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OBM Neurobiology

Original Research

Assessment of a Person's Social Success Through the Characteristics of Interpersonal Relationships in a Virtual Environment

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Academic Editor: Vsevolod Konstantinov

Special Issue: The Neuropsychology of Interpersonal Relationships in an Era of Pandemic and Cultural Integration

OBM Neurobiology
2023, volume 7, issue 4
doi:10.21926/obm.neurobiol.2304195

Received: April 30, 2023
Accepted: November 06, 2023
Published: November 13, 2023

Abstract

The sudden spread of the COVID-19 pandemic has convincingly proved the role of social networks in human life activity as an actor of interpersonal relations. The need for isolation and the limitation of face-to-face communication between people has significantly transformed the system of interpersonal connections through an extensive increase in social contacts in the virtual environment and the growing importance of online social services. In the study, we addressed the problem of diagnosing the indicator of social success of a personality, reflecting characteristics of its interpersonal relations in offline activity through the attributes of its virtual activity in social networks. The research was based on the methods of social network analysis and traditional ways of psychodiagnostics. Social networks were analyzed using social graphs - mathematical models that describe the characteristics of relationships between users in social networks through various metrics (friends, elements, edges, density, closeness centrality, degree centrality, clustering coefficient, etc.). The study aims to prove the predictive validity of social graph indicators as predictors of personality social success through correlations of graph characteristics reflecting the features of interpersonal relations of a social network user in a virtual environment with the socio-psychological hands of traditional psychodiagnostic tools. The study included 601 subjects. Data was collected using psychological questionnaires and personal profiles from the social network VKontakte. The results of the study showed correlations between several characteristics of social graphs (density, clustering coefficient, closeness centrality, etc.) and several indicators of psychodiagnostic techniques (Dominance index in relationships with others, Organizational abilities, Desire for people, Narcissism, etc.). The significant contribution of the research is to expand the methodological apparatus of psychological science and to open new methods of predicting interpersonal relations of personality through its activity in a virtual environment.

Keywords

Interpersonal relations; social success; psychological well-being; social networks; social graph; virtual behavior; predictors; personal profile metrics

1. Introduction

The problem of assessing social success is currently one of the key issues in general and social psychology. Research in this area is valued due to objective environmental factors significantly influencing an individual's current psycho-emotional state and mental health level in the long term [1, 2]. Such actual ecological factors include the atomization of society and social isolation [3-6], the development of online communication with the inherent concept of "status," and the formation of social groups of "opinion leaders" [7, 8]. The social groups of "opinion leaders" should be highlighted because, among young people, there is a focus on them in many instances when choosing the sphere of professional self-actualization. This is because young people have an opinion about the possibility of earning a living [9, 10] (i.e., professional activity) based solely on the breadth of the social network audience. The many users who actively visit the pages of such groups allow them to create a target audience for the distribution of commercial advertising on a paid basis, thus making a profit directly from the page visits [11].

The epidemiological situation adds a particular poignancy to the problem [12]. Given the limitations of social contact and the opportunities for traditional socialization through face-to-face interpersonal contact, virtual communication has become a fundamental way of maintaining social status [13]. However, because virtuality-mediated communication is limited in terms of full-fledged feedback (communication is more of a ritual nature [14]), the subject compensates for the lack of contact depth with quantitative characteristics, an increase in the number of contacts [15]. Of course, it should not be forgotten that, with a non-zero probability, the pursuit of the number of connections and virtual interactions creates a risk of neurotic dependence [16, 17] on the quantitative results achieved. An equally significant problem is the blurring of the boundaries of individuality when immersed in a virtual environment, completely replacing the core of identity with a set of templates and masks [18].

One of the leading platforms for virtual communication today is social networks. Millions of users on these platforms unite into various groups and communities, expanding the boundaries of their social and psychological space through interaction. Thus, social networks, acting as a virtual version of the modern model of socio-psychological reality, are one of the primary sources of information about the virtual activity of individuals and the features of their interpersonal relationships.

The paper shows the results of solving one of the tasks of the interdisciplinary project, which is being implemented from 2019 to the present. Previously, the authors have demonstrated the possibility of predicting such aspects of personal life activity as academic and professional success through quantitative and qualitative characteristics of personal profile metrics in the VKontakte social network [19] and proposed theoretical foundations for a neural network psychometric model of cognitive-behavioral predictors of private life activity [20]. Working on this model highlighted the need to elaborate on another of its components - social success.

There is no unambiguous understanding of the essence and content of the concept of social success in science [21]. In this study, social success is understood as an integral quality of the communication actor, which determines their ability to establish and maintain social ties, form and transmit social ideas and attitudes, and influence partners' behavior in touch.

If we look at the chosen problem from a sociological point of view, it is enough to calculate the visit rates of the most popular user pages in the social network. A psychological approach, however, requires analysis of the psychological characteristics of the owners of the most popular pages to highlight psychologically and psychometrically assessable predictors of social success. The presented research is an application of methodology designed to identify objective-sociological predictors of individual success in the socialization and communication process in the virtual environment.

The study aims to substantiate the predictive validity of social graph indicators as predictors of personality social success by identifying the interrelation of graph characteristics reflecting features of virtual activity of VKontakte social network users with the social and psychological hands of traditional psychodiagnostic tools.

The novelty of this study carried out within the framework of general research problems of the psychology of social networks, is to substantiate the possibility of predicting the social success of individuals through psychological validation of sociometric - indicators of social graphs of users in the social network VKontakte.

The study's general hypothesis is the following assumption: it is possible to predict the level of a person's social success in offline life based on the analysis of the data of their activity in the digital communication environment. The study is based on traditional psychometric diagnostic procedures and prediction of social success indicators.

2. Theoretical Framework

Since social success is a particular case of general success, it is appropriate to consider the correlation between these two concepts.

Success, as defined by the Cambridge Academic Content Dictionary, is when an individual has achieved something they want and have been trying to do or get [22]. A more precise definition, given by H.P. Mirvis and D.T. Hall, defines psychological success as the experience of achieving goals that are personally meaningful to the individual rather than those set by parents, peers, organizations, or society [23]. Both definitions focus more on the individual's satisfaction with the outcome of an action or process than on receiving approval or praise from external, significant social institutions or groups. Considering the classical definitions of success accepted in psychology, it is appropriate to note that D. McClelland came closest to the concept of social success because his theory of motivation is based on the social needs of a person.

