectations, especially from her mother, and following rigid rules was her way to feel adequate and accepted.

The elaboration of T1 and T2 throughout therapy clarified the actual experiences and clinical nature related to them, thereby allowing us to test the interpretation of the corresponding questionnaire items.

Table 4. ACQ interpretation of ambivalent and obsessive items. (a) Harry and Erika gave similar ratings of Am1–Am4. However, additional ACQ information allowed us to deem Erika's answers on these items as having a depressive meaning. (b) Similarly, Jordan's and Beth's ratings of Ob1–Ob4 were comparable. Nonetheless, additional ACQ information allowed us to reckon Beth's answers on these items as having a somatic meaning.

(a)	Case Study	Prevalent Dimension	Additional ACQ information used to score Am1–Am4
1	Harry	Ambivalence	None [ambivalence as prevalent dimension]
2	Erika	Depressivity	(1) Depressivity scores [depressivity as prevalent dimension] (2) Previous depression diagnosis (3) Childhood depressive experiences with mother (4) Life history inconsistent with prevalent ambivalence
(b)	**Case Study**	**Prevalent Dimension**	**Additional ACQ information used to score Ob1–Ob4**
3	Jordan	Obsessivity	None [obsessivity as prevalent dimension]
4	Beth	Somaticity	(1) Somaticity scores [somaticity as prevalent dimension] (2) Feeling significantly under pressure due to others' expectations (3) Childhood somatic experiences with parents (4) Life history inconsistent with prevalent obsessivity

(S3) ACQ scoring test 1. The ACQ blind interpretation of the ambivalent and obsessive items—in particular, Ab1–Ab4 and Ob1–Ob4—was first tested against the information gathered by the therapists throughout the t-period and reported in the detailed profiles therapists had prepared. (1) Erika showed a depressive profile with a profound sense of loneliness consistent with high scores on the ambivalent items touching on rejection and abandonment. Moreover, she never showed marked signs of ambivalence such as anger and protest for having her needs unmet. (2) Similarly, Beth was soon identified as predominantly somatic. She was strongly dependent on reference figures for approval and tended to follow rules to feel aligned with others' expectations. Beth never showed signs of obsessivity such as feeling compelled to do some actions to avoid terrible consequences. What she tended to term a sense of guilt was informed by failing at being included rather than causing some harm, as obsessivity would suggest. Overall, the profiles of these two patients that emerged in therapy supported the non-default interpretations of their ACQ ambivalent and obsessive scores as depressive and somatic, respectively.

(S4) ACQ scoring test 2. Finally, the examination of the patients' writings on items Am1–Am4 and Ob1–Ob4 confirmed the profiles that the therapists had formulated throughout treatment, pointing to Harry's, Erika's, Jordan's, and Beth's answers as being driven by a predominant ambivalent, depressive, obsessive, and somatic meaning, respectively. No information emerged that could reasonably suggest a different interpretation.

4. Discussion

This study investigated the potential of a questionnaire to assess personality, proposing a novel item interpretation approach. We put forward the hypothesis that items can be understood differently by different respondents, impacting assessment and related decision-making. As a result, self-reports developed through standard statistical methods—in particular, FA—are intrinsically limited, since they identify items that statistically cluster together but cannot capture what motivates answers. To overcome this limitation, we suggest adopting more complex designs and methodologies that allow the scorer to interpret responses by cross-referencing data from various sections and scales. This pattern recognition ability belongs to expert humans (clinicians, for instance), but we know from the literature that it can be reproduced by an AI model—like a neural network—that is adequately trained [79,80]. Indeed, the problem of recognizing patterns in a personality inventory and the suitability of AI to solve it can be exemplified by imagining all questionnaire items arranged on a two-dimensional plane as the pixels of an image, where the scores of each item will correspond to the pixel color in a grayscale code (e.g., 0 for black, N for white). Neural networks have demonstrated excellent performance in learning to recognize complex visual patterns for a variety of applications [81–83], with a review finding that 61 out of 81 studies reported AI performing comparably or better than the expert clinicians in diagnosing from medical images [84].

