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The OCEAN Framework: Mapping Human Traits in the Digital Landscape

A Narrative Literature Review of Personality Trait Extraction and Validation in the Era of Artificial Intelligence

Contents

Abstract

In today's technologically advanced society, AI and digital technologies are revolutionizing how we research personality using social media profiles. Personality models such as OCEAN are being used to create advanced machine learning techniques. This narrative literature review covers a broad spectrum of research, including review papers, empirical/validation studies, applied research, methodological papers, conceptual/theoretical papers, consumer psychology studies and digital/ai-driven personality research. The papers converge on the understanding and revelation of how online activities, especially social media use, can reveal personality insights with accuracy. This approach has the potential to make computational tools for social-media personality analysis more precise and effective. It shows that psychological frameworks, particularly the OCEAN model, link traditional personality assessments with modern AI techniques. This approach supports building smarter AI systems that better understand human behavior and personality.

Keywords - OCEAN personality model, digital personality assessment, social media personality extraction, artificial intelligence and personality.

1. Introduction

Historical Origins of Personality Concept

The word “personality” comes from persona, which refers to the theatrical mask worn by Roman actors during the 1st and 2nd centuries B.C.E. Greek physician and philosopher, Galen of Pergamon (AD 130–200), later proposed that the predominance of one or more humors - choleric, melancholic, sanguine and phlegmatic, resulted in a characteristic emotional style or temperament.

Early Theoretical Frameworks

In the twentieth century, Carl Jung put forth a personality theory based on a framework of four psychological functions (Thinking, Feeling, Sensation, and Intuition) and two attitudes (Extraversion and Introversion). These elements combine to create eight primary personality types. His work has been further developed by others such as Katharine Cook Briggs and her daughter Isabel Briggs Myers, leading to practical applications like the Myers-Briggs Type Indicator (MBTI). Since 1936, the trait approach has been a major theoretical framework in the study of personality. Traits are like personality patterns. These patterns don't change much over time or in different situations. They help explain why we behave the way we do. Everyone has different traits, which makes us all unique.

Pioneering Personality Trait Research

Gordon W Allport is known to be the pioneer of the study of personality. He studied the history of the word “personality”. Along with Henry Odbert (1936), he analyzed 17,953 terms in Webster's New International Dictionary from 1925 to identify personal dispositions. Approximately one-fourth of the words described personality traits. He proposed a hierarchical structure of traits, including cardinal traits (dominant and defining), central traits (general characteristics), and secondary traits (specific and situation-dependent).

Development of Personality Measurement Methods

Hans J Eysenck, in his 1947 book Dimensions of Personality, described two personality dimensions called extraversion and neuroticism. The third dimension, psychoticism, was added to the model in the late 1970s, based upon collaborations between Eysenck and his wife, Sybil B. G. Eysenck.

Raymond Cattell, identified 16 fundamental personality traits that he believed were the core building blocks of personality. These traits, known as source traits. Surface traits of personality are readily observable and determined by source traits (Cattell, 1956). He used three methods to measure personality:

Life records (L-data): Observing a person's behavior without being an expert. Sometimes the family or friends of the person may help to get this data.

Questionnaires (Q-data): Having a person rate themselves using a questionnaire similar to an application form or information sheet.

Personality tests (T-data): Using objective tests that a person can't easily fake.

He then developed a famous personality test called the 16 PF, which measures 16 key personality traits. This test is widely used for various purposes, including predicting job success, diagnosing mental health issues, and researching personality.

In the middle of the 1970s, Paul T. Costa Jr. and Robert R. McCrae made a revolutionary breakthrough in the study of personality when they determined that only three variables should be measured: neuroticism, extraversion, and openness to experience. By 1987, two new qualities, agreeableness and conscientiousness, were being tested using the NEO Personality Inventory.

This framework, now known as the Big Five personality traits, has since become a cornerstone in understanding human behavior.

The Five Factor Model in the Age of Artificial Intelligence

Human nature is complex, with our words and actions reflecting this intricacy. The study of personality shall exist and continuously evolve and individuals will continue to actively express their traits through behaviors and interactions. The rise of social media has amplified this, allowing people to observe, express, and learn within their networks.

