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Predicting User Behavior in e-Commerce Using Machine Learning

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***Abstract*: *Each person's unique traits hold valuable insights into their consumer behavior, allowing scholars and industry experts to develop innovative marketing strategies, personalized solutions, and enhanced user experiences. This study presents a conceptual framework that explores the connection between fundamental personality dimensions and users' online shopping styles. By employing the TIPI test, a reliable and validated alternative to the Five-Factor model, individual consumer profiles are established. The results reveal a significant relationship between key personality traits and specific online shopping functionalities. To accurately forecast customers' needs, expectations, and preferences on the Internet, we propose the implementation of two Machine Learning models, namely Decision Trees and Random Forest. According to the applied evaluation metrics, both models demonstrate fine predictions of consumer behavior based on their personality.*

***Keywords*: *Machine learning, Personality, Big Five, Human factors, User behavior, Decision making, e-Commerce.*

1. Introduction

Each individual possesses distinct characteristics that align with their personality and behavioral traits. Similarly, they have and apply their special approach in the decision-making process, because personality significantly influences human choices and interests. Thus, considering that people with roughly similar personal profiles own also the same behavior and habits, it could be assumed that they also have similar behavioral style, priorities, and attitudes in the process of online shopping. However, in the field of E-commerce, instead of classical market segmentation, personalization based on Machine Learning (ML) is an effective and innovative method of users' classifying that applies approaches providing a more efficient forecast of consumers' specifics and preferences.

Building upon the aforementioned points, the objective of this paper is to observe the way users with similar personality profiles behave in the process of online purchasing and how the specific traits they own affect their preferences and decisions. Accordingly, to estimate to which extent the different users rely on certain online store features in the process of decision-making are formed several mathematical equations that adopt the main personality domains (openness to experience, conscientiousness, extraversion, agreeableness, and emotional stability) as input and yield a value showing how important to the customers is each one of the observed web shop's functionalities.

The study's findings demonstrate that certain functionalities of e-commerce websites are preferred by specific user groups. By understanding consumers' personality traits and employing Machine Learning techniques to predict user preferences, it becomes possible to create models that accurately depict user behavior and decision-making in the online commerce domain. Consequently, user interfaces can be personalized to better align with their expectations and requirements, thereby enhancing the overall user experience.

2. Related works

Personality is generally defined as an individual unique and relatively stable pattern of thoughts, values, priorities, and emotions that significantly impact human perception. In other words, personality influences how we process and interpret information from a specific environment and situation. It is the fundamental determinant of the individual behavior [11]. The human decision-making process is not always based on principles of rationality. This is often an outcome of careful assessment of possibilities and results. People with similar traits are observed to have a high tendency to behave in a particular way and use similar decision-making styles under certain situations [10].

Personality traits have a substantial influence on our preferences and explain the wide variety of human behaviors and decisions. At the same time, the use of ML methods allows a reliable estimation of user preferences regarding users' individual specifics. However, the existing literature on this subject in the field of E-commerce is limited, with only a few studies addressing this particular area. One of them is the research conducted by Kazemenia, Kaedi and Ganji [12], which examines the decision-making behavior in online shopping. The study involves a sample of 194 individuals and also incorporates the extraversion scale of the Big Five personality traits. It has been identified that online shoppers with a higher degree of extraversion tend to buy accessories that match the product they buy. The authors applied Multiple Linear Regression and optimized Decision Trees to make a forecast of user preferences based on their personality and decision-making style. An investigation of Bayram and Aydemir [3] which has applied the Decision-Making Style Questionnaire (GDMSQ) and Big Five Inventory (BFI) has found that extraversion has a positive relation with rational and intuitive decision-making style and a negative relationship with avoidant decision-making style. Another notable example is the TITAN project, which sought to investigate and implement personalized product and service offers in E-commerce based on users' personality profiles [4]. The authors of the project reported that the initial results are promising and indicate the validity of the innovative approach.

