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Analysis of Interpersonal Relationships of Social Network Users Using Explainable Artificial Intelligence Methods

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Abstract

The emergence of the social networking phenomenon and the sudden spread of the coronavirus pandemic (COVID-19) around the world have significantly affected the transformation of the system of interpersonal relations, partly shifting them towards virtual reality. Online social networks have greatly expanded the boundaries of human interpersonal interaction and initiated processes of integration of different cultures. As a result, research into the possibilities of predicting human behavior through the characteristics of virtual communication in social networks has become more relevant. The aim of the study is: to explore the possibilities of machine learning model interpretability methods for interpreting the success of social network users based on their profile data. This paper uses a specific method of explainable artificial intelligence, SHAP (SHapley Additive exPlanations), to analyze and interpret trained machine learning models. The research is based on Social Network Analysis (SNA), a modern line of research conducted to understand different aspects of the social network as a whole as well as its individual nodes (users). User accounts on social networks provide detailed information that characterizes a user's personality, interests, and hobbies and reflects their current status. Characteristics of a personal profile also make it

possible to identify social graphs - mathematical models reflecting the characteristics of interpersonal relationships of social network users. An important tool for social network analysis is various machine learning algorithms that make different predictions based on sets of characteristics (social network data). However, most of today's powerful machine learning methods are "black boxes," and therefore the challenge of interpreting and explaining their results arises. The study trained RandomForestClassifier and XGBClassifier models and showed the nature and degree of influence of the personal profile metrics of VKontakte social network users and indicators of their interpersonal relationship characteristics (graph metrics).

Keywords
Interpersonal relations; social networks; success; predictors; explainable artificial intelligence; machine learning; Shapley values

1. Introduction

Over the last two decades, the socio-psychological reality has witnessed a significant transformation in the system of interpersonal relations. The first significant driver of qualitative changes in interpersonal interaction has been the phenomenon of social networking, the emergence of which has rapidly transformed people's ideas about the possibilities of communication and communication. By enabling users from different countries to communicate with each other and join various groups and communities, social networks have significantly expanded the boundaries of their interpersonal interaction and forced the processes of integration of representatives of different cultures. Rapid and massive development of social networks has actualized authors' interest in psychological research on the role of the most popular social services (primarily Facebook, Odnoklassniki, VKontakte, Instagram, and Twitter) in people's communications, relationships and behavior. Moreover, the successful experience of using data on users of social services to influence their behavior in political decision-making has shown the wide application possibilities of social networks. First of all, these are the events of 2016 related to the outcome of D. Trump's presidential campaign and the vote on Britain's exit from the European Union (BREXIT).

A second significant driver of significant change in interpersonal relationships was the sudden spread of the coronavirus (COVID-19) epidemic worldwide in 2020. The isolation and prohibitive measures imposed by most states have affected most people worldwide and severely limited their ability to move freely and communicate with one another in person. This, in turn, has further shifted the vector of people's interpersonal relations to the virtual plane and increased social media's importance in communication and communication.

The research question of this article is related to the problem of predicting various aspects of human behavior from the characteristics of his activity in a virtual environment. As part of the transformation of interpersonal relationships and the development of social networks, contemporary works highlight the "self-virtual", a new component in the structure of personality directly related to another component, the "self-actual". In social networks, interaction occurs through the processes of their communication mediated by the digital environment, and throughvarious products of their virtual activity. These products within social networks are

manifested as metrics of a user's profile (e.g., audio materials, video content, photos, posts and reposts, likes, communities, followers, groups, etc.). These metrics, characteristics of her "self-virtual", reflect her self-real. Thus, the personal profile metrics of a social network user act as predictors through which one can predict the person's behavior in real life. A significant pool of research on the psychology of social networks supports the validity of this assertion. For example, an analysis of the Web of Science database from 2004 to 2015 by a group of Palestinian authors showed an annual increase in the various publications on the study of the psychology of social networks [1]. It should be noted that this issue remains relevant and in demand after 2015 and up to the present.

Methodology. We used computer models based on machine learning algorithms (RandomForestClassifier, XGBClassifier) to predict various aspects of user success in the social network VKontakte and to identify the most significant predictive parameters based on the SHAP method. The SHAP (SHapley Additive exPlanations) method allows us to determine the strength of the influence of each input parameter of a trained machine learning model on the prediction result of the variable under study. As input variables, professional success was chosen as the target variable and VKontakte social network users' personal profile metrics and sociometrics - indicators of their social graphs.