Traits, often seen as fundamental to our behaviors, have long been studied, with Galton in 1884 suggesting language as a tool for understanding personality. Today, AI and machine learning offer a means to detect patterns and overcome human biases, using public data to analyze traits reliably.

The Five Factor Model (FFM)—Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism—remains a validated framework for understanding personality. Integrating AI with the FFM ensures precision and reliability, while alternatives risk inefficiency and inaccuracy. This synergy of psychology and technology offers new depth in personality assessment.

2. Understanding OCEAN's Comprehensive Trait Framework

Basic Assumptions of the Five Factor Model

According to Costa and McCrae's work in 1996, people have individuality, but they are not unfathomably unique. The common trait dimensions of the FFM make variability comprehensible. It is important to note that traits do not determine behavior independently of the situational context. Contemporary measures of the FFM are evaluated in terms of replicability of factor structure, retest reliability and stability, convergent (how closely a test is related to other tests that measure the same (or similar) constructs) and discriminant validity (specifically measures whether constructs that theoretically should not be related to each other are, in fact, unrelated).

Factor Analysis

The Five Factor Model is the product of factor analyses of personality descriptions obtained from self-reports and observer ratings. Factor Analysis is a set of statistical techniques that looks for interrelationship among the variables of the research. It helps remove redundancy or duplicity and reduces the amount of data. This method identifies orthogonal factors that are independent of each other. The prerequisite to perform this procedure is for the variables to possess linear correlation as well as exhibit high degree of correlation with each other. This model's lay-observer ratings converge with between-observer ratings and self-reports on both structure of personality traits and standing of individuals on trait dimensions. Expert ratings and behavioral observations further support the model.

Validity of OCEAN

Every psychological test or measurement tool is designed to measure a specific construct, which can be abstract or complex, like personality traits. The key is that the measurement tool must accurately reflect the essence of that concept. Validity refers to the extent to which a study is measuring what it is supposed to be measuring. Construct validity is grounded in the theory behind the construct being measured. This means that the construct should be defined in a way that is consistent with the theoretical framework. Two distinct techniques: peer ratings - having people evaluate their peers' qualities and behaviors, and self-reports - people describing themselves, were used (Costa & McCrae, 1987) to validate the OCEAN traits.

Nomothetic Approach of the Five Factor Model

The approach that looks for common patterns in people by using methods like experiments and personality tests is known as nomothetic. It focuses on clear, repeatable results that can apply to large groups. Personality psychology uses this approach to find universal traits, like those in the FFM, making it useful for research across different cultures and groups.

Comprehensiveness of the model

The five domain traits, commonly abbreviated as OCEAN or CANOE, is an outcome of several decades of studying and understanding human personality. Some claimed that five factors were too many, while others said they were too less. A few researchers also proposed additional factors. All these claims have been resolved, and it stands today that the FFM is a broad framework, and that more specific traits can be explored within each factor.

Domains and Facets of OCEAN

The FFM is based on research that analyzed how people describe themselves and others. The model suggests that personality is made up of five key dimensions, represented by the acronym OCEAN or CANOE. They are Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism. Each of these domain traits have six facet scales (Costa & McCrae, 1995), see Table 1.

Table 1 *Domains And Facets Of Five Factor Model*

Domains	Facets
Openness	Fantasy
	Aesthetics
	Feelings
	Actions
	Ideas
	Values
Conscientiousness	Competence
	Order
	Dutifulness
	Achievement striving
	Self-discipline
	Deliberation
Extraversion	Warmth
	Gregariousness
	Assertiveness
	Activity

	Excitement seeking
	Positive emotions
Agreeableness	Trust
	Straightforwardness
	Altruism
	Compliance
	Modesty
	Tender-mindedness
Neuroticism	Anxiety
	Angry Hostility
	Depression
	Self Consciousness
	Impulsiveness
	Vulnerability

Openness involves intellectual curiosity, imagination, and appreciation for art and new ideas. Facets of openness implies that the individual is artistic, curious, imaginative, insightful, original and possesses wide interests.

Conscientiousness involves organization, diligence, self-discipline and goal-oriented behavior. The precise facets of this trait point to the qualities of being efficient, organized, planful, reliable, responsible and thorough.