To test our hypothesis, we examined the cases of four patients who completed the ACQ—an attachment-related personality inventory—and underwent psychotherapy for 18 months. The ACQ allows the therapist to build a picture of the respondent's life context (ACQ first section), current state of mind (ACQ second section), and childhood caregiving experiences (ACQ third section) (cf. 2.2.1). This information can be used to interpret ambiguous answers (i.e., answers that may not have been interpreted by the respondent according to their default scale).

Our study could not have been carried out using standard self-reports such as those based on FA since they do not allow the scorer to interpret items and possibly allocate them to a different scale. For example, the FA-informed Big Five Inventory (BFI) [85], which measures the five traits of *openness*, *conscientiousness*, *extraversion*, *agreeableness*, and *neuroticism*, always associates 'being talkative' with extraversion and 'worrying a lot' with neuroticism, without considering possible alternative attributions of meaning. To apply our study's rationale using an FA-based self-report, such a questionnaire should be adequately extended with extra-scale information that enables interpretation, and therapy should gather the same kind of data. On the other hand, performing FA represents a form of statistically-based pre-interpretation, and is therefore a possible impediment to the subsequent personalized attribution of meaning.

4.1. Item Interpretation and Related Statistical Methods

Although available instruments are generally rigid (i.e., non-interpretable), various statistical methods have been developed to create more flexible and informative self-reports. We reviewed two classes of such methods (cf. 1.2) for DIF detection (cf. 1.2.1) and LPA (cf. 1.2.2), which we can now compare to 'Item Interpretation', as we intended it in our work (here in capital letters to facilitate comparison) (Table 5):

(1) DIF concerns the possible discrepancies in responses given by different subgroups of the population, usually a reference and focus group, as related to characteristics not assessed by the instrument such as different ages, genders, or knowledge, for instance. In education, items often imply a correct answer, providing which depends on a cognitive ability. In this case, accounting for DIF allowed us to avoid possible biases, a typical example being the case of native vs. non-native speakers when reading and understanding the item. On the other hand, when measuring personality, DIF can depend on divergent attitudes of different subgroups such as being more inclined to describe oneself as a rational person in males vs. females. Therefore, DIF detection and Item Interpretation are both concerned with variations in answers from different respondents. However, these approaches have crucial conceptualization differences, particularly relevant when considering a personality inventory. While DIF detection addresses response divergences linked to external variables identifying an entire subgroup and not measured by the instrument (e.g., age, gender), Item Interpretation looks at how the respondents may answer differently given their personal

attribution of meaning concerning what the instrument is intended to assess (e.g., trait A vs. trait B). Moreover, when DIF is detected, the item is treated in a particular way, depending on the case (i.e., scoring it differently depending on the group or excluding it from scoring). Instead, when Item Interpretation signals a non-default meaning, the item is only moved to the corresponding scale (e.g., from scale A to scale B).

Table 5. Main features of DIF analysis, LPA, and 'Item Interpretation' as intended in this work. The table demonstrates the different conceptualizations of the three approaches, primarily expressed by their different focuses and objectives.

	DIF Analysis	**LPA**	**Item Interpretation**
Focus	Subgroups of respondents with different probabilities to answer a given item in a certain way	Clusters of respondents identifiable by a specific pattern of answers	Personal meaning attributed to each item by the respondent
Variables Involved	External characteristics not measured by the questionnaire (e.g., age, gender)	Latent traits not measured by the questionnaire	Latent traits measured by the questionnaire
Objective	To preserve psychometric properties and to avoid unintended consequences (e.g., biases)	To identify and describe subgroups (latent profiles) within the population	To interpret answers according to the respondent's attribution of meaning
Result	Revising, removing, or treating items differently	Extracting latent profiles not directly measured	Moving items to the correct scales