D. McClelland, following H.A. Vital Murray, defines four critical social needs, which correspond to four groups of motives: achievement, power, affiliation, and avoidance. Each group of explanations performs a specific function in this model: the Achievement motive contributes to the activation of behavior aimed at achieving a particular state; the Power motive forms the behavior that affirms the position of the individual in the group, his authority and influence; the Affiliation motive activates behavior aimed at following group norms, the Avoidance motive acts as a guard against excessive risky decisions [24].

The satisfaction of these social needs leads to the state of success satisfaction. Therefore, it is appropriate to state that, in this case, we are talking about the interpretation of social success, not just psychological success. Based on this, McClelland's model was used as the methodological framework for the study.

At the same time, social success is a socio-psychological construct with many meanings and variables. This object is considered in several ways in private studies of social success.

First, it is necessary to point out the culturally conditioned differences in understanding success [25]. In the context of this division, it should be understood that the content of the concept of "success" in representing the sample of Russian subjects will be predominantly Western. This is due to the geographical proximity to the centers of Western civilization and the social reality in which society has been predominantly Western-centered since the 1990s.

The second concern regarding the content of "social success" is the age of the subjects. Teenagers and young people are often involved in modern research [26-28]. This study follows this pattern because this age group has the most significant problems related to self-assertion, self-expression, and self-actualization.

The third problem is due to the uncertainty of the actor of social success. The search for studies on similar topics often gives a false-positive result in the form of publications describing the patterns of social demand (success in market terms) of a product (goods or services), while in this study, the actor of social success is unambiguous - it is an individual.

In general, when giving a working definition of the term "social success," the authors tend to follow the meaning given in the work of O. Kobzeva: social success is a unique state of equilibrium with the surrounding social environment, in which the individual is satisfied with the ratio of their capabilities to interact with the environment and needs in this interaction [26]. This means that the person, on the one hand, is widely known (has a wide range of contacts with whom a constant connection is established) and, on the other hand, has a positive reputation in the eyes of partners in social interaction (is considered friendly and responsive). To achieve such a position, a socially successful individual must have adequate self-esteem, productive motivation, behavioral flexibility, communication, adaptability, and orientation toward self-development. Since we are talking about social success, economic indicators (wealth, social status, origin) were not included in the working model of "success" in this study.

Social success is traditionally understood as a result achieved in face-to-face communication. However, the intensive development of telecommunication systems combined with biogenic (COVID-19 epidemic) and socio-political phenomena leads to social success for a part of the human population, mainly in the digital communication environment. In this regard, there is a demand for research into the specific features of the content (and attributes) of the social success of individuals who communicate predominantly online. In this regard, the publication by N. Hoda and A. Naim [29], where a detailed view of activity in social networks as a resource for personal and business efficiency is presented, is worth mentioning.

In this article, we have addressed the problem of predicting the social success of a personality through the characteristics of its behavior in social networks. Currently, studies on the correlation between a person's online activity and real-life personal factors are pretty standard. In particular, publications have analyzed the following psychological and social characteristics: the correlations of social network user personal profile indicators with extraversion [30], gender [31], self-esteem [32], and emotional states [33, 34] with narcissism [35]; with social activity in real life [31, 36]; with well-being [37]; with self-esteem [33]; with personality life satisfaction [38]; with sexual orientations [39]; with different personality traits [40].

In more specific studies, the involvement in social networking as a means of emotional release [41], the satisfaction of the need for belonging and confirmation of social status [42], entertainment [43], modeling the image of Social self, and solving business issues [44] is considered.

Of particular interest in the context of psychological studies of the person’s online activity is the study by S. Pande and his colleagues [45], in which an attempt was made to develop a system for indicating the psycho-emotional state by markers of behavior in a social network. In particular, these authors point to sentiment analysis (SA), natural language processing (NLP), and user profiling as important indicators of depression risk. The essential tools of this team are based on several machine learning (ML), deep learning, and data mining methods.

The connection of this study with neuropsychology is confirmed in particular by the works above of S. Chancellor and M. De Choudhury [46] and A. Benton et al. [47]. The first one [46], a review of existing publications, provides a significant list of works in which the problems of interrelations between the behavior of users of a virtual communicative environment with pathological symptoms, including neurological ones, are considered. Authors point out that social networks provide extensive material for early diagnosis of psychological, psychosomatic, and neurological disorders using behavioral and speech clues. Also, this paper analyzes the range of methods and algorithms of information processing by computer technology. The second study [47] shows the applied aspect through the use of neural network methods to analyze language cues in social network utterances for predicting suicide attempts of individuals with identified suicide risk. Multitask learning (MTL) was used as the neural network processing mechanism. The value of these works, from the point of view of our research, is to demonstrate the possibility of constructing a prognosis of psychopathological and neurological symptoms based on the study of user activity.

The research of a team of authors led by M. Stankevich [48] is of particular interest because the social network "Vkontakte" was used as a platform for data collection. In this study, as in most of those already mentioned above, the emphasis was placed on finding correspondences between verbal clues in the subjects' posts and psychometric indicators (Beck's depression scale).

To date, there are various studies of correlations between the indicators of a social network user's profile and his psychological and social characteristics. The results of such studies make it possible to describe the psychological profile of a user and predict their behavior and interpersonal attributes with a high degree of probability. The following are analyzed as metrics of a social network user's profile: degree of virtual activity of a social network user (frequency of use of social networks by the user); features of a person's communication with other users in social networks; openness of a person in social networks to other users; number and content of posts and reposts of a user in his profile; frequency of status updates of a user's profile in social networks; frequency of posting "selfies" (digital self-portrait) of the user and their content characteristics; the number of friends, etc. Peters et al. [49] and Grave [50] used a similar approach and metrics list.