Extraversion is characterized by positive emotions, sociability, assertiveness, and energy. The facets of this trait encompass the active, assertive, enthusiastic, energetic, outgoing and talkative nature of extroverts.

Agreeableness reveals traits like kindness and cooperation. Its facets state that agreeable people are appreciative, forgiving, generous, kind, sympathetic and trusting.

Neuroticism reflects a tendency for negative emotions and poor coping, while low levels indicate calmness and emotional stability. The facets of neuroticism talk about how the high scoring individual is anxious, self-pitying, tense, touchy, unstable and/or worrying by nature.

3. Digital Footprints and Machine Learning in Personality Prediction

Digital Footprints and Personality Traits

Digital footprints are the information and data generated through online activities. The likes, posts, friend networks, and language features, can point at qualities related to extraversion, openness, conscientiousness, agreeableness, and neuroticism. The prediction accuracy varies, e.g., openness has one of the highest accuracies (Kosinski, M et al., 2013). A meta-analysis by Azucar, D et al. in 2018 revealed insights such as extraversion associated with higher activity and larger networks, while neuroticism correlates with sharing more personal information and using negative language and that public or private account settings don't significantly affect prediction accuracy. Conscientious users are more careful about their profiles and post fewer pictures. Piedboeuf, F et al., 2019 discuss that LinkedIn, due to its professional nature, reflects a dual personality (professional and personal) of users, providing unique personality markers.

Machine Learning Techniques

Machine learning models, like XGBoost and Support Vector Machines (SVM), are commonly used for personality prediction, with XGBoost achieving the highest accuracy in some studies according to a study reported by Tadesse, MM et al., 2018. Textual and non-textual features (e.g., linguistic patterns, interaction metrics) are analyzed using techniques like Term Frequency-Inverse Document Frequency (TFIDF) and clustering algorithms to infer traits in a comparative study done by Al-Fallooji, AS and Miyazawa, A, 2022. Social media language, including the use of specific words and emotional expressions, correlates with personality traits. Language-based assessments are particularly effective for predicting openness and agreeableness. Emotion-related posts (e.g., tweets) are linked to traits like openness (positive posts) and neuroticism (negative posts).

Construct Validity in Machine Learning

Machine learning-based assessments are highly effective at predicting personality traits, but they often lack transparency in how they arrive at their results. This lack of interpretability makes it difficult to understand whether these assessments truly measure core personality traits or simply reflect associated behaviors. To address this, integrating traditional personality theories into machine learning models is essential for construct validity purposes. This combination ensures that the predictions are not only accurate but also theoretically grounded, helping to validate the psychological constructs being measured. To create robust and meaningful personality models, it's important to focus on three key aspects of validity, namely structural (ensuring that the relationship between the test items and the personality traits being measured is logically and empirically sound), substantive (verifying that the model reliably and consistently measures the intended traits across different contexts and populations) and external (confirming that the model's results correlate with real-world behaviors and other established measures of personality) validity (Bleidorn, W et al., 2019). Platforms like LinkedIn allow recruiters to infer personality traits from professional profiles, helping them assess candidates for cultural fit, leadership potential, or role suitability. Personality insights derived from social media behavior can be used to customize digital interfaces, making them more user-friendly and aligned with individual preferences.

Implication

Finding Personality Traits in Digital Footprints by Using OCEAN Features

Machine learning algorithms that use OCEAN features can discover patterns of significant personality qualities by looking at digital footprints. Highly active users with extensive networks may be outgoing and receptive to networking opportunities. Individuals showing high content engagement may be innovative and open to exploring new solutions. Positive or negative sentiment in language correlates with Agreeableness or Neuroticism. Content-sharing habits and profile management practices indicate conscientiousness and openness. Social media usage patterns, such as frequency and type of interactions, provide insights into consumer motivation and engagement tendencies. Extraversion and Openness were the most reliably predicted traits, particularly when using social network features. Users with dense networks and high activity levels can be targeted with social, event-based ads or experiential marketing campaigns. Linguistic features indicating creativity or curiosity can guide personalized recommendations for innovative or niche products. Insights from emotional language use can tailor campaigns to emphasize security and positivity.

Predictive Accuracy of OCEAN Traits in Social Network Analysis

Advances in models like XGBoost show promise for improving prediction accuracy, especially with richer datasets combining multiple social media platforms. The language-based model successfully predicted the Big Five personality traits, with a strong agreement to both users' responses on personality questionnaires and third-party assessments from people familiar with the users.