(2) LAP concerns the identification of clusters of respondents characterized by specific patterns of answers in terms of questionnaire indicators such as item or subscale scores. The identified patterns define the extracted latent profiles. Since it focuses on the individuals sharing the same traits rather than on the scored variables, this analysis is person-centered. Therefore, LPA and Item Interpretation both look at the individuals and aim to profile them. Nonetheless, again, the two approaches differ substantially in their conceptualization. First, unlike Item Interpretation, LPA is interested primarily in the pattern of answers (profile) rather than the single answer (item). Although identifying two LPA profiles that share the same items can correspond to assigning a differential role to such items, this assignment is based on a group characteristic, and not on a personal one. Put differently, we can say that LPA can give the item a group meaning rather than a personal meaning, as Item Interpretation does (for example, considering the study from He et al. (2018) [58] discussed above (cf. 1.1.2), in the two profiles with secure attachment to parents and different attachments to peers (i.e., SePa-SePe and SePa-InPe), the items corresponding to the secure attachment to parents can have differential functioning since they belong to two different profiles). Moreover, while LAP explores latent variables not measured by the instrument (i.e., profiles to be discovered), Item Interpretation analyzes answers to determine the profiles the instrument is meant to assess. Finally, since LAP profiles are initially undetermined, the model outcome depends on how many profiles are selected, with the principle of parsimony usually leading to excluding the uncommon ones (i.e., those including a small proportion of the sample). Conversely, Item Interpretation is bound to the traits measured by the instrument (the seven attachment dimensions in the ACQ case) and corresponding profiles, none of which is excluded.

This analysis suggests that DIF detection, LAP, and Item Interpretation have some similarities but fundamentally distinctive features (summarized in Table 5). In particular, they are characterized by a specific focus and different objectives.

4.2. Results Analysis

Despite the efforts of a questionnaire designer, the respondents can interpret items in multiple ways. The statement "*The relationship with my mother was affectionate*", for example, can have radically different meanings for two different individuals, from "*We sometimes went to the park together*" to "*My mom cuddled and reassured me when I was down*".

Nonetheless, these two individuals can rate that statement similarly on the questionnaire. An unexpected meaning attribution cannot be detected by usual, rigid-scale instruments but can be identified if more comprehensive information is provided and the data can be cross-referenced. The resulting scale flexibility is what the ACQ enables. The clinician can interrelate multiple pieces of information to make sense of their patient's ambiguous responses. When located in a broader context, items assume a specific meaning and contribute to building an individual story. Starting from this central ACQ feature, we can divide the analysis of our results into the following four steps.

(1) ACQ scoring. From the ACQ, the scorers could build a narrative of each patient's experience consistent with their life context, current state of mind, and childhood caregiving experiences, finally producing an attachment-related personality profile. Their assessments led to concentrating attention on the dimensions of ambivalence and depressivity on the one hand (Harry and Erika), and obsessivity and somaticity on the other hand (Jordan and Beth). Our study focused exclusively on these dimensions for the specific characteristics of the recruited patients. Other patients could have taken the analysis in different directions depending on their prominent clinical features (dissociative symptoms and separation anxiety, for example). While in the case of Harry and Jordan, the data appeared coherent, suggesting predominant ambivalence and obsessivity, respectively, some dissonant elements were found in the stories of the other two patients (as summarized in Table 4). Only interpreting the ambiguous items in a non-default way could we restore the overall consistency. When Erika's ambivalent answers were put in a depressive perspective and Beth's obsessive answers in a somatic one, inconsistencies were solved, and their comprehensive stories became clear. In other words, putting information into context changed the personality assessment.

(2) Therapy profile. The therapists conducted the first 18 months of treatment unaware of their patients' ACQ scores, making the treatment entirely independent of the questionnaire results. Since attachment-informed therapy requires time to build a secure relationship [12,77,86,87], this t-period was deemed indispensable to allow the clinicians to reach a reliable understanding of the cases. Following their patients' inputs, the therapists were gradually able to gather pieces of information concerning their most clinically relevant attachment dimensions and put them together into a coherent narrative. In other words, the clinicians built an informal attachment-related personality profile of their patients that informed their therapeutic decisions. It is noteworthy that therapy was relevant to our purposes only for the provided data, regardless of the details of its course and outcome.