According to S t a c h l et al. [20], personalization based on personality can serve as an intelligent and effective method for enhancing the usability and appeal of a product or service. This approach can lead to increased usage, higher customer satisfaction, improved loyalty, and greater acceptance among users. Technology is rapidly evolving and although design patterns and trends change over time, specific users' priorities and evaluation methods of network reliability have been stable over the years. That's so because personality remains quite stable over the lifetime [2]. Personality holds relevance and applicability in various computing domains that involve the understanding or prediction of human behavior, human risk perception, and decision-making. In line with this, P o p c h e v and O r o z o v a [18] highlighted that the growing complexity of technologies is accompanied by a substantial increase in diverse risk factors on the Internet. Consequently, deeper investigation into the field of human decision-making processes becomes necessary to address these evolving challenges.

3. Empirical research

Considering the international nature of the study and the requirement for all respondents to have a thorough understanding of the survey questions (which include multiple-choice and rank-order formats), the survey has been translated into 3 languages: English, German, and Bulgarian. The survey comprises four sections, outlined as follows:

Online store features/ User preferences. The data collection is based on a set of 19 questions, classified into three different sub-categories (content and appearance, user interface tools, and risk reducers) associated with some of the key online store's features and attributes. To assess shoppers' attitudes towards each observed attribute, a five-point Likert scale measurement has been employed, ranging from 1 (never) to 5 (always).

10 characteristics that determine the personality profile. To ensure a more concise assessment of the Big Five personality domains, the TIPI test developed by G o s l i n g, R e n t f r o w and S w a n n [11] is considered more suitable. This test has demonstrated satisfactory levels of validity and reliability. With a total of only 10 items, the TIPI test effectively captures each of the five main determinants that shape an individual's personality.

Risk averseness. Observing risk perception and its significant impact in the field of e-Commerce could be defined by people's inclination to take or avoid risks and this information has an essential role when it comes to consumer decisions and behavior. However, it is important to note that this particular aspect is not a part of the TIPI test. Therefore, the results pertaining to risk aversion are beyond the scope of this paper and have been appropriately published separately [17].

Demographic analysis. The last section obtains five select demographics (age, gender, education, residence, frequency of online shopping) influencing consumers' online shopping behavior.

4. Results of empirical research

The investigation aims to draw broad conclusions regardless of consumers' national and cultural backgrounds. Therefore, the survey specifically includes respondents who have lived in over 10 countries worldwide during the previous five years at the time of the survey (Table 1). This is crucial in the context of online shopping because relocating to different places naturally influences customers' preferences, shaped by the local lifestyle, cultural perspectives, and societal structures.

All 226 participants are adults, most of them in the active stage of their lives, so the Internet takes a significant part of their daily lives (Table 1). According to data collected, 85% of respondents have a higher level of education and 66% of them state that they have a high and very high propensity to purchase online. None of the respondents indicated a lack of experience in the field of online shopping.

Table 1. Demographic data

Demographic sample	Criteria	% of Sample
Place of residence in the last five years	Bulgaria	65%
	Germany	17%
	Great Britain	5%
	USA	2%
	Spain	2%
	Denmark, Switzerland, Austria, Italy, Slovenia, Czech Republic, Australia, Netherlands, France, Russia, Canada, South Africa, Belgium, Ireland	9%
Age	18 – 30 years old	27%
	31 – 45 years old	60%
	46 – 60 years old	11%
	61 – 70 years old	2%
Gender	Man	43%
	Woman	56%
	Other	< 1%
Education	Secondary	14%
	High	85%
	No answer	1%
Online shopping frequency	Very often	31%
	Often	35%
	Sometimes	28%
	Seldom	6%

After assessment of respondents' personality profile and gathering data about the way users engage with certain features of web stores, a bivariate analysis is conducted to investigate the existence of a significant relationship between the five personality traits (independent variables) and each of the examined 19 online shop functionalities (dependent variables). For this purpose the PSPP program (GNU software) is applied, and only the significant correlations between the variables with correlation levels $p < 0.05$ are considered. Here p is the corresponding tail probability, or p-value, namely, the probability of getting a difference between the estimate and the parameter greater than or equal to that actually observed, and r (1) represents the coefficient of Pearson's correlation [23], that is a measure of the relationship between the variables x and y:

(1) $$r = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{(\sqrt{n\sum x^2 - (\sum x)^2)(n\sum y^2 - (\sum y)^2)}}}.$$

The significant relationships between the observed dependent and independent variables are set out below.

Openness to experience. Regarding the obtained results, users who score high levels of openness are prone to comment and ask questions about the considered products (r = 0.121). They enjoy engaging in discussions and sharing their thoughts and insights. Obviously, commenting provides them with an opportunity to contribute their ideas, ask questions, and learn from others.