2. Literature Review

Modern research widely presents the problem of predicting various personal and behavioral characteristics of users through the features of their virtual activity in social networks. Among them: Narcissism [2-5], loneliness [4, 6-8], anxiety and neuroticism [4, 6, 9, 10], cognitive abilities [11], self-esteem [12, 13], extraversion [3, 9, 10, 14], subjective well-being [15], Big Five personality traits [11, 16, 17], communication motivation [18], sexual orientation [19], antisocial or violent behavioral tendencies [20], work performance and academic achievement [11, 21].

Various variables related either to the elements of the personal profile or to the characteristics of the virtual activity in the virtual environment act as predictive criteria. For example, G. Nave et al. showed the possibility of predicting several personal characteristics of an individual by the characteristics of his/her music preferences in social networks [14]. In [22], the possibility of predicting various personality characteristics (race and party affiliation, gender, sexual orientation, religion) through "likes" on the social network Facebook was revealed. Facial images [9, 19], the main profile frame, the wall, info and photos [11], and status update features [3, 7,15] also act as possible markers in social networks. A study [13] shows that the self-esteem level of social media users is related to participation in different types of online behaviors. For example, lower self-esteem is associated with feeling attached to Facebook, unsubscribing oneself more frequently in photos, and accepting friend requests from users one does not know much. Research [23] has shown that social networks facilitate the creation of extensive social ties, both through distant types of relationships (acquaintances and occupational ties) and through close relationships and relationships with strangers. In [24], the authors prove that the most active Facebook users are women, young people and those not currently in a serious relationship. At the same time, regular use of social networks positively affects the adaptation of users (using the example of teenagers). It is not associated with any negative consequences for them [25].

Thus, the analysis of various research projects shows that the peculiarities of interaction and behavior of users in social networks, as a new form of interpersonal relations of people, opens wide opportunities in predicting various personal characteristics of an individual through the variety of content characteristics of his profile in social networks (content of photos, audio content, posts, likes, avatars, etc.). At the same time, given the significant sample sizes, including tens and hundreds of thousands of possible respondents, integrating psychological methods with information and communication technologies through constructing information-analytical systems based on machine learning algorithms to optimize and automate such studies is particularly important. For example, A. Kachur et al. proved the possibility of predicting all Big Five traits for men and women through real static facial images based on training neural network models [17].

One of the promising directions in the study of social networks is the analysis of social graphs - mathematical models consisting of vertices and edges connecting some pairs of vertices [26] and reflecting the socio-interpersonal relations of social network users. In the study, we denote this as "sociometric", considering various characteristics (number and density of ties, cliques, various centrality measures, clustering coefficients, reciprocity, cohesion, etc.). At the same time, sociometric correlate with traditional sociometric indices and allow diagnosing such parameters of interpersonal relations as status, influence, structure and dynamics of relations in the user group, degree of cohesion-disunity of the user group, degree of information dissemination in the user group, etc.

Graph construction allows us to extend the standard metrics of user profiles by adding graph metrics to them and obtain more accurate results of social network analysis [27]. At the same time, machine learning methods allow us to more accurately determine the predictive power of the variables under study. In previous works, we have already developed approaches for predicting user success by analyzing qualitative and quantitative data from the VKontakte social network, based on machine learning algorithms and artificial neural networks [28, 29].

Machine learning algorithms are often used to solve problems in various fields of science using data corresponding to these fields [30]. As the number of input parameters increases and algorithms become more complex, researchers face the problem of the interpretability of models, asking which of the transferred parameters affects the results of problem-solving more than others. Model interpretability methods have become increasingly important in recent years as a direct consequence of the increasing complexity of models and the associated lack of transparency [31]. Model understanding is a hot topic for research and a major area of practical applications using machine learning in various domains. Various methods have been developed to implement the explainability of trained machine learning models. One of them, the SHAP method demonstrates an improved computational performance and better fits to human intuition than many other approaches [32]. Therefore, scientists began to use their research SHAP methods for interpreting machine learning models in various fields. S.M. Lauritsen, M. Kristensen et al. used electronic medical records of patients for early prediction of diseases, accompanying the results with explanatory information about the impact of various clinical parameters of patients (blood pressure, heart rate, etc.) on prognosis [33]. A comparative study was conducted to evaluate the interpretation models' effectiveness, their strengths and weaknesses analyzed in [34], and the problems that arise when applying these methods. H. Chen, and S.M. Lundberg developed the G-DeepShap method for explaining complex machine learning models and tested its comprehensive performance evaluation on biological, medical and financial datasets [35]. In [36], a study was