(3) ACQ therapy test. We tested the blind scoring of the ACQ against the information therapists gathered throughout treatment. To ensure an unbiased test, the clinicians reported their profiles in written form before learning their patients' ACQ responses. This information led us to confirm that while Harry and Jordan's predominant dimensions were ambivalence and obsessivity (respectively), Erika and Beth provided non-default ambivalent and obsessive answers. As a depressive, Erika suffered from a pervasive sense of loneliness [88,89] that involved feelings of rejection and abandonment typical of ambivalence [28,78]. Therefore, her depressivity was consistent with high scores on the ambivalent items. Similarly, as a somatic, Beth tended to focus on social acceptance and to feel compelled to comply with social standards [6,67,71]. This inclination led her to strive for extraordinary achievements and recognition by following rigid rules. However, since the same tendency to adhere to a strict code of conduct is also a typical obsessive manifestation [90,91], it is not surprising that she scored high on the obsessive items. In this case, it is worth noting that the senses of guilt characterizing Jordan and Beth were also clinically different. While Jordan felt morally obliged to abide by his code of conduct, Beth followed her rules to pursue social recognition and affiliation. These two tendencies corresponded to a sense of deontological and altruistic guilt, respectively [92].

(4) ACQ patient test. The additional test of the blind ACQ scoring against the response explanations directly provided by the patients further confirmed the blind interpretations.

Analysis interpretation. Our analysis indicates that in cases like those presented here, the possibility to interpret items makes a difference. A univocal attribution would entail producing a misleading profile. In particular, Erika and Beth would be mistakenly considered ambivalent and obsessive. Moreover, differences in personality assessments can lead to expecting different clinical features, and hence making different treatment choices. In our case, the ambivalent and depressive did not experience the same sense of rejection, and the obsessive and somatic experienced a sense of guilt essentially different (deontological and altruistic, respectively). In Table 6, we summarize our analysis and its rationale, outcome, and interpretation.

Table 6. Summary of the results analysis. The table illustrates the four steps of our analysis: (1) ACQ scoring, (2) therapy profile, (3) ACQ therapy test, and (4) ACQ patient test, summarizing its rationale, outcome, and interpretation.

	Step	Analysis	Analysis Rationale	Analysis Outcome	Analysis Interpretation
1	ACQ Scoring	Personality-related items were analyzed considering extra-scale information (e.g., current life context, childhood experiences).	Building a clinically relevant story of the respondent's life will allow the scorer to interpret ambiguous items.	Ambiguous items were moved to non-default scales according to their interpretation (in our case: (1) Erika's ambivalent answers moved to the depressive scale, and (2) Beth's obsessive answers moved to the somatic scale).	Moving items to non-default scales can significantly change the personality profiles.
2	Therapy Profile	Information concerning relevant life events was analyzed focusing on attachment-related traits.	Conducting cognitive-evolutionary, attachment-informed therapy will provide personality-related information.	Attachment-related personality profiles were built using the diverse data that emerged throughout therapy (in our case, the four profiles: (1) Harry: ambivalent, (2) Erika: depressive, (3) Jordan: obsessive, (4) Beth: somatic.	Therapy data can allow clinically-supported personality profiles to be built.
3	ACQ Therapy Test	The blind ACQ scorings (i.e., the ACQ personality profiles) were compared to the attachment-related personality profiles provided by the therapists.	If the ACQ scorings (using item interpretation) and the therapy profiles provide the same results, ACQ scoring is supported.	The personality profiles provided by the ACQ scoring (using item interpretation) corresponded to those provided by the therapists.	Item Interpretation may improve personality assessment (since ACQ scoring was supported by the therapy data).
4	ACQ Patient Test	The interpretations of ambiguous ACQ items were compared to the explanations provided by the patients.	If the interpretations of ambiguous ACQ items correspond to the patients' explanations, ACQ item interpretation is supported.	The interpretations of ambiguous ACQ items corresponded to the patients' explanations.	Item Interpretation may improve personality assessment (since ACQ item interpretation was supported by the patients' explanations).

In conclusion, our results suggest that the self-report assessment of personality, and the possible consequent clinical decision-making, may be improved by instruments that allow the scorer to personalize profiles by discerning between the possible different meanings the respondents can convey with their answers. Moreover, they imply that the automation of the process would require more advanced pattern recognizers than FA or other similarly rigid methods, which AI may provide. By mimicking the human understanding of deep personal meanings, AI may enhance personality assessment, overcoming the limitations of standard statistical methods.