Value of Language-Based Models in Enhancing Personality Insights

Language analysis added distinct value, offering insights beyond informant reports, such as subtle emotional patterns or cognitive tendencies embedded in written language. Users with language reflecting curiosity or creativity (e.g., using abstract or innovative terms) can be targeted with ads for new technologies, niche products, or educational opportunities. People using negative or anxious language may respond better to campaigns that emphasize reassurance, well-being, or emotional support. Positive, empathetic language use can indicate potential leads for socially driven products or services, such as charitable causes or community-focused events.

Consumer Psychology: A Multidisciplinary Perspective

Machine learning models that analyze social media profiles to predict personality traits based on the OCEAN model offer a valuable way to understand consumer behavior. By looking at digital footprints like user engagement, content-sharing, and language use, businesses can gain insights into traits such as Extraversion, Openness, and Agreeableness. These insights can improve customer relationship management (CRM) by helping businesses better understand purchasing habits, brand loyalty, and emotional connections. Research shows that personality traits are key predictors of consumer preferences, making it easier to personalize marketing strategies and enhance customer experiences. Consumer psychology is a multidisciplinary field that investigates motivation, affect, and social influence in consumer behavior (Haugtvedt, C et al., 2018). It is the study of how consumers' perceptions, feelings, and values interact with their decisions related to products and services in a global context (Cathrine, V et al., 2016). Financial aspects are strongly influenced by personality traits - specifically, conscientiousness shows positive correlations with financial literacy, income, and net worth (Exley, J et al., 2021), while being negatively correlated with financial risk tolerance (Mukhdoomi, A.M. & Shah, F.A., 2021). Conversely, extroversion positively correlates with risk tolerance (Mukhdoomi, A.M. &

Shah, F.A., 2021) but negatively with financial literacy. Neuroticism generally shows negative correlations with financial metrics, including income and net worth(Exley, J et al., 2021). Environmental consciousness in consumption is particularly influenced by personality traits, with openness and extraversion driving positive preferences for eco-friendly products, while agreeableness and neuroticism tend to dampen such preferences (Soliño, M, Farizo, B.A., 2014). Word-of-mouth behavior is strongly associated with extroverted, conscientious, and agreeable personalities, who typically report higher satisfaction with their purchases (Butt, A et al., 2021). In the fashion domain, while demographic factors play a role, personality traits account for a much larger variance in shopping proneness - with agreeable, extroverted, open-minded, and emotionally stable individuals showing greater inclination toward fashion shopping (Roy, S et al., 2016). Regarding technological adoption, particularly in automobiles, traits like imagination, agreeableness, and social factors positively influence attitudes toward advanced technology, subsequently affecting willingness to pay (Bhat, U.M. et al., 2022).

4. Conclusion

The OCEAN personality model represents a pivotal breakthrough in understanding human behavior through digital footprints and this framework provides a robust theoretical foundation for computational personality assessment, bridging traditional psychological research with cutting-edge artificial intelligence. With the support of machine learning techniques, researchers can now extract nuanced personality insights from social media profiles with remarkable accuracy. To implement machine learning-based personality assessments (MLPA) effectively, it is essential to ensure structural validity by analyzing digital features to differentiate expected and unexpected patterns and examining their consistency across platforms and over time. Substantive validity requires enhancing reliability, validating models on diverse datasets and ensuring consistent links between features and traits. External validity involves aligning predictions with real-world behaviors, ensuring traits are not overly correlated, and combining MLPA with traditional methods for robust validation. Digital footprints offer unprecedented opportunities for understanding individual psychological characteristics, enabling more personalized approaches in fields like marketing, recruitment, and consumer psychology. For customer relationship building and management, tracking OCEAN traits through digital footprints enables targeted profiling: openness aligns with diverse interests and innovation-focused leads, conscientiousness identifies reliable and task-oriented individuals, extraversion aids in engaging social and networking-based leads, agreeableness supports community-focused and CSR campaigns, and neuroticism informs well-being or stress-relief solutions. This approach transforms targeting in sales, marketing, HR, and UX design, enhancing precision and insight.

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