Conscientiousness. Individuals who are high in conscientiousness tend to pay special attention to detail and strive for high-quality outcomes. As they are goal-oriented, when it comes to online shopping, they would like to have the possibility to choose between more than one alternative item and to compare their details as well (r = 0.164) [5]. Therefore, not only the product evaluation based on its specific criteria is especially important for them (r = 0.120) but also the detailed photos of offered items (r = 0.154). There are also positive significant relationships with the need to check the actual availability of items, the delivery time (r = 0.194), as well as offering different delivery options (r = 0.133). They would like to be allowed to track the order status in each stage of shopping and delivery (r = 0.176) and to be offered alternative and more secure payment methods (r = 0.226) such as PayPal for example.

Extraversion. According to the obtained data, there are positive significant relationships between extraversion and the opportunity to buy additional products and accessories, related to the already chosen item (r = 0.205) together with the opportunity to write and read comments (r = 0.110). The literature also confirms the achieved results on this topic and states that more extraversion people have a natural inclination towards expressing themselves and engaging with others. This means also a higher frequency and intensity of relationships [1].

Agreeableness. Agreeableness is a core personality trait that is typical for people who are compliant, pay special attention to products' descriptions and their informativeness (r = 0.122), to items' expert evaluations (r = 0.162), as well as to comments of previous consumers (r = 0.117).

Emotional stability. Concerning personality factor emotional stability in the context of E-commerce, there is a significant positive relationship between the offering of different delivery options (r = 0.120) and the offering of a variety of more secure payment options as well (r = 0.226). The reason for this is that emotional stability is often associated with a preference for predictability, control, trust, and reliability. On the other side, a significant negative correlation between the determinant emotional stability and the possibility for free return of an already bought item (r = –0.114) is observed. Additionally, the more neurotic and emotionally unstable people prefer to have the possibility of a free return because often it is complicated for them to cope with stressful situations [21].

5. Applying machine learning for prediction of user behavior

Although the ML models have sometimes a bad reputation because of their limited interpretability, they are also very appropriate in cases when psychological constructs are used as input features or predictor variables to make predictions or classifications related to human behavior or psychological outcomes. The reason for this is that these algorithms typically treat data as unknown and prioritize predictive accuracy. Consequently, within the scope of this study, two regression models – Decision Trees and Random Forest, have been employed to forecast users' preferences based on their personality profiles.

The implementation is carried out in Python, specifically, version 3.8 (64-bit), and both regression models have been evaluated by applying three of the most common metrics for evaluating predictions on regression machine learning problems [16] – the Mean Absolute Error (MAE) (2), which is the average of the absolute differences between predictions and actual values, the Mean Absolute Percentage Error (MAPE) (3) – considered as a loss function, MAPE defines the error expressed as a percentage of the actual value, providing a measure of model evaluation, and the Root Mean Squared Error (RMSE) (4), which is a measure of how concentrated the data is around the line of best fit. For all the above-mentioned evaluation metrics, the lower the value, the better the model's performance:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|, \tag{2}$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{y_i} \times 100, \tag{3}$$

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n}\frac{1}{n}(y_i - \hat{y}_i)^2}. \tag{4}$$

The initiation of the implementation process for both regression models begins by importing the required libraries. Following that, the data is divided into separate training and testing datasets. Specifically, 70% of the data is utilized as the training set, while the remaining 30% is allocated as the test set.

The implementation of the Decision Tree has utilized the *scikit-learn* library, where in regression, the evaluation returns the value of Mean Squared Error (MSE). In other words, the tree selects the result with the smallest MSE value (Fig. 1).