conducted on individual parameters that affect the prediction of diabetes in patients. Authors used various combinations (LIME - local interpreted explanations and SHAP). K. Kawano, Y. Otaki et al. developed the methods to predict 5-year human mortality based on the data obtained from a medical examination, and identify the consequences of each disease using the SHAP method [37]. Comparative analysis by [38] showed that SHAP value analysis is a promising method for incorporating explainability in model development and usage and might yield better and more trustworthy ML models in the future. The interpretable machine learning models help physicians more accurately predict the mortality risk in intensive care unit patients with heart failure. They can increase the transparency of the model and facilitate understanding the reliability of the predictive model [39]. In work [40] authors show that the fusion of the dietary data set with the geo-economic variables provides more accurate modeling of the country-wise COVID-19 mortality rates, and that the explainability of the obtained results is equally essential in the data fusion methods. In work [41] authors proposed using of local model-agnostic and counterfactual explanations (LIME and SHAP) to reduce the probability of being At-Risk students. Because the predictors of being At-Risk are identified using the model-agnostic methods, authors evaluated the use of generating counterfactual explanations that describe for individual students why they are At-Risk, and how to switch from being At-Risk to being not.

Based on different XAI methods, it is possible to better understand the trained machine learning modelsand their prediction and identify the influence of parameters on the models' predictions by obtaining quantitative measures of their predictive value.

3. Materials and Methods

3.1 Study Design and Population

The study is based on data obtained from the social network VKontakte. Based on the information-analytical system specially developed within the research, which allows monitoring data from open personal profile pages of users, data on several metrics (number of friends, followers, interesting pages, audio and video recordings) of 65741 users was obtained.

Then local graphs were constructed for each user (vertices - user, his friends, friends of his friends, edges - the existence of "friendship" connection between these vertices). Graph metrics (clustering coefficient, centrality by degree, centrality by proximity) characterizing the central vertex (the user for whom the local graph was constructed) by its connections with other vertices were calculated using the constructed graphs. The graph metrics were added to the total dataset of each user. Thus the following metrics were defined for the study:

"Audio" - the number of audio content on the user's page; "Video" - the number of video content on the user's page; "Subscribers" - the number of people on VKontakte social network who follow the virtual activity of a particular user; "Interesting Pages" - communities and pages subscribed to by a particular user; "Friends" - number of friends recorded in the user's profile; "Proximity centrality" - degree of information distribution across the user's social graph; "Degree centrality" - influence of a user in a social graph as a ratio of number of connections of a certain node to a total number of other nodes; "Clustering Coefficient" - how much the user is involved in the social graph. An example of the raw data for 9 subjects is shown in Table 1.

Table 1 An example of the raw data.

clustering_coefficient	0.0246	0.0946	0.0693	0.0637	0.0602	0.0362	0.0671	0.0722	0.065
degree_centrality	0.0087	0.0087	0.0088	0.0098	0.008	0.0092	0.0120	0.0089	0.0086
closeness_centrality	0.5022	0.5021	0.5022	0.5024	0.5020	0.5023	0.503	0.5022	0.502
friends	199	126	494	182	197	235	46	200	222
followers	157	59	250	95	352	49	16	163	317
pages	37	60	58	478	27	9	17	27	509
audios	332	6	12	1	279	81	175	94	1845
videos	6	2	8	8	27	37	8	6	642
succes	1	0	1	0	1	1	1	1	0

Predicting user success means predicting a particular VKontakte social network user's success as a real-life professional. To solve this task, we obtained data from the job seekers' profiles on the HeadHunter website (hh.ru) and then the same people were found in the social network VKontakte. Based on the HeadHunter website profile information, each user was categorized as a successful or unsuccessful. After clearing the data of omissions, the original sample size was reduced to 2,840 users.

3.2 Methods and Techniques

We used RandomForestClassifier and XGBClassifier as machine learning methods. The Random Forest algorithm is a universal machine learning algorithm based on an ensemble of decision trees that can be used in most problems. The decision tree itself provides an extremely low-quality of classification, but due to the large number of them, the result is significantly improved. XGBoost is based on the gradient-boosting algorithm for decision trees. Gradient boosting is a machine learning technique for classification and regression problems that builds a prediction model in the form of an ensemble of weak predictive models, usually decision trees. The models were trained on predicting social success, as input data (features) we used data obtained from the social network Vkontakte.

