



Commentary

Artificial Intelligence and Personality Tests: Connecting Opportunities

Eva Lahuerta-Otero^{a,b*} | Rebeca Cordero-Gutiérrez^c

^aFaculty of Business and Economics, University of Salamanca, Salamanca, Spain

^bIME Multidisciplinary Enterprise Institute, Salamanca, Spain

^cFaculty of Computer Science, Pontifical University of Salamanca, Salamanca, Spain

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1. Introduction

The advent of artificial intelligence (AI) has presented marketers with a unique opportunity to know more about their audience than ever before. By using AI to predict personality traits and purchasing behavior, brands can begin to understand how people behave and respond to marketing messages. Artificial intelligence is a significant technology that has revolutionized how humans interact with computers and electronic devices. AI is used for everything from personalized shopping experiences to content creating and targeting. It's also one of the most exciting changes impacting digital marketing. It uses algorithms to anticipate customers' needs, which is particularly helpful for digital marketers looking to improve their marketing efforts through better targeting and communicating messages.

When it comes to AI and marketing, the goal is to use artificial intelligence to predict personality and human behavior so that we can understand how people think and act, and then connect with them in a unique and personalized way. Using machine learning methods, you can train an AI to learn from your data, which is usually customer data and get to know your audience better. This and many other recent challenges can find robust answers through the combination of AI and psychology. AI tools perform tasks at a much greater

speed, scale, or degree of accuracy than humans, so these algorithms can eventually evolve into commercial solutions that companies can use, opening a new host of developments.

This article will explore how artificial intelligence is currently being used to predict personality traits of website visitors for digital marketing purposes as well as provide some examples of how it can be used.

2. Big Five personality model

The Big Five personality model (also called the Five Factor Model of Personality) (Digman, 1990; McCrae & John, 1992) is one of the reliable, predictive, and efficient personality assessment models (Ahmad & Siddique, 2017) and has been used in multiple research projects to analyze users in social media contexts (Kim & Kim, 2018; Al-Samarraie et al., 2017; Celli et al., 2016; Eftekhari et al., 2014; Ross et al., 2009). It is impossible to find two individuals alike as each has specific personality traits. Individuals are different from each other but may have similar traits (Sitaraman, 2014) and they interact daily on different social media (from social networks such as Facebook, Twitter, LinkedIn, and Instagram, to blogs or websites of different kinds). Every time an individual communicates through these media, their language generates a great deal of psychological content, and



Corresponding author:

Eva Lahuerta-Otero | eva.lahuerta@usal.es | Faculty of Business and Economics, University of Salamanca, Salamanca, Spain. IME Multidisciplinary Enterprise Institute, Salamanca, Spain.

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their use generates a valid and rapid personality assessment (Gupta et al., 2017). This model establishes five traits that represent the personality of a user (extraversion, agreeableness, conscientiousness, neuroticism, and openness) (Wehrli, 2008). Briefly, extraversion deals with how easily users engage in social interaction. Agreeableness refers to cooperation, kindness, and peer acceptance. These two variables associate positively in the literature with social interaction (Anderson et al., 2001; Wehrli, 2008). Conscientiousness refers to users trying to be careful, responsible, and organized. Therefore, they are expected to limit their presence on social network sites to avoid distraction (Wehrli, 2008). Neuroticism deals with an individual's anxiety, sadness, embarrassment, or depression and it is negatively related to social relationships (Klein et al., 2004; Wanberg et al., 2000). Lastly, openness measures the propensity of individuals to display imagination or an open mind, which would relate positively to the use of social technologies (Wehrli, 2008). Each of these five traits can determine the online behavior that different individuals will develop.

Language is the most common way to express our feelings, thoughts, and inner emotions so that others can understand us. This is where psychology and communication come together (Tausczik & Pennebaker, 2010) and in turn, allow the marketing area to understand the customer to satisfy them. The first works on predicting personality from language were based on dictionary-based characteristics such as Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al., 2007). Argamon et al. (2005) pointed out that personality could be detected using certain words, in line with later works by Argamon et al. (2009), Mairesse and Walker (2006), or Mairesse et al. (2007). Subsequent studies equally confirm that the best way to predict personality traits is through overt vocabulary (Iacobelli et al., 2011).

