Agent-Based Modeling Financial Services in Social Networks

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Abstract— A promising direction for the transformation of social networks is the connection of commercial and financial communications to them. This solves a whole range of problems: monetizing social networks, retaining users in networks, and increasing network traffic; receipt of financial and commercial services by network users in the process of network communications; and expanding the client base of financial institutions. At the intersection of financial services and social media, a new phenomenon has emerged – access to financial services on online social media (FS OSN). The novelty and the first steps in the formation of financial inclusions require conceptual justification and determination of approaches to their study. It is equally important to analyze the effectiveness of incorporating FS OSN into the general system of knowledge, business processes and social communications. This analysis is carried out from an institutional point of view and agent-based modeling. The article proposes methods and models that allow analyzing the socio-economic behavior of consumers of financial services in social networks from the moment they start applying for financial services (e.g., clicking on ads) to making decisions, as well as providing financial services. both through social media channels and bypassing them but using them at different stages of subsequent maintenance. The agent-based approach to the design of financial inclusions in social networks allows us to identify the conditions for the stability of the system and the conditions for transition to other states, as well as to establish the relationship between the evolution of financial intermediation and the social network and the innovative mission of digital financial technologies and social networks. Specific nodes, links and their strengths and weaknesses are the main structures of analysis important for determining the behavior of financial intermediaries, social networks, and their participants, as well as building a model of interaction between nodes. These interactions are considered as a set of social and business contacts in the network.

Keywords - Online Social Networks, Financial Intermediation, Agent-Based Modeling

I. INTRODUCTION

Social networks are an example of spontaneous development [1] and represent a high level of self-organization [2]. They are constantly in motion – moving from one state to another. Recently, social networks offered an increasingly wide range of financial and commercial services. For this, various recommender-based applications have been developed [3]. They help network users make decisions in the face of information overload and help financial institutions and retailers promote their services and products [4] and retain customer [5]. As a result, there are changes in the information, commercial and financial space, in the organization and structure of intermediation, as well as in the forms and methods of providing financial services to end users. Social networks are also changing their functionality and commercialization are expanding. They are increasingly offering their users a wide range of financial services and goods [6], which allows network users to make transactions in a "one-stop shop" – receive services and buy goods when communicating on social networks. In addition, financial services are not tied to business hours and office/shop location but are tied to the location of the network user. Equally important is the personification of the offer of services and goods. At the same time, it becomes possible to individualize services and consider the interests of network users more fully. As a result, the previously dominant universality, mass character and homogeneity of financial services are giving way to personalized offers. However, the prospects for the penetration of e-finance and e-commerce into social networks are still unclear [7]. A powerful accelerator of the commercialization of social sites is the monetization of social media platforms, the scaling of financial services and commerce, and the desire to retain users and increase traffic. The commercial success of financial and commercial applications in social networks acts as a kind of guarantee for the further development of this process. Financial and business applications in mobile communications are especially rapidly gaining momentum [8].

Modern social media platforms are based on Web 2.0 technologies, which have opened a wide range of opportunities for companies to connect to social sites [9]. The transition to Web 3.0 [10], which combines machine and human intelligence to create new ideas and values, greatly expands these opportunities. This shift will greatly expand the boundaries of social online technologies. The transition to Web 4.0 implies the further development of the mobile space (allows you to combine real and virtual objects and users to create new value). At the heart of Web 5.0 is a sensory-emotional space that will further expand the boundaries of social sites to include additional features [11], [12].

Financial intermediaries are moving to better platforms as they connect businesses with end-users. The interaction between a financial intermediary, a social network, and a user can be viewed as a multi-agent system [13]. Doing business on a social platform provides stakeholders with the information they need to achieve their goals. The introduction of the Internet and e-commerce has led to the automation of many of the tasks performed by financial intermediaries and merchants and has led to the emergence of new intermediaries and structures. In some cases, the importance of complementary intermediary relationships is increasing significantly, leading to a change in the role of traditional financial intermediaries and traders. However, the key is usability and the value that new links create. It is no coincidence that social networks have included financial services in their activities. There were appropriate prerequisites for this, among which the intermediary function stands out, which is the basis of both financial activity and social communications.

