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Risk Averseness and Emotional Stability in e-Commerce

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Abstract**:** *The study aims to examine the issue of the relationship between Emotional stability, one of the fundamental personality determinants, and users' Risk Averseness, on the one hand, and user behavior in the field of e-Commerce, on the other hand. In the beginning, a brief overview of today's primary benchmark for the measurement of human personality – the Big Five Model is proposed. A study with 226 participants has been conducted for the aim of the research, based on the TIPI test. The TIPI test is a validated and abridged version of the Five-Factor model. The result of the conducted survey confirms the existence of significant relationships between personality determinant Emotional stability and consumer's Risk awareness, on one side, and some of the observed main functionalities of the online stores, on the other side. Two regression models of the field of Machine Learning* (*Linear Regression and Random Forest*) *have been implemented to make a reliable forecast about the user's preferences in the process of online shopping. The conclusions made rely on the obtained results and analysis.*

Keywords**:** *Personality, emotional stability, risk averseness, TIPI, machine learning, e-Commerce, consumer behavior.*

1. Introduction

As each person is different in terms of his or her personality traits, identifying individuality in terms of consumer behavior becomes an invaluable asset, which helps companies to create a revolutionized marketing strategy and to provide more personalized solutions, services, and experience for their customers. More attention should be paid that personality may be defined as the underlying cause not only of the general shopping behavior and perceptions but also generally of our choices, perceptions, and the way we deal in different situations [29].

Thus, combining personality insights and modern technologies could be beneficial for consumers and businesses, as well. This enables providing of higher-quality services, develops a seamless shopping experience, and eventually successfully leads to an increase in customer satisfaction.

The study aims to investigate the relationship between Emotional stability and users' Risk Averseness as personality traits, on the one hand, and user behavior in the field of e-Commerce, on the other hand. Based on the obtained results, it also aims to create models for reliable prediction of consumer preferences and behaviour in the purchasing decision-making process in the field of e-Commerce.

2. Personality measurement

In psychology, there are many theoretical approaches and models, involving different concepts about the way the human develops and forms, but today's primary benchmark is the Five-Factor Model (also known as the "Big Five Model") [3, 10]. It states and measures human nature, as a result of five mainly biological-determined domains (Openness to experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism/Emotional stability) [9], which contains additional aspects explaining in detail the individual's behavior. However, unfortunately, this framework is not always applicable due to its length, for example, in the context of e-commerce, when almost instantaneous user identification is required. Therefore, the literature presents several shorter, but validated questionnaires, which also successfully apply the Traits theory of personality including the HEXACO model [1], the RIASEC model by Holland [12], and for example, the Ten-Item Personality Inventory by Gosling et al. [10] based also on the main five personality dimensions but including only ten elements.

3. Risk averseness and personality

As personality is a psychological construct explaining the wide variety of human behavior it is also a good starting point for predicting customer behavior – especially in electronic markets [15], where along with convenience in the process of online shopping, some users are often cautious, and the lack of trust is the main reason for this. Therefore, when the consumer is feeling uncertain about decision-making, he/she needs more information to reduce perceived risk and to evaluate all alternatives, but at the same time, keeps the framework of his expectations [15]. In turn, the risk is considered even as a critical explaining factor in the field of e-commerce influencing the decision-making process and choices [20], which is also a function of basic individual characteristics such as gender, age, education, income levels.

4. Related works

Previous research on single components of the five factors and computer-mediated communication led to diverse findings. Considering that the Big Five Model is one of the major frameworks currently used in the field of psychology [3, 9], various authors investigate the relationship between personality and differences in utilization of the Internet. Although all five individual determinants correlate with problematic internet use in general, authors maintain the existence of a link between Extraversion and Internet usage [11]. In turn, Kayis et al. [13], Cao and Su [2], and Kumar and Singh [18] point out that the relationship between Internet use and Neuroticism appears the most established. Moreover, T s a o and C h a n g [29] maintain that from the viewpoint of e-commerce a neurotic person may be more sensitive, and it is harder for him to control his emotions and purchases on a whim, maybe because the neurotic people view technology advances as stressful and this trait is usually negatively related to acceptance. In the field of social media, emotional users tend to use the Like function more frequently [15].

Personality remains quite stable over the lifetime [3], users' priorities and evaluation methods of network reliability are stable over the years, although design patterns and trends change over time. Since different types of personality traits make people distinctive in their behavior and preferences, this also means that everyone takes decisions differently – some people rely on their intuitions, while others prefer to discuss their choices with friends or carefully consider various alternatives [14]. In this regard, from the point of view of e-commerce, each user relies more heavily on certain features of the e-store to make decisions and pays less attention to others.