In our study, social success is the independent variable. In this regard, we turned to another promising area of contemporary research - social networks analysis (SNA). In this approach, interpersonal relations are considered in terms of graph theory. In this case, social networks are viewed and analyzed as a social graph, where the vertices are the social network users, and the edges are the links between the users [51]. Therefore, graph theory methods have been intensively used to analyze social networks [52, 53]. In modern scientific works, researchers are developing various methods for analyzing clusters in social networks [54]. The structure of social networks is analyzed from three levels: micro-level, meso-level, and macro-level based on the regular graph model, exponential random graph model, small world network model, and network model without scale [55], various models and algorithms for generating social networks are also being developed [56]. Review articles [57-59] provide a detailed analysis of current advances in identifying important nodes from a social network perspective, as well as the various social network centrality measures that have been developed. By analyzing the graph and improving the accuracy of predicting the behavior of social network users [60], additional indicators are added that reflect its interpersonal characteristics (number and density of connections, clicks, various measures of centrality, clustering ratios, reciprocity, cohesion, etc.). These indicators largely correlate with traditional sociometric indices, allowing the reveal of such parameters of users' interpersonal relations as status, influence, structure, and dynamics of user group relations, degree of user group cohesion-disassociation, degree of information dissemination in the user group, etc.

3. Materials and Methods

This interdisciplinary study integrates theoretical and methodological approaches adopted in psychology with the methods of information theory and mathematical sciences. The main psychological approaches to the study are the provisions of self-concept and activity behavioral, cognitive, and sociometric approaches.

The main methods of the mathematical-informational direction are methods of big data, social network analysis, and methods of mathematical statistics (correlations, descriptive models of intelligent analysis). Graph theory methods provide the basis for analyzing social networks.

In this paper, sociometrics - indicators of interpersonal relationships of social network users - serve as indicators of a person's social success. Sociometrics are measured by analyzing social graphs - mathematical models consisting of vertices and edges connecting some pairs of vertices and reflecting social network users' social and interpersonal relationships. The study is focused on the leading indicators of personal social activity, which are based on sociometrics and describe the position of users in the social graph. The following indicators have been calculated based on currently available data.

Friends- the number of friends recorded in the user's profile;

Elements- the number of friends of the user and his friends' friends, i.e., the population of the social graph;

Edges- the number of connections between people in the social graph - how connected they are to each other;

Density- describes how dense the chart is in terms of edge connectivity. This measure gives the ratio between the edges present in the graph and the maximum number of advantages the graph can contain. The density of an undirected graph is quite simply calculated as

$$Density = \frac{m}{n(n-1)/2} = \frac{TotalEdges}{TotalPossibleEdges} \tag{1}$$

Network density is critical because it can help us understand how connected a network is versus how connected it could be. Also, when comparing two networks with the same number of nodes and the same type of relationships, this measure can help us to understand how these networks differ. Also, the density of the graph gives us an idea of how many edges we can still add to the network.

Closeness centrality. The centrality measure shows the position of the specific node about other nodes and the network as a whole. There are different measures of centrality: degree centrality, closeness centrality, betweenness centrality, etc. In this work, we used closeness centrality, which measures how close a given node is to all other nodes in the network. Closeness centrality of a node **u** is calculated as the reciprocal of the sum of the lengths of the shortest paths between a node and all other **n-1** reachable nodes i**n** the graph [61], by the formula

$$C(u) = \frac{n-1}{\sum_{v=1}^{n-1} d(u,v)}, \tag{2}$$

Where **d(v, u)** is the shortest path distance between nodes **v** and **u, t**hus, the more central a node is, the closer it is to all other nodes. Closeness centrality is a valuable measure that evaluates how fast the flow of information through a given node will be to other nodes. Closeness centrality can help identify influential individuals in the same cluster.

Degree centrality - is an easy-to-calculate measure of centrality that characterizes the importance of a particular node in terms of the number of connections to other vertices in the network. In our work, degree centrality values are normalized by dividing by the maximum possible degree in a simple **n-1** graph, where **n** is the number of nodes in the whole graph.

Clustering coefficient. Clustering is a local measure of a network that characterizes the degree to which a given node's nearest neighbors interact with each other. In social networks, nodes tend to create tightly knit groups characterized by a relatively high density of connections. The clustering coefficient of the node you use is the fraction of possible triangles that exist through this node, i.e.,

$$c_u = \frac{2T(u)}{deg(u)\,(deg(u)-1)}, \tag{3}$$

Where **T(u)** is the number of triangles through node **u**, and **deg(u)** is the degree of **u**.

Clustering is interesting because it measures the extent to which nodes tend to cluster together; therefore, this measure is used to investigate the existence of so-called structural holes in a network in which there are no connections between a person's neighbors. Structural holes can be helpful for a central apex whose friends have no links since they give power over the information flow between those friends. Therefore, the local clustering coefficient measures the degree of influence of a person in this sense.

The construction of social graphs and calculation of graph metrics was done using the Python package NetworkX.

The proposed sociometrics primarily reflects such parameters of classical sociometry as status, influence, structure, and dynamics of relations within the user's group, degree of cohesion - dissociation of the group where the user resides, degree of information dissemination within the user's group, etc.

This research's experimental data source is the social network VKontakte (vk.com). This virtual platform connects millions of users and allows them to communicate and interact with each other. For this research, we collected empirical data from users' pages publicly accessible within the social network.

The risks associated with protecting the confidentiality of personal data were mitigated through the automatic transfer of empirical data into an anonymized data system (ordinal numbers of the subjects). This way, even in the event of data leakage and the desire to use it for specific purposes, the parties concerned are deprived of this possibility.

The indicators of the methods reflecting the main working hypotheses were used as a psychodiagnostic base. It is recognized that the following tests adequately reflect the socio-psychological characteristics of the individual:

"Leary Interpersonal Behavior Inventory" (T. Leary, adapted by L.N. Sobchik) is a technique relating to tools for assessing socio-psychological traits. It was taken in the basic version, where the examinee, answering the test questions, had to characterize themselves on their behalf. The questionnaire was used in the study based on its ability to measure Friendliness and Dominance tendencies and their more private components (octants), which are integral components of the system of social relations [62]. This technique can be correlated to the needs of Power and Affiliation.

"Communicative and organizational dispositions" (Sinyavsky-Fedorishina). The test is used because individuals with communicative and organizational dispositions are highly likely to form like-minded groups around themselves and are, therefore, highly ranked nodes in the language of the graph concept. The content of the items in this questionnaire can reflect the subject's expression of satisfaction with the need for Achievement.