Intermediation refers to the ability of social networks, first, to provide various value-added services, following the example of traditional financial intermediaries; secondly, to compensate for the negative consequences of additional costs arising in the process of value creation due to the appearance of additional links in the intermediary chain [14]; thirdly, to unite the efforts of all participants in the value chain in the context of adding a new element and new functions to the function; fourthly, to transfer the function of trust from one person to another [15]. A general approach to intermediary value chain analysis has been proposed by Bakos (1998) [16]. The analysis of value-added intermediary services requires an integrated approach, including the analysis of the relationship between the buyer and the seller, the search for a pricing mechanism and price compromises, facilitation of transactions and the provision of appropriate infrastructure. Social media offered all these elements. The social media platform is fully suited for offering goods and financial services to online users [17].

Conceptualization of new knowledge and processes based on the introduction of financial and commercial services in social networks is possible and necessary with the accumulation of the necessary statistical data. However, a hypothetical review of changes is possible at an early stage. It allows you to assess the current situation and consider possible trends and options for changes in financial intermediation and social networks. Financial and commercial services are becoming a prominent trend in the development of social media, financial intermediation, and e-commerce [18]. Social sites do not have restrictions on the time and place of the provision of services, unlike real offices and shops. Mobility, combined with the flexibility afforded by modern recommender systems embedded in social networks, allows such services to capture the attention of online users [19]. Social distancing and lockdowns caused by the COVID-19 pandemic have accelerated the spread of financial services and social media commerce [20]. As a result, the phenomenon of inclusive financial and trading participation in social networks has emerged, which serves to provide financial services and trade through social networks.

Although financial and merchant services have become a prominent trend in the development of social networks on the Internet, some restrictions may affect their further development. Among them, the following financial restrictions stand out: firstly, in a number of countries there are state restrictions on the development of financial services through social networks - from direct prohibitions (for example, in China) to requirements for licensing financial activities; secondly, financial institutions are introducing direct communication with customers - blogs, managers, networks interacting with customers online; thirdly, digital platforms are emerging that organize direct links between money holders and borrowers, which excludes financial institutions from the process of lending and investing. The article addresses the following questions. How can microfinance and micro trade determine the macroeconomic structure, in particular the development of the financial sector, and contribute to the creation of a unified information and financial environment? Is it possible to analyze these processes using agent-based modeling? What new financial technologies make it possible to expand the functions of financial intermediation and combine them with information mediation? Is the advent of financial services on social media a milestone in the development of financial and social intermediation, or just one of many passing phenomena?

II. THE STRUCTURE OF THE STUDY AND ITS FORMAL BASIS

There is a wealth of academic and practical literature on social media and its commercial functions [21], as well as financial intermediation [22], [23]. However, it is extremely rare to find works explaining the inclusion of financial services in social networks [24], and the behavior of participants in financial interactions in social networks. In addition, there are no works on the conceptualization of the nature of financial intermediation in social networks and on agent-based modeling of systems of financial and commercial recommendations in social networks. The literature on both social networks [25] and recommender systems [26], as well as the microstructure of the financial market [27], including cash and investment retail [28] and e-commerce [29], is extensive and includes both academic and industry publications. It is difficult, if not impossible, to give even a superficial overview in a few pages of these two, until recently, completely unrelated areas. However, with the digitalization of finance and retail and the advent of recommender systems, financial and merchandise social media applications have been developed. As a result, financial and commercial functions have been incorporated into social networks. At the same time, there was an institutionalization of financial and commercial services in social networks in the form of financial inclusions (FI) and commercial inclusions in social networks.

The novelty and the first steps in the development of FI require the conceptualization and definition of approaches to the study of this problem. No less important is the choice of practical approaches related to its effective inclusion in the overall system of knowledge, business processes and social communications. There is a wide field of activity here, as information, trade and financial flows merge into a single organizational form, which opens great prospects for business and social communications and can influence the behavior of markets and social users. The new engine emerged from financial and commercial applications integrated into social networks based on recommender systems. At the first stage, the initiators of their formation were trade and financial institutions. Later, key social networks began to develop this niche. In some cases, they used the services of trade and financial intermediaries; in others they included the functions of the latter within their scope. To this end, social networks have included licensed banking or settlement operators in their structure. A lot of work has been done in academia and business practice to develop the theory and economic use of social networks, recommender systems, e-finance, and e-commerce; the relationship between these areas is still unclear. This article presents an innovative idea that allows you to integrate these areas and move on to conceptualization based on building an agent model and analyzing the mechanism for optimizing the interaction of agents.