In some studies, online customer behavior is analyzed considering not only some of the main individual determinants but also in terms of risk perception and trust [20]. According to P o p c h e v and O r o z o v a [25] the complexity and mutual involvement of these emerging technologies are accompanied by a significant increase of the risk factors and risk perception on the internet, which requires investigation and decision-making about the risk. Here it should be also mentioned that risk propensity, so called risk-taking tendency, has a mediating role between personality and risk perception. It actually measures the extent to which someone would avoid risk and would pay more attention to the negative consequences and possibility of loss or, on the other hand, he would take a risk and would focus more on the potential benefits [5]. Considering all possible risks, in the context of e-shopping users rely not only on traditional sources of information but mostly on product ratings and comments that significantly affect people's attitudes [20].

According to M i y a z a k i and F e r n a n d e z [20], the consumers detect risk not only in the credibility of online information, but they also associate it with the quality of chosen product and financial transactions, as well as with confidentiality of personal data and deficiencies existing in a security system. Consequently, to allay customer fears, companies should present an interface that compensates for exciting risks through features designed to increase the trust – security policies, help buttons, and customization features.

5. Methodology of empirical research

For the aim of the current study, a survey is applied as a tool for a primary data collection, which is randomly distributed to 250 people via e-mail communication in combination with a personal contact on a social network. The questionnaire is translated into three languages (Bulgarian, English, and German), as the project requires all respondents to be acquainted in detail with the meaning and content of the questions, which are multiple-choice and rank order. 226 of all respondents (90.4%) filled in it accurately and completely online. According to the literature, the achieved sampling size meets the needs of the current study, so in the end significant conclusions on the researched problem could be reached [27]. The study includes four sections as follows.

- **Section 1. Online store's features and elements/ User preferences.** The respondents are asked to answer 19 questions related to some of the main web store's features and elements. Information about consumers' preferences, behavior, needs, and requirements is collected, whereupon all the questions are organized into three subgroups – Content and Appearance, User Interface Tools, and Risk Reducers [21]. The assessment of each of the observed elements is according to a five-point position of the Likert type (from 1 = never to 5 = always).
- **Section 2. Assessment of determinant "Emotional stability".** Although the Big Five Model is today's primary benchmark for personality measurement, which is strongly applicable in all major cultural regions of the world [9], due to its significant length the original structure is inapplicable in the context of e-commerce. For this reason, we consider as more appropriate to apply a brief measure of the Big Five personality domains – Ten Item Personality Inventory (TIPI) by Gosling, Rentfrow and Swann [10] to assess respondent's level of Emotional stability. The frame reaches adequate levels of validity and reliability and consists of only 10 elements (two descriptors giving information about each of the five personality determinants).
- **Section 3. Risk averseness.** Risk perception is a critical factor, which defines a person's current tendency to take or avoid risks and has a significant role in consumer's decisions and behavior. Considering this issue, we apply in the current survey a Risk Propensity Scale by Donthu and Gilliland [5] including only three elements to measure participants' risk perception. The lower value of result is associated with a higher level of risk awareness, while higher – with a lower level of risk awareness (i.e., higher level of risk avoidance).
- **Section 4. Demographics analysis.** In its last section, the inquiry provides five demographic questions related to age, gender, education, citizenship, place of residence, and the frequency of online shopping as well.

6. Analysis and results of empirical research

Demographic profile. Based on data received neither men (43%) nor women (56%) have priority in the sample. Additionally, it should be noted that the survey participants are representatives of more than 10 countries (Europe, North America, Australia, and Africa) and so the research is not concentrated on a certain geographical area or consumers' national and cultural background.

More than half of the survey's respondents (65%) have a Bulgarian origin and live in the country at the time of the study. The rest of the sample (35%) includes people, who are foreigners or Bulgarians, who have lived for more than five years abroad. The place of residence of the respondents is considered because the active geographical mobility observed in recent years becomes a significant characteristic of consumers. Changing the place of residence naturally leads also to changes in the preferences of customers based on local lifestyle, cultural understandings, the social structure of society, and so on [4].

The “Age” factor strongly influences the likelihood of online buying. Considering this according to Farag, Krizek and Dijst [6], age is inversely related to the intensity of online shopping. In the case of this study, all participants are adults, as most of them (almost 80%) are in active stage of their life and the Internet is a significant part of their daily life (Table 1).