Different algorithms have been used to predict personality through texts in different platforms or formats obtaining very acceptable percentages, others have approximated these personality traits through handwriting (Ahmad & Siddique, 2017; Gupta et al.,

2017; Carducci et al., 2018; Kunte & Panicker, 2019; Wu et al., 2020; Rohit et al., 2020). This paper investigates the success rate percentages of an AI tool developed by Versen (Cognitive Data S.L), a Spanish firm that, thanks to advances in the field of personality prediction, was able to develop an algorithm that predicts personality based on language. Versen decided to opt for this type of prediction because of its greater cross-cultural stability concerning other types of variables studied in the literature. Such a tool is based on a predictive artificial intelligence model performed under Convolutional Neural Network techniques (Albawi et al., 2017; Gu et al., 2018; Li et al., 2021; O'shea & Nash, 2015), a type of Deep Learning, with natural processing techniques such as Bi-Directional Encoder Representations From Transformers (Bevilacqua & Navigli, 2019; Brown et al., 2020; Ji et al., 2021; Kaliyar, 2020; Ravichandiran, 2021; Sun et al., 2019) and using the Python programming tool with libraries such as Keras, Torch and Sklearn (Bird et al., 2009; Vasiliev, 2020). The model has been developed with a database of more than 500,000 records, including variables linked to the score in the Big Five model and texts written by different users. The tool has been trained to easily approximate these personality traits of individuals through text analysis.

3. AI tools to predict personality: an exploratory analysis

The objective of this preliminary study is to scientifically validate the predictive power of the tool and to lay the foundations for future research through this exploratory study. The detection of problems, errors, or goodness of fit of the tool will contribute to the improvement of its efficiency and will contribute to future investigations to develop complex causal analyses that allow linking the personality traits of individuals to behaviors both in the marketing field and in the business management area. To answer the proposed objectives, we conducted a questionnaire with a reduced version of the Big Five model composed of 50 items (obtained from an adaptation of the article by Goldberg (1992), and translated into the native language of the users of the sample, in our case, English and Spanish). In addition, participants were asked for

a text of approximately 200 words written by themselves in their first language. This text was processed with the tool to perform the detection of personality traits through textual analysis. Next, the results will show whether the tool under study can detect the personality of the users through these texts, and the accuracy percentages in relation to the scores obtained in the Big Five test. The analysis shows that Versen’s tool can reliably capture the personality traits of individuals, offering high percentages of similarity.

Analyzing the data in more detail, we can see that openness is the trait that obtains the lowest percentage of correct answers with 67.65%. Despite being the lowest result, it can be seen that, even with a small sample, the tool can obtain correct percentages well above 50% for this personality trait. In contrast, the agreeableness trait is detected by the tool at 82.35%. The traits extraversion, conscientiousness, and neuroticism are detected in the texts written by the users in percentages above 75%, namely 76.47%, 76.47%, and 79.41% respectively. In addition, the efficiency percentages also vary according to gender. Thus, in the case of women, the percentages of effectiveness increase up to 83.33% in neuroticism and conscientiousness and decrease in the case of men. And, on the other hand, the efficiency percentages rise in the case of men for the agreeableness trait (with a percentage of over 86%). For the openness and extraversion traits, the percentages between genders are similar.

Table 1. Accuracy percentages comparing Versen AI tool and the Big Five personality test

	Total	Male	Female
Extraversion	76.47%	77.27%	75.00%
Agreeableness	82.35%	86.36%	75.00%
Conscientiousness	76.47%	72.73%	83.33%
Neuroticism	79.41%	77.27%	83.33%
Openness	67.65%	68.18%	66.67%

4. Results, opportunities, and further research

The results show that the tool developed by Versen demonstrates excellent success rates. This finding greatly facilitates the automatic detection of personality traits through small texts elaborated by individuals

in different contexts, for example on social media posts, emails, or LinkedIn bios. These benefits obtained by the tool provided by Versen are not invasive, but on the contrary, is a fast and easy method that can be adapted and applied in different situations and contexts. Much of the success of this solution lies in the fact that users naturally write their texts or messages without being able to hide or manipulate their true personality, making it a reliable mechanism to get to know the deepest feelings of an individual.

This technological solution offers endless practical applications in the business context; thus, it can be used both for attracting talent in recruitment and selection processes or for example and from a marketing point of view, it allows the configuration and creation of extremely customized content and commercial messages current or potential customers that will have greater engagement, increasing conversion rates.

Therefore, artificial intelligence and personality research make a natural fit. Now marketers have the opportunity to connect consumers’ personality features with the way they respond to different marketing messages. And not only that. AI can help build marketing strategies bringing better engagement and meeting their needs more effectively.

Although advances in AI and machine learning have accelerated over the last decade, there still remains a crucial gap between the massive amount of data currently available and the ability to understand it. The key challenge is how to integrate unstructured customer data into a comprehensive picture while protecting the privacy and ensuring that all data is responsibly used. The opportunity here is to make accurate predictions without the need for complex data variable collection but, since this exploratory study uses a small sample, future research should validate the reliability of this tool with larger and more varied data from different sources to confirm the robustness of results.

ORCID

Eva Lahuerta-Otero

 | <https://orcid.org/0000-0003-4019-8659>

Rebeca Cordero-Gutiérrez

 | <https://orcid.org/0000-0003-3352-7696>

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