Machine learning models and neural networks are often referred to as "black boxes" because they often use many inputs and complex data processing. Therefore, it can be difficult to determine why the model makes a particular decision. Attribution methods solve the problem of explainability by quantifying the importance of an input feature for model prediction. These methods evaluate the input data based on the predictions the model makes, that is, it assigns predictions to its input parameters or functions using the scores for each parameter. Formally, attributions are defined as the influence of an input feature on the output data - forecasting results.

In this work we developed program modules based on the methods of explainable artificial intelligence to analyze, interpret and attribute trained machine learning models, as well as to identify the degree of influence of factors and characteristics on the forecast of professional success. As an attribution method the SHAP method was used. SHAP - is a method that interprets machine learning models using the Shapley value (a measure of the contribution of each feature after considering all possible combinations). The SHAP method was used to interpret the trained machine learning models (RandomForestClassifier, XGBClassifier) and to estimate the measure of the contribution of each feature to the prediction of the variable under study after considering all

possible combinations. A unified method for interpreting the predictions of machine learning models - SHAP (Shapley Additive ExPlanations) was first presented in a paper [32].

Computer programs have been written in Python programming language. For obtaining data from Vkontakte social network we used a VK-api interface, pandas library was used for data preprocessing, Scikit-learn - for machine learning models (RandomForestClassifier), NetworkX -for creating, managing and exploring complex networks (graphs), and XGBoost - for implements gradient-based boosting over decision trees.

3.3 Ethical Aspects of the Study

Ethical issues related to personal information about social media users derived from online sources and the protection of the collected data were addressed according to the recommendations and guidelines disclosed in [42]. The following conditions, which eliminated the need for participant consent, were included in the design of a given study:

- personal information was taken from the open profiles of social network users, i.e. they deliberately released it for public access;
- all data collected in the study were anonymized and no attempt was made to de-anonymize them;
- there was no attempt at any interaction or communication between the experimenters and the individuals in the sample;
- The study doesn't publish or illustrate information that can be attributed to an individual, including demographic profiles, text samples or other content.

4. Results

The following machine learning models were built and trained during the study: RandomForestClassifier and XGBClassifier. These models were trained on the training sample, while performance analysis was performed on the test sample.

The dataset containing 2840 records was divided as follows: 70% (1988 records) were used as a training set and 30% (852 records) were used as a test set. All input datasets were balanced (equal amount of data in the two categories). In this way, the representativeness of the "Accuracy" metric was achieved, allowing it to be used as the main estimation metric of the models. The value of the "Accuracy" metric for the trained RandomForestClassifier and XGBClassifier models was 0.8 and 0.77 respectively in the test sample.

The TreeExplainer (see Figure 1) and Explainer (see Figure 2) methods from the SHAP library were used to determine the effect of the input parameters on the classification results of the RandomForestClassifier and XGBClassifier models, respectively. The visualization of the results is presented as beeswarm graphs.

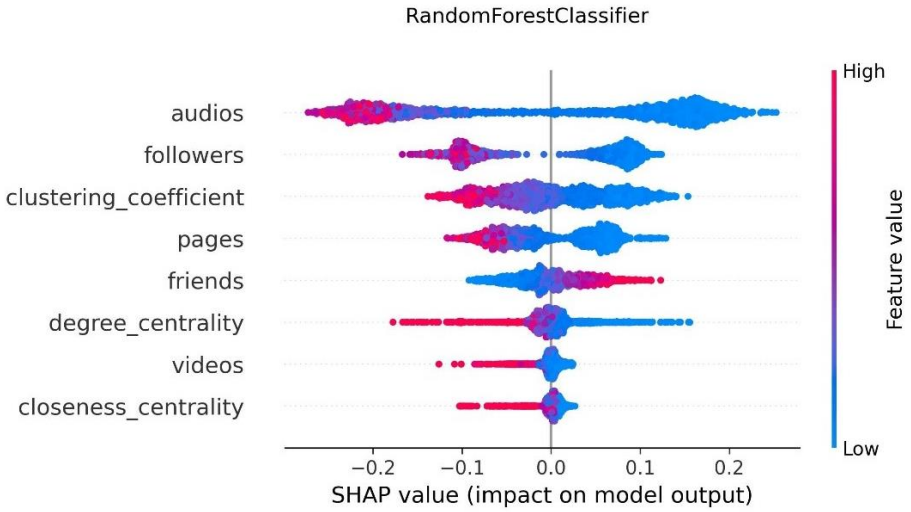

Figure 1 Visualisation of the importance of input parameters based on SHAP values for the RandomForestClassifier model.