Table 1. Sample demographic data

Demographic sample	Criteria (226)	Number	% of sample (100%)
Age	From 18 to 30	61	27%
	From 31 to 45	136	60%
	From 46 to 60	24	11%
	From 61 to 75	5	2%
Gender	Man	98	43%
	Woman	127	56%
	Other	1	1%
Education	Secondary	31	14%
	High	193	85%
	No answer	2	1%

Another determinant of literate and skillful Internet use is education because the lack of education would cause significant barriers in the process of adopting new technologies and working with them and especially in the case of e-Commerce. The received data shows that 85% of the sample has higher education and 14% – secondary. Additionally, 66% of respondents define the intensity of their online shopping experience as high and very high, 28% say that sometimes order items, but not rare. At this point, it is notable that the survey sample includes people, who are familiar with both the Internet and the risks associated with the process of online purchasing. None of the respondents declared that they had never shopped online. At the same time, the majority of respondents (90%) define themselves as risk avoiders considering all possible negative consequences related to e-Shopping. This could mean that today’s consumers prefer online shopping as a more comfortable way to receive the desired goods, but more of them apply the rational style of decision-making when it comes to possible risks.

- **Analyzing the relationship between Emotional stability, Risk perception and Consumer preferences.** Since personality is a set of specifications influencing human behavior [19], the availability of data related to someone’s individual characteristics provides information that can be used to predict his or her actions in various situations.

In this regard, a bivariate analysis is conducted to check the existence of a significant relationship between two independent variables (Emotional stability and Risk averseness) and each of the observed 19 functionalities of the online stores (dependent variables). The results show that there is an existence of eight significant correlations (Table 2). Using the PSPP program (GNU software), only significant correlations between variables at correlation levels 0.05 are considered.

Table 2. Significant correlations between 2 independent and 19 dependent variables

No	Web store features	Emotional stability	Risk averseness
1	Product descriptions give me the necessary information to able to make a decision		
2	Instead of single score, I prefer detailed product ratings		
3	I read the expert reviews. They are essential in the decision-making process		
4	I read comments, which other users have left for different purchases		
5	I check the product availability as well delivery time before I make a purchase		
6	I prefer to be able to see where I am in the product purchasing process		0.125 [a]
7	I prefer to see real-time shipping quote estimates		0.110 [a]
8	I prefer to take a look at detailed product images		0.115 [a]
9	I seek to buy accessories that go along with the product I purchase (accessories and complementary offers, which complement the chosen product)		
10	I prefer to by complementary accessories (like insurance and extended warranty) as a bundle		
11	In order to be able to choose the right product for me I use product categorization resp. featured product filter		
12	In order to be able to choose the right product for me I use product categorization resp. featured product filter		
13	I tend to use different features in the cart like one-click reorder, calculate end price etc.		
14	I normally prefer to check different delivery options	0.120 [a]	
15	I tend to use different contact/support possibilities, in order to ensure myself about certain product features resp. to continue the buying process		
16	I tend to write and comment product reviews. They help to clarify uncertainties about desired products		
17	I avoid saving my personal data in web stores, so I usually prefer to buy as a guest		0.180 [a]
18	I prefer to check the free return possibility; it is essential for me	–0.114 [a]	
19	I normally check for alternative (secure) payment methods like PayPal, etc.	0.127 [a]	0.157 [a]

[a] Significant relationship at the level 0.05.

- **Emotional stability.** By the factor Emotional stability in the context of e-Commerce, a significant positive relationship with the offering different delivery options (r = 0.120, p < 0.05) is detected, as well more secure payment methods (r = 0.226, p < 0.05). Here r denotes the coefficient of Pearson's correlation, which is a measure of the relationship between two variables x and y:

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

and p is the corresponding tail probability, or p-value [30], namely, the probability of getting a difference between the estimate and the parameter greater than or equal to that actually observed. The reason for the detected significant positive relationship with the offering different delivery options, as well more secure payment methods is that emotionally stable people tend to behave confidently and calmly and usually use a rational approach to problem-solving [10] that is associated with a more detailed information search, as well as analysis and logical evaluation of the provided alternatives [28]. A significant negative correlation between the determinant Emotional stability and the possibility for free return of an already bought item ($r = -0.114$, $p < 0.05$) is also found. This means that for more emotionally unstable people, the ability to return the item free is especially important because they are neurotic and cope difficult with stressful situations [29]. That is why, according to some scholars, there is a negative relationship between Neuroticism and rational decision-making style [28].