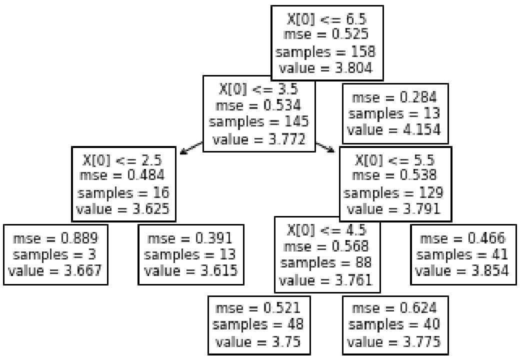

Fig. 1. Decision Tree – the importance of product description as a result of conscientiousness

The Decision Trees method offers several advantages. It is capable of handling both numerical and categorical data, making it versatile for various types of datasets. It requires minimal data preparation, saving time and effort in the preprocessing stage. Decision Trees are well-suited for multi-output problems, making them applicable in scenarios where multiple outputs need to be predicted. Additionally, the simplicity of Decision Trees allows for easy understanding and interpretation, as the trees can be visually represented. However, there are certain disadvantages associated with decision-tree learners. One drawback is the potential for creating over-complex trees that fail to generalize the data effectively, resulting in overfitting. Additionally, decision-tree learners may generate biased trees if certain classes dominate the dataset. Furthermore, Decision Trees are not well-equipped to express complex concepts like XOR or multiplexer problems, which can pose challenges in learning such concepts [16].

The implementation of Random Forest also involves the *scikit-learn* library, wherein the number of trees is specified as 150 (*n_estimators* = 150). Similar to the Decision Tree, in order to measure the quality of the splitting function, the algorithm utilizes MSE (Fig. 2).

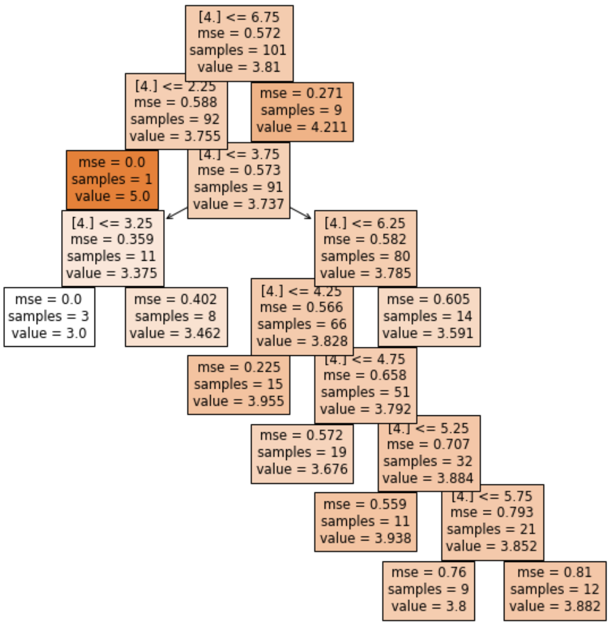

Fig. 2. Random Forest – the importance of product description as a result of conscientiousness

Random Forest is indeed a highly suitable ML algorithm for personality research due to its unique characteristics. It constructs and merges multiple decision trees, typically trained using the “bagging” method, in order to attain enhanced prediction or classification accuracy and stability. A notable advantage of Random Forest is its capability to mitigate overfitting in decision trees, leading to improved predictive performance. Additionally, this versatile algorithm effectively handles both categorical and continuous values, and can automatically handle missing values present in the data, further enhancing its usefulness in research applications.

Additionally, the Random Forest algorithm offers the advantage of not requiring data scaling as a preprocessing step. It is often perceived as relatively easier for hyperparameter tuning compared to some other algorithms [16]. However, it is important to note that Random Forest does have certain drawbacks related to computational requirements and resource usage. When dealing with large datasets or a high number of trees, significant computational power is necessary to effectively combine their outputs.

Equations have been developed based on the identified significant relationships, where the personality traits are considered independent and the preferences of the users as dependent variables. Table 2 illustrates the average values of the evaluation metrics for all 16 significant relationships. It may be summarized that both ML models employed in this study have yielded remarkably similar predictions when considering the evaluation metrics used. These results, as categorized by Lewis [13], can be considered highly suitable for the intended purpose.

Table 2. Average values of the evaluation metrics

Evaluation metric	Machine learning model	Average value, %
MAE	Decision Trees Random Forest	0.79 0.94
RMSE	Decision Trees Random Forest	0.97 0.97
Accuracy regarding MAPE	Decision Trees Random Forest	72.44 72.48

The observed relation between users' personality profile and their preferences is complex and can involve various non-linear effects and interactions. Flexible machine learning models, such as deep learning or ensemble methods like Random Forest, have the potential to capture and model these complexities, which can lead to improved predictive performance in understanding and predicting user preferences based on personality measurements.