III. CONCEPTUAL FRAMEWORK AND HYPOTHESIS

FI Concepts: Financial Intermediation & Social Media → Financial and Social Information Systems → Financial Recommender Systems; User-Oriented Systems → Agent-Based Models → Agent Behavior → Recommender System → System Optimization.

The problem of financial recommendations in this article is formulated as follows: let U is a set of users, S is a set of financial services; Then g: $U \times S \rightarrow R$, where R is a fully ordered set, that is, a utility function such that g(u, s) measures the gain in the utility of a financial service s for user u.

The main function of the network is to convey information and values that "flow" through the connections between nodes [30]. The flow of information between network participants is affected by the distance between nodes, the position of nodes in the network and the integration of nodes into the network, that is, contacts and their strength. In this case, mediation was ignored. However, in essence, mediation was recognized because the network was seen as a channel for the transmission of information. The introduction of social media financial applications has demonstrated the importance of online intermediation and the role of new embedded nodes in spreading information and influencing other nodes. The article discusses the mechanism for including financial intermediation in the system of social mediation. Financial investments in social networks have a high information and social-interactive potential, which has yet to be studied in detail. Network connections are critical to the efficient behavior and operation of agents in an agent society. The division of the network into the center and the periphery allows us to evaluate the dynamics of the network and the integration of new arrivals. How can financial inclusion use information to integrate into a dynamic network that runs from the periphery to the center? The agent model allows you to analyze not only the behavior of participants, but also the movement of information between them [31]. The problem is solved in different ways: (i) if the nodes that determine the input of financial information into the system are taken as the center, and users are taken as the periphery, then information about intermediation is collected, (ii) if network users are considered as central nodes, then the emphasis is on efficiency meeting their needs.

The environment in which recommender technology is commonly used has changed markedly over the past few years in terms of the scale, variety, and complexity of data available. Modern recommender apps not only have a matrix of user and item ratings, but also complex user experience data, detailed item profiles, and large-scale (own, public, or third-party) resources of many different types. For their successful functioning, various optimizers are used. Agent-based modeling is used as a lens to understand the nature of competing processes in recommender systems and the logic behind recommender development. The agent-based model of group behavior is used to model the logic of collective decisions, determined by reaching the consensus threshold. The key parameter of the model is the corporatism of interaction between agents. The probability of collective decisions depends on individual preferences and the strength of cooperation between agents.

The development of modern recommender systems has been accompanied by significant progress in the development of efficient algorithms for optimizing data input into recommender systems and in understanding the role of recommender functionality in various application areas. The availability and convergence of technologies and resources in social systems—personal user data, user interaction records, user-generated content, social networks, rich databases, geospatial information, and so on—have changed the context in which recommendations are made. Extensive information increases the ability to offer better solutions. However, the amount of information complicates the decision-making process. To simplify it, you need to optimize your data. Therefore, optimization problems become decisive in the process of making decisions and preparing recommendations.

A. Limitations/implications of the study

This research is limited to agent-based modeling of agent behavior when developing recommendations. The emerging collective behavior with consistent and non-deterministic individual decision-making can be modeled within the agent-based approach with local interaction between agents who are inclined to cooperate, considering the optimization of decisions.

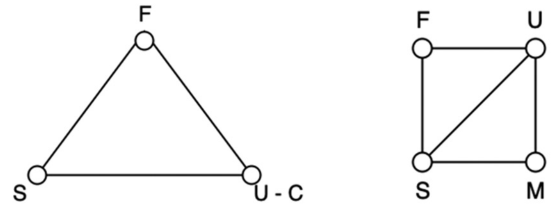
IV. AGENT-BASED MODELING

An important problem of economic theory is the modeling of the market, which is necessary to assess its state and predict its behavior in time and space (for example, to assess the prospects of markets in different countries). Rather conditionally, this task can be reduced to finding a certain law that allows, from the available information about the market at the initial moment of time , to determine its future state at any moment of time. Simulation allows (i) to understand the behavior of decentralized agents within financial and trade inclusions, (ii) to assess the behavior of such inclusions in social networks, (iii) to study the influence of individual behavior of agents, (iv) to assess the evolution of financial and trade inclusions, and (v) to optimize the interaction of financial and commercial agents with network users. At the same time, it becomes possible to assess the behavior of agents at the individual level - network users, financial institutions, shops, and social sites. A global vision of their behavior arises in the course of the activity of many agents, that is, as a result of modeling from the bottom up.