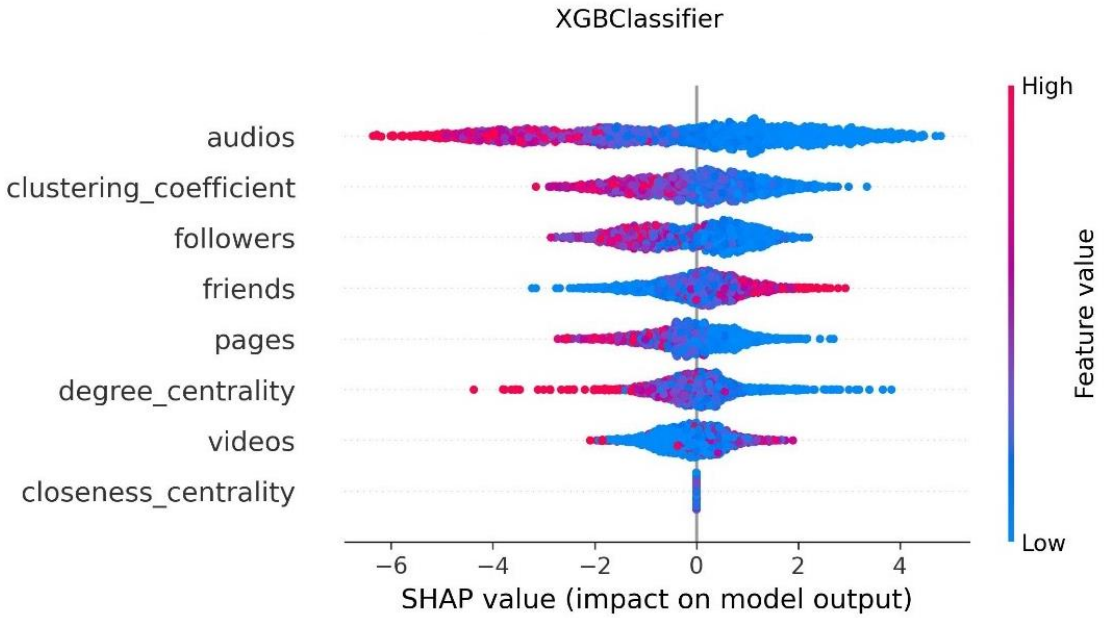

Figure 2 Visualisation of the importance of input parameters based on SHAP values for the XGBclassifier model.

The higher the SHAP value for a particular parameter, the more to the right that input parameter is located on the "x" axis. On the "y" axis, the input parameters are arranged in order of importance (the higher the position, the higher the influence of the parameter on the model results). The color represents the input parameter values (red for the highest values of the input parameter, blue for the lowest values).

Figure 1 and Figure 2 show that the "number of audios", "clustering coefficient" and "number of subscribers" (followers) have the main influence on predicting the professional success of users for both models. The "closeness centrality" contributes the least to the user classification results.

5. Discussion

The paper proposes the results of solving one of the research tasks of an interdisciplinary project, the implementation of which has been ongoing since 2019. This project is implemented by The joint efforts of psychologists and IT specialists implement this project. It aims to develop and test a psychometric model that reveals various cognitive-behavioral predictors of a person's life activity. Previously, the performers proposed the psychological and mathematical foundations of the developed model. Based on methods and algorithms of machine learning and big data analysis, several hundred thousand personal profiles of users of the social network "VKontakte" were analyzed. The choice of the VKontakte social network as an experimental platform was due to its availability and frequency of use in Russia. In addition, the advantage of using this service of interpersonal relations in the study is the content and quantitative informativeness of personal profiles, which include various metrics, unlike Instagram. As a result, the theoretical and methodological foundations of the neural network psychometric model for predicting an individual's academic and professional success as a manifestation of his/her life activity through the social network "VKontakte" were proposed [43].

The development of this model, in turn, made it necessary to include new metrics that reflect the peculiarities of interpersonal relations of social network users and are related to graph analysis. This study grouped these metrics under such a component as social success. Social success is another feature of personal life activity that social networks can predict. By the social success of a social network user we understand a person's ability in virtual communication to create broad contacts, exchange information, show interest in other users, involve others in their interests, create their own groups, and influence others.