"The Mehrabian Affiliation Tendency Questionnaire" (MAFF). This test includes two scales: Acceptance Disagreement and Fear of Rejection. Both are apparent indicators of the interpersonal relations system and reflect the balance of aspirations and fears, so they are directly related to social success. This technique is included in the battery to measure the Avoidance motive. The practicality of using the CAT and MAFF questionnaires for this purpose is confirmed, in particular, by A. Kozhevina's study [63].

"The Short Dark Triad" (SD3), a questionnaire that involves the diagnosis of neurotic traits such as Machiavellianism, narcissism, and psychopathy, has been introduced into the list of diagnostic procedures to assess socially harmful characteristics on the formation of a socially successful personality. This psychodiagnostic tool is used to measure qualities that reflect abuse tendencies in the area of power and achievement motives.

"Marlowe-Crowne Social Desirability Scale" (MC-SDS). The questionnaire was used to identify a possible link between social success and the tendency to misrepresent oneself in the eyes of others and to test the sincerity of all participants in the study.

"Fundamental Interpersonal Relations Orientation-Behavior" (FIRO-B). The questionnaire allows a differentiated assessment of the actor's actual and desired behavior in three dimensions of social activity - inclusion (belonging to a group), control (movement, ability to influence the environment) and affect (experiencing emotions in the process of communication). Due to the presence of these indicators, it was deemed appropriate to include this test in the psychodiagnostics battery. This test was successfully applied in the study of situational leadership [64], confirming the possibility and expediency of its application in diagnosing social success. In addition, this measuring tool correlates with the needs of Power and Affiliation described by McClelland.

The study involved 1,026 participants, a randomized sample. Before the correlation analysis was carried out, to avoid errors caused by omissions in the data, all participants for whom web metrics data were missing (due to a closed personal profile in the VKontakte social network and other artifacts) were excluded from processing. The data was then screened for validity and compliance with statistical analysis criteria, with a final research sample of 601 people.

The primary data were analyzed with the help of mathematical statistics using the IBM SPSS Statistics program. Checking the normality of the distribution did not reveal any deviations in the empirical data according to the criteria of asymmetry and excess. Thus, Pearson's correlation analysis was used to identify relationships between social success indicators from the test methods with social graph metrics. Descriptive statistics of the obtained data were also analyzed.

4. Results

Two types of empirical data were used for each participant as a basis of this study. The first - is the data obtained based on psychological testing using the psychodiagnostic testing mentioned above. The second - is the data obtained based on monitoring the participants' pages on the VKontakte social network and analyzing their social graphs.

In the first stage of the study, a sample of 1,026 people who owned VKontakte social network accounts was formed. Then, these individuals were asked to undergo a series of psychological tests listed above.

Based on the results of the psychometric procedures, the list of participants was updated: the results of subjects who ignored the psychometric tests or did not complete the trials were excluded. Also excluded were subjects who had passed the tests by the time the data collection was completed but had closed their social network profiles (and, therefore, did not provide the information necessary for processing by the metrics group). In total, final data processing was performed on a sample size of 601 subjects. Since this study was only interested in elements of objectively recorded personal activity in the virtual communication environment, demographic characteristics (gender, age, field of employment, etc.) were not considered. Another reason for not considering demographic characteristics was that this type of data can be easily falsified in the absence of face-to-face contact between the subject and the researcher. Each issue was identified only by the personal index of the social network Vkontakte (Table 1, Table 2).

Table 1 An example of data describing the social graphs metrics.

T	**friends**	**followers**	**pages**	**audios**	**videos**	**photos**
M	164.60	4021.44	129.90	348.66	114.38	78.26
SD	113.04	93378.45	207.44	875.08	386.57	513.71
T	**photos_count**	**photos_likes**	**videos_count**	**videos_likes**	**post_count**	**post_likes**
M	9.96	1564.58	106.84	240763.6	50.18	17776.59

SD	18.57	27767.2	375.49	715418.2	221.7	424053.8
T	**all_repost_count**	**all_repost_likes**	**repost_count**	**repost_likes**	**repost_comm_count**	**repost_comm_likes**
M	180.69	445.48	176.53	429.75	4.15	15.73
SD	1329.51	7188.14	1323.10	7120.56	20.09	92.26
T	**views**	**reverse_repost**	**page_degree**	**Elements**	**Edges**	**Friends**
M	422599.4	772.79	11.58	9091.94	11433.28	83.98
SD	10149322	18383.82	7.58	6315.66	8344.14	54.59
T	**Density**	**Clustering coefficient**	**Degree centrality**	**Closeness centrality**	**activity**	
M	0.000748	0.087	0.01	0.502	3.408	
SD	0.001996	0.081	0.0024	0.00062	1.471	

Note: T-metric title; M-average value; SD - standard deviation

Table 2 An Example of obtained data on the results of psychometric diagnostics.

T	Authoritarian type	Selfish type	Aggressive type	Suspicious type	Subordinate type	Dependent type
M	9.50	7.58	7.62	6.90	7.13	7.07
SD	3.22	2.96	2.94	3.47	3.53	2.89
T	**Friendly type**	**Altruistic type**	**Dominance index**	**Friendliness index**	**Communication abilities**	**Organizational abilities**
M	8.73	9.52	3.23	2.59	10.68	12.50
SD	2.86	3.18	8.31	8.40	4.20	3.27
T	**Desire for people**	**Fear of rejection**	**Machiavellianism**	**Narcissism**	**Psychopathy**	**social desirability bias**
M	119.36	122.84	29.71	26.55	21.31	9.18
SD	18.02	23.29	5.72	5.80	6.70	3.41
T	**Expressed inclusion behavior**	**Expressed control behavior**	**Expressed affect behavior**	**Demanding inclusion behavior**	**Demanding control behavior**	**Demanding affect behavior**
M	4.44	5.75	3.39	3.73	4.03	3.08
SD	1.59	2.27	1.62	2.24	1.88	1.79

Table 2 summarizes the results of psychometric diagnostics. The values were rounded to two decimal places.

Next, the relationships of all the studied indicators were analyzed using the r-Spearman correlation coefficient. The following results were obtained as a result.