- **Risk averseness.** The existence of five significant positive relationships between the level of risk perception and the observed basic functionalities of web stores is found in the current study – with consumers' expectations about the ability to track the status of their purchase ($r = 0.125$, $p < 0.05$), with direct calculation and display of the delivery price ($r = 0.110$, $p < 0.05$), offering detailed product photos ($r = 0.115$, $p < 0.05$), with the fear of sharing of personal data on the Internet ($r = 0.180$, $p < 0.05$), as well as with providing more secure payment methods such as PayPal ($r = 0.157$, $p < 0.05$). The data shows again that the number of risks that people try to overcome in the online purchasing process is still significant and makes consumers be more cautious [29].

7. Applying of machine learning for prediction of user behavior in Internet

In order to respond to the research aims resp. to be able to make a forecast of user preferences regarding their personality, two regression models have been implemented – Linear Regression and Random Forest. The equations take the personality traits as input and yield a value showing how important functionality is to the user. The implementation is done in Python, version 3.8 (64-bit), and all the regression models are evaluated applying three of the most common metrics for evaluating predictions on regression machine learning problems [17, 22]:

- The Mean Absolute Percentage Error (MAPE) can be considered as a loss function to define the error termed by the model evaluation; MAPE estimates the accuracy in terms of the differences in the actual v/s estimated values; the lower the value, the better is the model's performance,

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

where n is the total number of data points, y_i are the actual values, and $\hat{y}_i$ are the predicted values.

- The Mean Absolute Error (MAE), which is the average of the absolute differences between predictions and actual values; the lower the value, better is the model's performance,

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|.$$

- The Root Mean Squared Error (RMSE) where the errors are squared before they are averaged; in this metric also the lower the value, better is the performance of the model,

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

The implementation of **Linear Regression** starts with importing the necessary libraries and after that splitting the data into training and testing datasets. In total, 70% of the data is used as the training, and 30% as test set. In this way, using Linear Regression, equations are developed based on the identified significant relationships. The personality traits are considered as independent and the preferences of the users as dependent variables. Table 3 illustrates the average values of the evaluation metrics for all significant relationships.

Using the library scikit-learn, the implementation of **Random Forest** is similar to the Linear Regression. The dataset is randomly split into training (70%) and testing (30%) datasets, and the number of the trees is set to 150 (*n* estimators = 150) (default value is 100). After the predictions are made for all significant relationships, the estimated results are evaluated using the applied metrics for evaluation (Table 3).

Table 3. Average values of the evaluation metrics

Evaluation metric	Machine learning model	Average value
MAE	Linear Regression Random Forest	0.81 0.83
RMSE	Linear Regression Random Forest	1.00 1.02
Accuracy regarding MAPE	Linear Regression Random Forest	71.44 71.10

Based on the results, it may be summarized that both machine learning models have achieved quite similar predictions regarding the applied evaluation metrics and according to L e w i s [19] they could be categorized as quite appropriate for the aim. The biggest advantage of Linear Regression models is the linearity; it makes the estimation procedure simple and, most importantly, these linear equations have an easy-to-understand interpretation on a modular level. This is one of the main reasons why Linear Regression is so widespread in academic fields such as sociology, psychology, medicine, and many other quantitative research fields. At the same time, linearity is its greatest limitation.

The Random Forest algorithm builds multiple decision trees and merges them together to get a more accurate and stable prediction. Random Forest adds additional randomness to the model while developing the trees. Instead of searching for the most important feature while splitting a node, it searches for the best feature among a random subset of features, which leads to a wide diversity that generally results in a better model. Some of the disadvantages are that the model requires much computational power as well as resources as it builds numerous trees to combine their outputs and that it requires much time for training as it combines a lot of decision trees to determine the class [22].

Although the customer decision-making process is often viewed as a linear proceeding, actual researches have shown that decision-making on Internet has a non-linear nature [29]. The relationship between human personality and user preferences is very complex, therefore flexible machine learning algorithms, capable of modeling non-linear effects and interactions, might even allow researchers to use the peculiarities of psychological measurements to increase predictive performance. Random Forest uses an ensemble of decision trees as a basis and therefore has all advantages of decision trees, such as high accuracy and no necessity of scaling data. Moreover, it also has a very important additional benefit, namely perseverance to overfitting, which occurs when a model incorporates random variation in a given dataset that is not caused by the underlying, true relationship between predictors and criterion variables. Random Forest algorithm does not require data scaling and has higher prediction accuracy, and it is easier for hyper parameters tuning [16], which makes the algorithm very appropriate for research in the field of personality.