The results correlate with the research on the possibilities of predicting various personality traits through the virtual activity of social network users, which is presented in the literature review of this article. The specifics of this study are as follows. First, the use of neural network algorithms based on the SHAP method in predicting professional success of personality. Second, the interpretation is based on quantitative measures of personal profile metrics. Third, the inclusion of sociometric - socio-psychological metrics based on users' social graphs.

In the proposed study we have shown the possibilities of using artificial intelligence in building models for interpreting the behavior of individuals through the analysis of their interpersonal interactions in social networks. In this case, the SHAP method, which was used as a method of interpretation of the constructed machine learning models (RandomForestClassifier, XGBClassifier), showed rather high accuracy in assessing the measure of the contribution of each feature to the prediction of the studied variable.

The category of interaction, in our opinion, most accurately reveals the mechanism linking the "real self" with the "virtual self". The predictors of the manifestation of such interaction are cognitive-behavioral products reflected in the metrics of the personal profile of social network users. These metrics, acting as potential markers of the self-virtual personality, provide ample opportunities to predict a person's behavior in his/her every day (non-virtual and non-digital) activity. The metrics in the study were quantitative measures of the social media user in terms of audio recordings, followers, friends, pages, and social graph metrics (clustering coefficient, degree centrality, and proximity centrality). These metrics reflect the results of his various mental processes (intellectual, motivational, behavioral, etc.) and the results of his Internet activity. As a result, social

networks offer great opportunities for analyzing interpersonal relationships and predicting an individual's social success. It is especially valuable today - in the era of transformation of socio-psychological reality, which is characterized by strengthening the role of virtual space in the life of modern man.

6. Conclusions

In this paper a study of people's professional success was conducted based on data from the social network Vkontakte and graph metrics. RandomForestClassifier and XGBClassifier models were trained to classify users as professionally successful and unsuccessful. The performance of the models was evaluated based on the "Accuracy" metric on the test sample (RandomForestClassifier - 0.8, XGBClassifier - 0.77).

An analysis of the influence of input parameters on the results of the classification of professional success was carried out using the SHAP library. It was found that the parameter "audio" has the greatest impact on predicting professional success. The lower the value of this parameter, the more likely a person will be classified as professionally successful. "Clustering coefficient" and "number of subscribers" (followers) were also among the significant parameters. The study showed further prospects of developing neural network models for predicting various aspects of success (academic, professional, social) and using sociometric (various indicators of social graphs of VKontakte social network users).

6.1 Limitations of the Study

Some limitations of this study should be noted. The data was collected based on the social network VKontakte without considering other popular Internet social interaction platforms (e.g., Facebook or Instagram). Therefore data analysis and interpretation is carried out on a sample of Russian users. Therefore, caution should be exercised when generalizing the results to users from other countries.

The work didn't consider the gender and age characteristics of the users, which is seen as a further research perspective.

Several difficulties in the study were related to the problem of some users' closed accounts, which significantly reduced the number of subjects and could affect the analysis of social graph indicators. The problem of closed accounts is also a prospect for further research, which currently has no clear solution and requires further reflection in terms of leveling the effect of influence.

The study may also be influenced by the social desirability factor associated with the desire of some users to make as many contacts as possible (friends metric), which may distort the results of the analysis of their actual social activity. The solution to this problem is seen in the further development of algorithms for analyzing the social success of users, taking into account the interaction of different indicators of their virtual activity in social networks.

Because between variables may exist relationships, the variable contributions obtained in this study are only predictive contributions. The SHAP method makes it easy to examine each variable in isolation, but variables can have more complex interactions. Therefore, future studies will need to use methods to identify relationships between variables using methods like [44]. Also, it should be noted, that the SHAP method is particularly effective in large dimensions and gives understandable global explanations. However, it lacks accuracy about local explanations, for

example, for a more detailed analysis of individual objects. Methods based on [45] coalition are computationally expensive in high dimensions but offer better local explanations. It is also necessary to consider that the machine learning model's overfitting problem is possible, due to which the models trained in this study may show lower results on other data.

Author Contributions

Conceptualization, F.G. and P.U.; methodology, F.G and P.U..; software, F.G. and A.B; investigation, F.G., P.U. and A.B.; data mining, A.B.; writing—review and editing, N.S, P.U. and A.B.; supervision, F.G. and P.U. All Authors contributed to write paper and approved the final manuscript.

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Competing Interests

The authors have declared that no competing interests exist.

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