Agent-based modeling can be viewed as an alternative to DSGE models since in some cases they can better represent financial markets than standard models. Such modeling serves as a kind of background for the decision-making process.

A. Agent-based models

At the heart of the model construction of the proposal: each agent is interested in the realization of their own interests and, therefore, focuses on their own costs and benefits; private costs and benefits depend on other interests - financial and commercial agents in social networks; each agent promotes its interests and seeks to benefit from other agents. The state of agents has the following graphical structures: three-agent system - relations of a financial intermediary with social networks and network users (Fig. 1a) - FSU; four-agent system - relations of financial and commercial intermediaries with social networks and network users (Fig.1b) - USFM, where F is a financial intermediary, S is a social network in the network, U is a network user, M is a seller. In a four-agent system, the financial intermediary is the dependent variable - the actions of the financial intermediary depend on the buyer's choice of the purchase method, and the buyer is the independent variable - he determines the purchase from his own or borrowed funds.



Figures 1. (a) Three-agent– F-S-U and (b) four-agent system – U-S-F-M

The success of financial intermediaries and merchants largely depends on the number of online users. In turn, users also benefit from the number of network participants. First, financial, and commercial intermediaries grow their business through participation in social networks and benefit from their scale; secondly, costs decrease as the number of users of financial and commercial services increases; thirdly, the effectiveness of collective action increases with the increase in the scale of the network and financial and commercial activities. User groups with financial and commercial interests are defined as "inclusive" groups [32]. In contrast, "exclusive" groups attempt to promote targets for which the average benefit falls as group membership grows or is independent of group size. Therefore, financial and trade inclusions can be seen as a digital version of interactions that can be viewed in terms of the microeconomic structure of contracts and the theory of firms [33].

The sociometric approach to social and financial networks considers the location of nodes in the network [34]. Thus, network methods and graph theory allow us to proceed to the establishment of the centrality index [35]. It identifies the most important nodes in the network [36]. The centrality index characterizes both the uniqueness and the direction of the events and information on the site on a certain key topic (for example, financial and commercial). Centrality determines the position and state of financial and commercial services and their functions in social networks. The increase in the value of these functions is associated with their transition from peripheral to central. At the heart of this transition lies on the one hand, the digitalization of finance and its transfer to big data, and on the other hand, the transformations in social networks associated with the completion of their explosive growth and the transition to some slowdown [37].To stimulate development, social networks are moving from extensive mechanisms to search-intensive ones.

All this leads to an increase in networks and the number of network nodes, as well as to a change in the centers of influence of nodes in the network [38]. The rise of the typology of flow processes [39] determines the emergence of financial functions and their integration into the network mode [40] Centrality issues become the subject of research not only for commercial, but also for credit and investment networks when determining the relationship between interest rate, investment premium and risk [41]. Graphs of financial investments in the network allow you to determine their connectivity, optimize paths between nodes and, thereby, determine the best recommendations, as well as improve the efficiency of connecting users to financial services and commercial transactions.

B. State and properties of agents

The graph denoted by G is represented by a set of nodes - a financial institution (F), a store (M), a social network (S), and a network user (U), connected by edges. In the model, the graph is denoted by G and is represented by a set of nodes - a financial institution (F), a store (M), a social network (S), and a network user (U), connected by edges. The number of ribs depends on the nodes in a particular group, in which financial activities, trade, communication services, and social, commercial, and financial needs are concentrated.