4.3. Limitations and Future Work

While our preliminary study provides an essential basis for further investigation into interpretation-oriented personality inventories, it also presents several relevant limitations. We discuss a few of them here.

(1) Given the characteristics of our participants, we considered alternative interpretations concerning ambivalence and obsessivity. Other attachment/personality dimensions will need to be investigated. Administering the ACQ to numerous clinical patients allowed us to identify various questionnaire items that were given non-default meanings but could

not be covered in this work. For example, phobic items are sometimes read from a somatic perspective, and depressive items from a disorganized one. As discussed next, collecting more data will allow us to deepen our understanding of the phenomenon.

(2) Given the clinical nature of our study—based on only four case studies and qualitative analyses—we could only collect evidence to substantiate our hypothesis, without aiming to reach statistical relevance and draw any definitive conclusions. Future work will need to involve a sample large enough to apply statistical procedures and generalize the results. In pursuit of this objective, we are currently collecting a large sample to develop a machine learning (ML)-based model capable of scoring the ACQ and validating the instrument formally (indeed, if an ML model can learn a pattern, it proves that there is a pattern to learn). Introducing the potential of ML in this study served two objectives: (a) enhancing personality assessment and profiling by using multiple cues, and (b) emulating the human comprehension of profound personal experiences, transcending the constraints of conventional statistical methods. Technically, these goals are interrelated and can be pursued through suitable methods. Notably, neural networks and decision trees offer valuable assistance in achieving these objectives. Several existing approaches are already advancing in this direction such as deep learning-based methods [93–95]. The only limitation of applying deep learning approaches is their reliance on extensive data. However, we believe that a promising starting point could involve using decision trees and neural models that do not depend on large datasets. Furthermore, statistical techniques, such as bootstrap and boosting, can be employed to address data scarcity. An issue that may arise with deep networks pertains to the 'explainability' of the model outputs (e.g., estimated attachment dimensions) in relation to their corresponding input data (e.g., questionnaire entries). Explainable artificial intelligence is still a matter of research [96]. However, this could be a further opportunity to investigate the most relevant questionnaire entries adopted by the ML model for making the decision, since the lack of data would orient toward avoiding deep learning approaches. Additionally, since similar entry configurations may be associated with different attachment dimensions, supplementary cues may be required. In other words, we may need to rely on multiple classification approaches, a strategy employed in various domains including plant disease detection, cancer diagnosis, and EEG-based personal recognition [97–102].

(3) The ACQ interpretability and usability are essential features whose improvement requires deep understanding and further investigation. Therefore, we will administer the ACQ while applying the *think-aloud protocol*—asking subjects to speak out their thoughts during the questionnaire completion. This procedure will allow us to directly evaluate the different meanings that individuals can attribute to the items and possibly enhance the user experience.

(4) Relying on a cognitive-evolutionary approach, we focused on attachment-related aspects of personality using a specific self-report, the ACQ. Considering other personality models and inventories was beyond the scope of this work. Nonetheless, the investigation of Item Interpretation should concern other cases, starting from the well-established ones such as the Big Five model [7] and the instruments assessing its dimensions (as the above-mentioned BFI, for example). In the case of the Big Five, since its inventories were not designed to explore the possible alternative meanings underpinning each item, information not included in the questionnaires will be necessary. A theoretical framework will also be required to interpret the answers since the model does not refer to any.

5. Conclusions

Personality inventories are an invaluable source of data in clinical psychology and psychiatry. Nonetheless, their effectiveness depends on how the information is extracted from the collected responses. Traditional designs apply consolidated statistical procedures to group items. Despite identifying fundamental dimensional properties, these procedures do not allow for personalizing profiles by considering alternative item interpretations. Relying on four case studies and the ACQ, we showed that different individuals can read the same statements differently, according to their personal meanings. This evidence suggests that a self-report designed to account for this possibility could improve personality assessment. Automatic scoring could be realized by an ML model adequately trained, of which we envision the first implementation steps. Our study is preliminary, and further research is indispensable to reach conclusive results.

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