As the optimization of any machine learning model is a very important step in the process of solving the global problem, optimization of Random Forest with cross-validation, applying the class GridSearchCV of the library scikit-learn is proposed and implemented. In the proposed optimization, GridSearchCV goes through all the combinations 10 times because the value of the cross-validation generator is set to 10 (cv = 10). In this case, there is a total of 120 fits.

In this configuration, the algorithm has improved the results regarding MAPE in 6 of all 8 significant relationships. The improvement of the average accuracy for all 8 significant relationships regarding MAPE is 0.56% or from 71.10% to 71.50% accuracy. According to the MAE and RMSE metrics, there is also a slight improvement, which varies in the different relationships. At the same time, because of its nature, GridSearchCV is a quite time-consuming procedure. A better solution would be a combination with a random search, whereupon RandomizedSearchCV firstly makes some iterations, and after that, GridSearchCV is applied to optimize the results.

8. Results

According to the study results, emotionally stable people tend to behave confidently and calmly, as well as to use a rational approach by problem-solving [10]. It is clear that they also prefer to have different delivery options and more secure payment methods, whereby the Random Forest algorithm after optimization achieves over 75% accuracy of the MAPE forecast. The opposite of Emotional stability is Neuroticism, whereupon neurotic people control difficulty their emotions and their state of stress [29]. This also confirms the current study showing that neurotic consumers need to have the opportunity for a free return.

In accordance with the degree of digitalization in today's life and the growing risk of fraud on the Internet, the current study also confirms the existence of a significant link between users' risk perception and their willingness to share personal data and to use more secure payment methods on the internet (62% and 78% accuracy of the forecast with Random Forests according to MAPE). Moreover, the risk perception is positively related to consumers' preference to track the status of their order and to see timely the delivery price. It is also particularly important for online customers to see detailed product photos to reduce the likelihood of disappointment in the items after the delivery, whereby the Random Forest algorithm achieves 90% MAPE forecast accuracy.

9. Limitations and future research

Each investigation has its limitations, especially when it is human-centered. 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. In turn, this limits the application of the achieved results to some extent within these cultural sub-groups. Although according to the scholars, the Big Five concept is considered consistent and stable in different languages and cultures, Friedman and Schustack [7] states that studies related to personality are applicable only to the relevant cultural environments with similar political, social, and ideological structure and norms, and they would not be valid in other cultural societies. However, other authors claim that these differences are mainly associated with the translation of the measurement tool, as well as to the genetic difference between the participants [8]. Another problem would be related to the questionnaire – if the respondents do not understand the questions. However, in the case of the present study, this risk is overcome, because all questions are formulated clear and understandable as well as translated into three languages.

The individual specifics can be used as predictors of consumer behaviour and decision-making on the internet, but the key to personalizing an interface is the accurate prediction of user preferences, therefore such studies have to be carefully conducted in accordance with the scientific guidelines and recommendations.

Moreover, before widely applying the results in practice, it is recommendable to lead studies like this again and, if possible, with a larger sample. Another way to control the results could be a supplementary eye-tracking test with the participants.

As Popchev and Orozova [25] suggest, future research could also focus on new problem situations in interactions between different risks in the field of e-Commerce, such as conflict (collision) or amplification (resonance) to varying degrees between risks. In this way, unknown new systemic risks are formed, which can manifest themselves in cascading, hierarchical or complex multi-connected behaviour in cyberspace. In this context, a fuzzy logic based solution could be applied in order to describe the decision making process as close as possible to humans' decision making [23, 24, 26].

10. Conclusion

Knowledge of the user's risk perception as a personality trait, as well as the techniques allowing prediction of customer needs and preferences, opens further new horizons. Considering that the human factor plays a crucial role in social and economic processes, the topic of personality is applicable in various fields of science of the contemporary world.

The results of the study show that certain e-Shops' functionalities are more preferred by certain groups of users. Machine Learning approach treats the data as unknowns, and it is mainly focused on prediction rather than inference and aims at forecasting unobserved outcomes or future behaviour. Thus, knowing the consumers' risk perception and applying the methods of Machine Learning to predict what users' preferences would be makes it possible to optimize certain features in e-Commerce. For instance, this would make the personalization of the users' interface possible, and that could better meet their expectations and needs.

Combining the user's personality and his/her experience on the net builds a unique model explaining his/her behaviour, attitude, and decisions. This pattern also has a great impact on our perception of quality, and it does not change over the human lifespan.

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