As the **optimization** of any ML model is a very important step in the process of solving the global problem, it is proposed and implemented an optimization of **Random Forest in combination with TPOT (Tree-based Pipeline Optimization Tool)** [16], which uses Genetic Programming (GP). This powerful approach explores and evolves different pipelines for a given problem and recommends one with an optimal cross-validated score after a specified number of generations.

In the proposed optimization process, TPOT has to evaluate 1100 configurations as the population size is set to 100 and the number of iterations to the run pipeline optimization process is set to 10 (population_size + (generations × offspring_size)). By default, the number of offspring to produce in each genetic programming generation is equal to the number of population size. In this configuration, Random Forest has shown improvement in terms of MAPE for 14 out of the 16 significant relationships. On average, the accuracy has improved by 0.55%, increasing from 72.48% to 72.79% accuracy across all 16 significant relationships. Concerning the values of MAE and RMSE, there is also a slight improvement, which is varied across the different relationships.

6. Results and discussion

Openness to new experiences is associated with traits like active imagination, intellectual curiosity, and being open to considering novel ideas and trying new things. Individuals who score high on the openness trait tend to receive more opportunities to share their experiences, thoughts, and opinions with others because they are often interested in hearing different viewpoints and seeking validation for their ideas. They value the process of exchanging information with fellow users, particularly when it comes to clarifying issues or gathering insights related to chosen products and services before purchase decision-making [6, 21]. The results claim that people high in openness have a strong desire to comment and ask questions about the considered item to ensure their quality. In the current study, the Random Forest model demonstrates one of the lowest predictions regarding MAPE (53%). Nevertheless, according to L e w i s [13], this can be still considered an acceptable forecast.

More conscientious people are careful, diligent, well-organized, purposeful, and dutiful [5]. They also tend to pay special attention to details and prefer to have the ability to choose between alternative products. These assumptions correspond to achieved results – Random Forest forecast accuracy of 76% based on MAPE.

Based on the obtained data, when it comes to online shopping, the buying journey could deliver a greater buying experience if online users have the opportunity to see more detailed item photos (90% accuracy of the MAPE forecast) and also if the product evaluation is based on different sub-criteria (80% accuracy). Conscientious individuals are driven by goals and for that reason, they set clear objectives and are committed to completing the tasks associated with those goals [1]. Consequently, it becomes crucial for them to have the ability to check the current availability of items and their delivery time (with a forecast accuracy of 70%). This feature allows conscientious individuals to plan and organize their tasks effectively, ensuring that they can acquire the desired items within the desired timeframe, aligning with their goal-oriented nature. It is important for them to have different delivery options (78% accuracy) before their final purchase decision. These users tend to track their order status and use alternative and more secure payment methods. By this criterion, Random Forest achieves 79% MAPE forecast accuracy.

Extraverts are outgoing, enthusiastic, and talkative, and enjoy being around people, engaging in social activities, and initiating conversations. They also express their emotions openly and seek out exciting and stimulating experiences. On the other side, introverts are generally more reserved and prefer quiet environments [22]. Based on the results of this study, it might be summarized that more extroverted individuals would rather react positively if they gain additional articles or accessories appropriate to the already selected product, whereby after optimization Random Forest achieves 71% accuracy of MAPE. For these individuals, the ability to access and contribute to user comments is considered essential in their purchase decision-making process. They rely on the opinions and experiences shared by others to gather information and form judgments about products or services before making a purchase.

Agreeable individuals, who are known for being cooperative and considerate of others, tend to exhibit a greater openness to the perspectives of fellow customers.

They are inclined to be receptive to the opinions and experiences shared by others, as they value gathering information that can assist them in making well-informed decisions. This cooperative nature drives them to seek out a variety of viewpoints and insights from fellow customers before making their own choices. Reading comments and reviews allows them to tap into the collective wisdom of other customers, considering their feedback and experiences before finalizing a purchase [7] (Random Forest forecast accuracy of 81% based on MAPE). Individuals who are more agreeable may pay particular attention to the products' description from the perspective of its accurate and comprehensive information (84% MAPE forecast accuracy) and place importance on others' opinions and value expert evaluations (74% MAPE forecast accuracy).