Financial services in social networks can be represented in the form of financial inclusions in which there is a series of end devices – a set of nodes (F, M, S, U) on a plane, labeled with integer coordinates (i, j), each of which can be in one of the states $\sigma_{(i,j)}$:

$$\sigma_{(i,j)}(t+1)=\emptyset(\sigma_{(k,l)}(t)|(k,l)\in N(i,j), \qquad (2)$$

where N (i, j) is some neighborhood of the point (i, j), which according to von Neumann is defined as $N_N^1(i,j)=\{(k,l)|\ |i-k|+|j-l|\leq 1\}$; according to Moore as $N_N^1(i,j)=\{(k,l)|\ |i-k|\leq|j-l|\leq 1\}$. Various transition states arise, which are determined by the number of states σ and the number of other participants n: $N_r=\sigma^{(\sigma^n)}$.

The evolution of participants leads to the emergence of sequences that obey certain rules. These rules can be attributed to local stable connections that affect the behavior of the entire system. First, in the process of interaction, local stable connections are formed. They are based on financial advice and contacts based on financial advice and services. Second, local changes in the initial conditions affect the parameters of the entire system and lead to its evolution.

The state of the system depends on the values that the participants bring to it. As part of a financial inclusions, the value depends on the sum of all values - an online user, a store, a social network, and a financial institution. Various specific values are possible both for each participant and for the entire system. The agent-based model makes it possible to identify patterns in the development of a collective solution for various interactions of agents, as well as to study the influence of changes and behavior of agents during the transition from an individual solution to a collective one, that is, in the process of coordinating a solution. The agent model makes it possible to model the logic of collective decisions determined by the achievement of a threshold value [43]. The key parameter of the model is the cooperativeness of agents, which places the group in a certain financial and cultural dimension of individualism / collectivism. There are many types of collective action. All of them cannot be reflected using the same formal model. Any model requires simplification of actions and situations, which allows considering the required circumstances [44].

The transition to financial services begins after two separate agents (a network user and a financial institution) or three separate agents (a network user, a merchant, and a financial institution) have prepared a common solution, that is, in the process of reaching a collective decision. The likelihood of moving to a collective decision depends on individual user preferences and financial guidance, as well as the strength of collaboration between agents. Collaboration allows the behavior of individual agents to be corrected. The recommendation system is designed to prepare cooperation. Each agent has complex behavior. They are based on simple local interactions between agents. Some of these interactions are used in local optimization. However, general optimization of financial and commercial interactions on social media has not yet been used for global optimization.

C. Agents' behavior

Thus, special systems appear on social networks – FSU and FSUM, which are associated with financial and commercial services for social users, which are defined as financial investments. These systems can generate various types of behavior, from asymptotically stable to chaotic and unstable [45]. The stability of the system is ensured by the constant formation of supply and demand for financial services and goods, as well as by algorithms for recommendations for applications in social networks [46]. FSU and FSUM are multi-agent systems. They have a special architecture and behavior determined by their agents [47].

Dividing the FSU system into simple interactions reveals simple rules of behavior for each agent, their groups (U-F, U-S and FS) – subsystems and the entire system as a whole [48]. The action of each agent depends on the environment, the state of the system, and other agents. The state of each system depends on other systems (for example, the financial system and social networking site) and the interaction of agents in the subsystem. Coordination in such subsystems depends on the actions of agents. The actions of agents are generally rational, but asynchronous and random. Other systems affect the state of the system. Variations in the behavior of individual agents can affect the state of the entire system of financial inclusions and lead to the expansion or reduction of the scale of its functioning.

This study does not consider agents such as the state and its regulators, which have a significant influence on the development of the entire system. The design of legal standards can stimulate, change, or suppress trends that lead to the formation of financial investments (e. g., by licensing the financial activities of social sites. An important condition for the development of this system is also a change in the behavior of agents [49] towards the formation of both cooperative and non-cooperative behavior. As a result, changes are possible in the ways and dynamics of collaboration between agents [50], as well as in the scaling and diffusion of financial services. The emergence of financial services will prompt a change in group behavior that can be described in terms of evolutionary game theory [51]. In this case, the actions of random netizens are assessed using simple adaptive rules of rational behavior, rather than a form of consistency of opinions and strategies [52]. Nash equilibrium means the correspondence between the behavior of a financial intermediary and a network user. As a result, equilibrium becomes a kind of reference point for a dynamic process at the level of netizens who have chosen financial services, rather than a form of coordination between beliefs and strategies. These interactions are not limited to the formation of a system of financial investments. They also change the status, properties, and place of agents in the network.