The Elements indicator (Figure 1) is positively correlations with the following psychodiagnostics indicators: Authoritarian type of attitude towards others ($r = 0.14$, $p = 0.001$); Friendly kind of attitude towards others ($r = 0.14$, $p = 0.001$); Dominance index in attitude towards others ($r = 0.10$, $p = 0.016$); Friendliness index in relationships with others ($r = 0.10$, $p = 0.013$); Communication abilities ($r = 0.20$, $p = 0.000$); Organizational abilities ($r = 0.11$, $p = 0.033$); Desire for people ($r = 0.15$, $p = 0.005$); Narcissism ($r = 0.23$, $p = 0.000$); Expressed inclusion behavior, that is, a person's desire to be among other people and belong to different social groups and communities (r = 0.14, p =

0.023); Demanded inclusion behavior, that is, a desire for other people to try to be around the person (r = 0.171, p = 0.007); Expressed control behavior, that is, a person's desire to control and influence others (r = 0.14, p = 0.033)

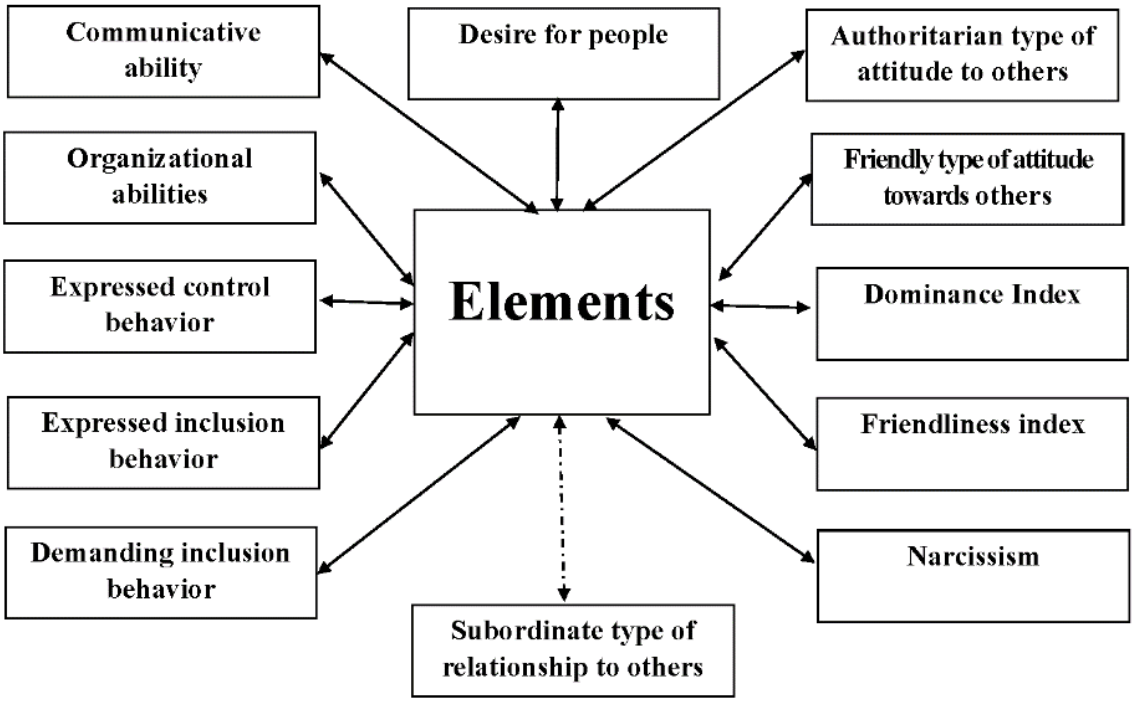

Figure 1 Correlations of the Elements indicator with psychodiagnostics' indicators.

Also, the Elements indicator has an inverse correlation with the psychodiagnostics indicator describing the Obedient attitude towards others (r = -0.10, p = 0.016).

The Edges indicator (Figure 2) shows a direct correlations with the following psychodiagnostics indicators: Authoritarian type of attitude towards others (r = 0.14, p = 0.001); Friendly kind of attitude towards others (r = 0.14, p = 0.000); Altruistic type of attitude towards others (r = 0.08, p = 0.044); Dominance index in attitude towards others (r = 0.1, p = 0.014); Friendliness index in relationships with others (r = 0.10, p = 0.012); Communication abilities (r = 0.20, p = 0.000); Organizational abilities (r = 0.12, p = 0.028); Desire for people (r = 0.15, p = 0.006); Narcissism (r = 0.24, p = 0.000); Expressed inclusion behavior, that is, a person's own desire to be among other people and belong to different social groups and communities (r = 0.15, p = 0.016); Demanded inclusion behavior, that is, a desire for other people to try to be around the person (r = 0.17, p = 0.006); Expressed control behavior, that is, a person's desire to control and influence others(r = 0.14, p = 0.031).