Emotionally stable people, who exhibit low levels of neuroticism, tend to display confident and calm behaviors and often approach problem-solving in a rational manner. About current findings, they value trust and reliability in their interactions and transactions and for this reason, they appreciate having different delivery options and more secure payment methods, whereby the Random Forest Algorithm achieves over 75% accuracy of the MAPE forecast. While emotional stability is characterized by lower levels of stress and anxiety, neurotic people may have difficulty regulating their emotions and controlling their emotional responses to various situations [21]. This assumption explains why users who are more neurotic tend to have a free item return.

7. Limitations and future research

Each investigation has its limitations, especially when it comes to human-centered research. It is crucial to acknowledge and take into account these limitations when interpreting the findings and implications of study results. Although the survey sample has a multicultural background and consists of 226 respondents living in more than 10 countries over the world, most of them are representatives of the European culture, which does not fully represent the diversity of the world population and limits the application of the obtained research findings to some extent within a particular cultural context.

Numerous cross-cultural studies have explored the universality of the Big Five traits, and the framework is widely accepted as a model for describing the universality of personality traits across different cultures. Friedman and Schustack [8] suggests that personality studies may only be applicable in environments with similar cultural and social norms. On the other hand, other authors argue that cultural differences within societies primarily arise from the translation of measurement tools and genetic variations among participants [9].

It is advisable to conduct replications of studies before widely applying the achieved results in practical settings. Replication studies help validate the robustness and generalizability of findings across different samples and contexts. In the field of e-commerce, one way to enhance the validity of research results is by incorporating supplementary eye-tracking tests. Eye-tracking can provide valuable insights into various aspects of an individual's cognitive processes, attention allocation, and visual perception. By utilizing eye-tracking technology, researchers can gather objective data on how individuals interact with e-commerce platforms, which elements attract their attention, and how they navigate through the website or product pages. These insights can offer a deeper understanding of user behavior and inform the design and optimization of e-commerce platforms to enhance the user experience and facilitate decision-making processes.

As the uncertainty is increasing with the rapid technology change, future research should include new problem situations in interactions between different types of risks in the field of e-Commerce, such as conflict (collision) or amplification (resonance) to varying degrees between risks. According to Peneva and Popchev [14, 15], new and unknown systemic risks could be formed in such wise, which can manifest themselves in hierarchical or complex multi-connected behavior in cyberspace and a fuzzy logic-based solution could be applied to describe the decision-making process analogical to the humans' decision-making, whereat different alternatives are considered [19].

Future research in this field should focus on exploring the implicit extraction of user personality in e-Commerce, aiming to improve its accuracy. It is crucial to investigate methods that can effectively capture and analyze implicit signals from user behavior, such as browsing patterns, purchase history, and interactions with the platform. By refining these techniques, a deeper understanding of user personality traits can be achieved, enabling personalized recommendations, targeted marketing strategies, and improved user experiences. Throughout the research process, it is paramount for researchers in this relatively unexplored field to adhere to legal and ethical norms. Respecting user privacy, obtaining informed consent, and handling data securely and responsibly are essential considerations. The results obtained from such studies should be utilized solely for the benefit of individuals and society as a whole, aiming to enhance user experiences, inform decision-making processes, and contribute positively to the field of e-Commerce. By upholding legal and ethical standards, future research can pave the way for advancements in understanding user personality in e-Commerce while ensuring the protection and welfare of individuals and their data.

8. Conclusion

The study successfully achieved its objective by demonstrating that understanding consumers' personalities can provide valuable insights for predicting their preferences and behaviors in the context of e-Commerce. By combining personality assessment with Machine Learning techniques, predictive models can be developed to comprehend and anticipate consumer behavior in e-Commerce settings. The study's results indicate that certain e-Commerce functionalities are favored by specific user groups, thereby enabling the possibility of personalizing the user interface to better meet their expectations and needs.

The application of personality assessment and predictive techniques in these areas aims to enhance our understanding of user behavior, improve decision-making processes, enhance customer experiences, and drive business success. As the user-centric approach continues to shape economic and social processes, the integration of personality knowledge and predictive techniques will likely play an increasingly significant role across various scientific fields and industries, including Strategic Management, Information Risk Management, Human Resource Management, Marketing and Advertising, Social Commerce, and e-commerce.

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