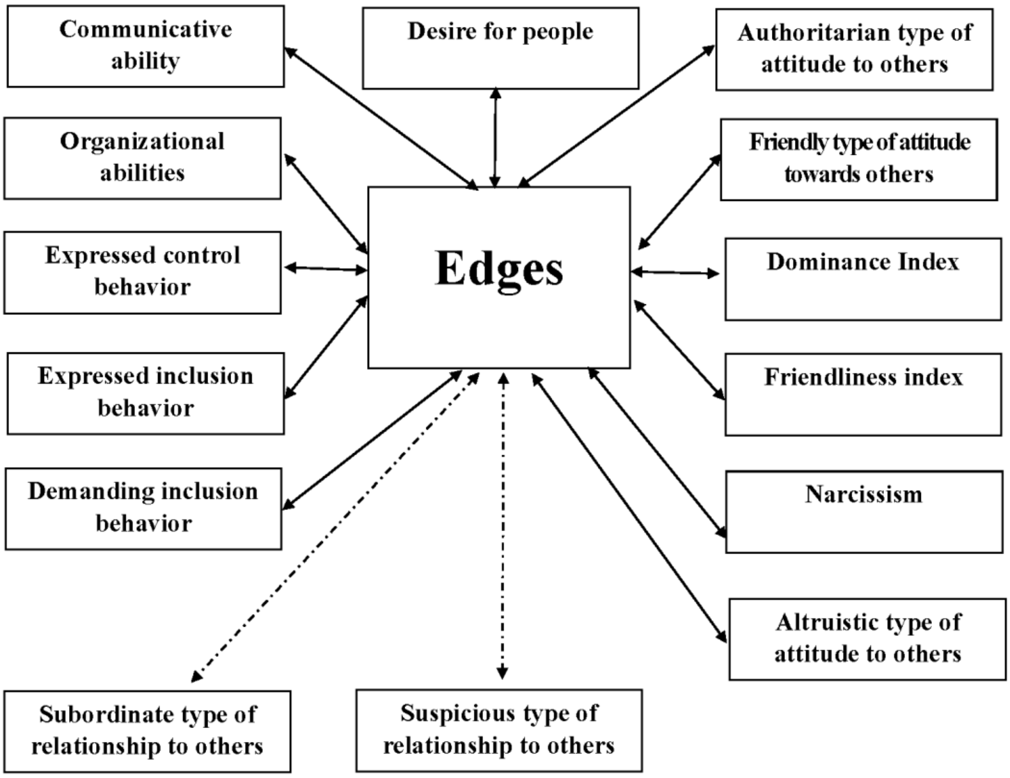

Figure 2 Correlations of the Edges indicator with psychodiagnostics' indicators.

The Edges indicator also shows inverse correlations with psychodiagnostic indicators characterizing Suspicious (r = -0.08, p = 0.049) and Obedient (r = -0.01, p = 0.015) attitudes toward others.

The Friends indicator (Figure 3) shows direct correlations with the following psychodiagnostics indicators: Authoritarian type of attitude towards others (r = 0.14, p = 0.001); Friendly kind of attitude towards others (r = 0.16, p = 0.000); Altruistic type of attitude towards others (r = 0.10, p = 0.017); Dominance index in attitude towards others (r = 0.10, p = 0.014); Friendliness index in relationships with others (r = 0.11, p = 0.010); Communication abilities (r = 0.194, p = 0.000); Organizational abilities (r = 0.11, p = 0.044); Desire for people (r = 0.15, p = 0.007); Narcissism (r = 0.24, p = 0.000); Expressed inclusion behavior, that is, a person's own desire to be among other people and belong to different social groups and communities (r = 0.149, p = 0.018); Demanded inclusion behavior, that is, a desire for other people to try to be around the person (r = 0.174, p = 0.006); Expressed control behavior, that is, a person's desire to control and influence others(r = 0.14, p = 0.023)

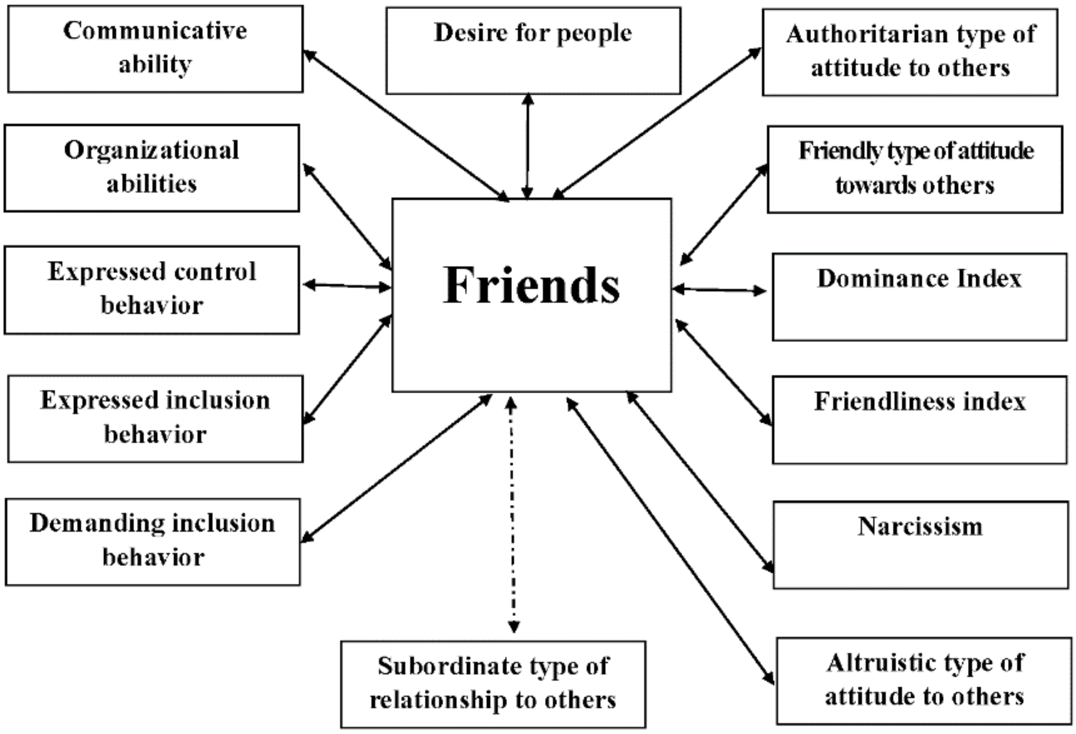

Figure 3 Correlations of the Friends indicator with psychodiagnostics' indicators.

Also, the Friends indicator is inversely correlated with the psychodiagnostics indicator describing the Obedient type of attitude towards others (r = -0.10, p = 0.018).

Thus, the "Elements", "Edges," and "Friends" indicators mentioned above are characterized by quite similar results in terms of the content of correlations with psychodiagnostic indicators describing socio-psychological characteristics of personality.

The "Density" indicator (Figure 4) found inverse correlations with the following psychodiagnostics indicators: Authoritarian type of attitude towards others (r = -0.13, p = 0.001); Friendly kind of attitude towards others (r = -0.13, p = 0.001); Dominance index in attitude towards others (r = -0.09, p = 0.021); Friendliness index in relationships with others (r = -0.10, p = 0.019); Communication abilities (r = -0.19, p = 0.000); Organizational abilities (r = -0.11, p = 0.047); Desire for people (r = -0.15, p = 0.006); Narcissism (r = -0.21, p = 0.001); Expressed inclusion behavior, that is, a person's desire to be among other people and to belong to various social groups and communities (r = -0.13, p = 0.041); Demanded inclusion behavior, that is, a desire for other people to try to be around the person (r = -0.17, p = 0.008); Expressed control behavior, that is, a person's desire to control and influence others (r = -0.13, p = 0.034)

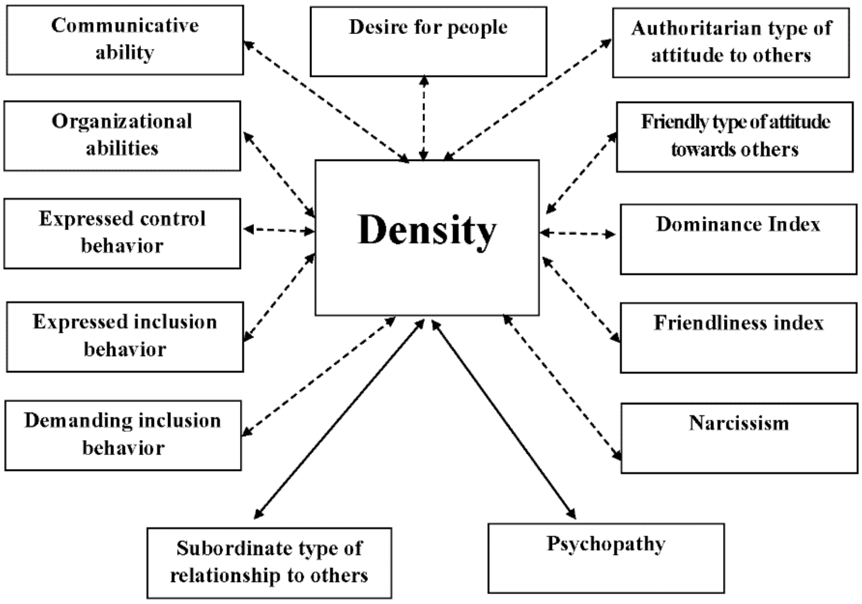

Figure 4 Correlations of the "Density" indicator with psychodiagnostics' indicators.

The Density score also directly correlates with Psychopathy (r = 0.13, p = 0.037) and Subordinate Attitude Type (r = 0.10, p = 0.020).

The correlation results for Density, which describes how interconnected the user's immediate friends are within their social graph, are pretty interesting. The content of the correlations of this indicator is similar to the previous three ("Elements," " Edges," "Friends"), but the direction of correlations is mirrored.

The Clustering Coefficient indicator (Figure 5) shows an inverse correlation with the following psychodiagnostic indicators: Inclusion Demanding Behavior, that is, the desire for others to try to be around the person (r = -0.15, p = 0.017); Controlling behavior, that is, the desire for the person to control and influence others (r = -0.14, p = 0.033).

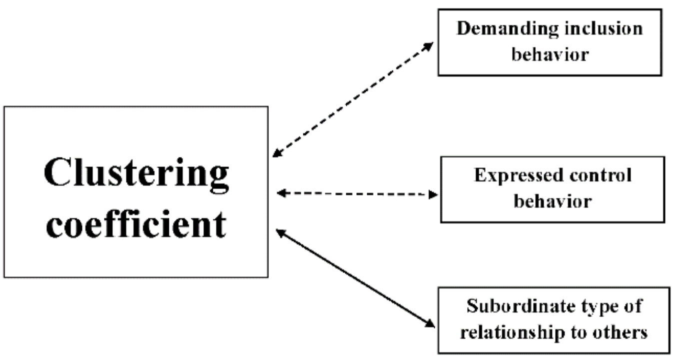

Figure 5 Correlations of the Clustering Coefficient indicator with psychodiagnostics' indicators.

Also, the Clustering Coefficient indicator directly correlates with the psychodiagnostics hand characterizing the Subordinate type of attitude towards others (r = 0.09, p = 0.024).

The "Closeness centrality" and " Degree centrality" indicators, which describe, respectively, the degree of information dissemination across the user's social graph and the degree of influence of the user in the social graph, were identical, according to the results of the correlation analysis (Figure 6). They showed direct correlations with Fear of rejection (r = 0.13, p = 0.014) and Psychopathy (r = 0.20, p = 0.002). Inverse correlations were found with Demanding Affective Behavior, the desire for others to try to be more emotionally intimate with a person (r = -0.13, p = 0.039).

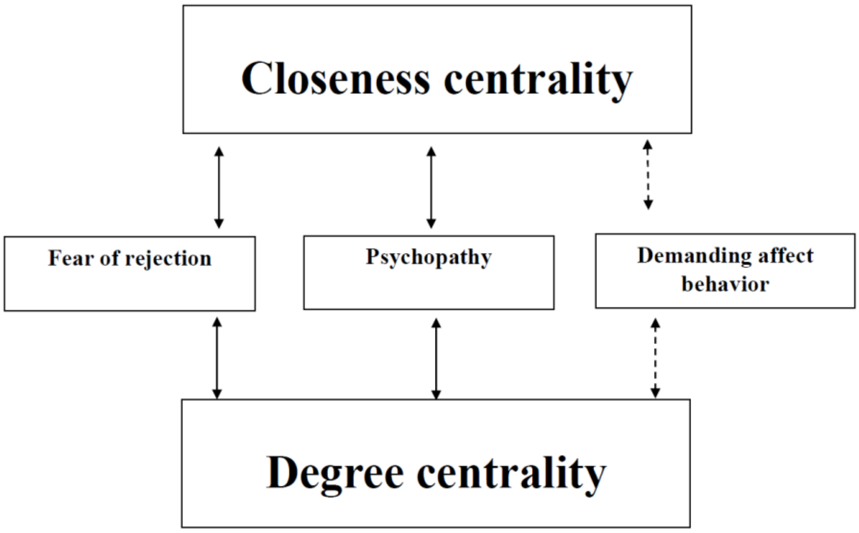

Figure 6 Correlations of "Closeness centrality" and "Degree centrality" with psychodiagnostics' indicators.

Thus, the study has shown the existence of correlations between some characteristics of social graphs (friends, density, clustering coefficient, closeness centrality, etc.) and several indicators of psychodiagnostic techniques (dominance and friendliness index in relationships with others, communication and organizational abilities, desire for people, narcissism, etc.). The results of the study confirmed the hypothesis that the level of social success of a personality, reflecting the characteristics of its interpersonal relationships, can be predicted by social graphs, reflecting the features of its virtual activity in social networks.

5. Discussion

The inclusion of social networks as a virtual model of socio-psychological reality in the subject area of contemporary research significantly expands the possibilities of the methodological apparatus of psychological science. This inclusion makes it possible to consider the dynamic changes constantly occurring in the modern model of social reality. Moreover, such inclusion extends the horizons of understanding human behavior phenomena in the real world. It opens up new opportunities for diagnostics and prognosis of psychological characteristics of a personality and its probabilistic behavioral patterns through peculiarities of its activity in virtual reality.

Due to the active introduction of machine learning technologies and Big Data methods into the field of psychological research, involving significant samples of tens and hundreds of thousands of participants, the reliability and validity of the results obtained have a high degree of credibility. As an additional result of research, we see possibilities for the creation of a new branch of psychology - sociological psychology, which studies psychological phenomena on samples in tens of thousands of participants, with in-depth revealing of characteristics of an internal world of the person that is not peculiar to social psychology. The results, revealing possibilities of psychological validation of indicators of social graphs with hands of traditional psychodiagnostic methods, act as one of the stages of sociological psychology's formation. Based on the obtained results, we see further steps of the project implementation in the empirical study of mechanisms and patterns of social (socio-communicative, socio-virtual) success of social network users with a possible prediction of such success. As a general result, we see a working model of social (socio-virtual) success prediction for social network users, which will become another link in the complex education of "life activity" of a person as an actor involved in academic, professional, and social life activity with its indicators of success.

The scientific significance of the study is defined, on the one hand, by the extension of theoretical understanding of the patterns and mechanisms of prediction of potential behavioral reactions of a person in real space through features of his virtual behavior. On the other hand, there are possibilities for the applied use of research results. The study's results expand the options of psychology in proposing principally new psychodiagnostic technologies of compiling a psychological portrait of a person based on analysis of his virtual activity and methods of research and forecasting of personality behavior through virtual space.

The study presented here differs from similar work in the field in its focus on predicting not so much potential threats to mental comfort or health as on predicting the potential for social success in currently existing digital communication systems. Indeed, the idea of studying parasocial relations is not new, as well as attempts of its clinical [65] or economic-psychological [66] analysis, but in this case, the purpose of the research was instead to determine the potential of social and psychological adaptation in conditions when insurmountable circumstances limit traditional, face-to-face forms of social contacts.

Makarevskaya and Ryabkina [67] express a similar idea about the possibility of predicting social success in the broadest possible range of behavioral activity, and these authors link social and professional success as indicators that are equally available for study through the analysis of the person's network activity. However, the research technology in the mentioned research is different and based on the participants' self-reports. At the same time, in this study, the basis for the analysis was objective data on social activity in digital communication environments.

In general, the potential usefulness of the described study lies in the fact that it combines a psychometric approach to measuring the social qualities that determine social success and social network analysis technologies that allow predicting with some probability the level of social success of a person based on the characteristics of their activity in the digital communication environment. In this way, the authors attempt to develop a standardized and psychometrically sound technology for predicting social success without directly examining the subject under study.

6. Conclusions

The study's results reflect the solution of one task of the research project aimed at developing and testing a neural network psychometric model for predicting the social success of an individual as one of the aspects of their life activity through sociometrics - indicators of social graphs of social network users. The study included construct validation of a set of variables represented by social graph indicators by finding their correlations with the hands of traditional psychodiagnostic questionnaires. In the future, the obtained results will serve as a basis for training a neural network model for predicting the social success of an individual based on the features of their virtual activity in the social network VKontakte.

Based on the obtained results, it seems possible to assert that the proposed method for assessing the social success of social network users through graph analysis looks promising. The study has shown that along with the metrics familiar to psychologists, new indicators can be used - social graphs, which can be presented as a mathematical model that operationalizes interpersonal relationships through mathematical concepts such as bond density, centrality measures, clustering and reciprocity coefficients, etc. The use of this method of assessment is quite relevant, especially nowadays, when the difficulty of face-to-face social contact leads to the growing importance of virtual communication mediated, among others, by social networks.

Additionally, the improvement of this approach makes it possible to carry out "non-contact psychological diagnostics," which ensures neutralization of the influence of social desirability on the results of the diagnostic procedure. The approach similar to using "big data" in behavioral economics and forecasting the economic behavior of an individual subject can also be applied in social psychology.

6.1 Limitations of the Study

The study has several limitations. First, the results were obtained from data downloaded from the social network VKontakte, characterized by the predominance of Russian-speaking users. Consequently, the results bear the imprint of specific mentality features inherent in Russian-speaking residents of the post-Soviet space. Any conclusions of this study should be interpreted cautiously when projecting them onto samples with other regional and cultural specifics.

Secondly, the study did not consider gender, age, and other demographic characteristics of social network users, which is seen as one of the study's prospects.

Third, the difficulties associated with the closed accounts of some social network users related to the subjects by the parameter "Friends" at the second (friends of the subject's friends) and third (friends of friends of the subject's friends) levels of the social graph. This may have partially affected the subjects' social graph metrics analysis. The problem of closed accounts of social network users currently has no unambiguous solution and is also one of the prospects for further research.

Fourth, social desirability, manifested in the need of some subjects to create as many contacts as possible (metric "Friends"), could partially affect the reliability of the results of the analysis of their virtual activity. Overcoming this limitation in the future involves developing algorithms for analyzing users' social success, which would take into account the interaction of various indicators of their virtual activity in social networks and reduce the distortions associated with the effect of social desirability.

Author Contributions

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

Funding

The study (all theoretical and empirical tasks of the research presented in this paper) was supported by a grant from the Russian Science Foundation (Project No. 19-18-00253, "Neural network psychometric model of cognitive-behavioral predictors of life activity of a person on the basis of social networks"), https://rscf.ru/project/19-18-00253/.

Competing Interests

The authors have declared that no competing interests exist.

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