The development of financial services provided on social media is happening in stages. At the first stage, social media includes simpler forms of financial services such as payments for goods and services and international money transfers. There is a gradual shift towards more sophisticated financial services, including investment and equity advisory, equity trading, lending, and insurance. As financial services expand, the properties of the system change. In the development of social networks, the introduction of innovations, certain leaps are possible. For example, the behavior of Facebook and its users may change due to the introduction of digital currency. This jump is probably reflected in the change in the company name proposed at the end of 2021. As a result, a certain parameter of the system changes. Similar transitions were observed earlier in various areas. This happened in graph theory during the transition to the study of random graphs [53]. During these transitions, agents update their state and some properties based on new information. In many cases, information is extracted from random data and noise [54] by crossing certain thresholds. In digital systems, thresholds can be variable [55]. In such cases, the accumulated changes overcome the threshold barrier, which allows the system to move to a new state and offer the system participants new forms and conditions of behavior and service.

V. STATISTICAL AND GAME APPROACHES

The evolution of financial services on social media can be viewed from a statistical point of view as the evolution of a multi-agent system. It has an initial matrix and transitions during a Markov process. The state of such a system at each time step is represented by a random variable. This is a vector. It contains the probabilities of certain parameters that determine the actual state of financial investments (for example, the positions of agents, demand and supply of financial services and their characteristics). In this case, the system of financial integration into social networks can be considered stable [56], since the distribution of states converges to an equilibrium distribution, that is, to the following position: $P(X_n = j) \rightarrow \pi j$ when $n \rightarrow \infty$. In this case, the system of financial inclusions is stable, since, for large values of n, the probability distribution of the states of the system is provided regardless of the time step n [57].

An agent-based approach to the design of financial services in social networks allows us to identify different states, including the conditions for the stability of a multi-agent system [58]. Among them, two conditions are distinguished that are important for optimizing the behavior of agents - adaptability and learnability. According to Jennings (2000) [59], agents are: (i) able to solve problems using well-defined constraints and interfaces; (ii) located in an environment that serves as an entrance to the operation; (iii) set specific goals and outline ways to achieve them; (iv) flexible and adaptive to changes in the environment: (v) able to control their behavior in the course of achieving their goals; (vi) active - able to respond to changes and be guided by its goals.

The proposed interpretation of the state of the system cannot easily be applied to multi-agent interactions leading to the formation of financial inclusions. There are several explanations for this. First, the apparent output of the system is discrete (expressed in multiple states) but continuous. Significant volumes of data with a high level of noise are difficult to process. It is especially difficult to identify unknown parameters behind a time-delayed noise system. Various noise-corrected identification methods are used for identification [60]. Second, all financial interactions are deterministic. The slightest changes in the initial conditions change the overall picture. By statistically interpreting more behaviors, only approximate values for a specific configuration are generated. Nevertheless, the evolutionary game theory allows one to determine the strategies of agents and their effectiveness [61], and in combination with evolutionary methods can establish the conditions for the formation and phase transition from one stage to another stage, as well as the type and state of financial inclusions [62]. Third, there is a significant accumulation of various nonlinear effects, which makes it difficult to assess the transitions between different states of the system. Transitions occur spontaneously and do not depend on the decisions of one agent. They are based on the cumulative decisions of all agents. When a multi-agent system is denoted by a continuous Markov chain with discrete time with a potentially unknown distribution of the transition probability, the stability of the system becomes a set of effects [63].

Learning in a multi-agent environment is difficult due to nonstationary, which is based on changing the behavior of both the financial intermediary and the network user. There are two possible answers to nonstationary: adaptability to the behavior of another agent (financial intermediary or network user), proactive influence on the stabilization strategy of another agent, which can limit the nonstationary caused by another agent. Some modern recommender systems based on neural networks has such abilities. Wang et al. (2021) proposed to define an uncontrollable reward for stability to teach a robotic system to deliberately influence another agent so that it stabilizes in the direction of a single strategy [64]. Stability refers to an advanced and relatively well-studied concept in physics in which it is viewed as the property of a system to continually return to a state of stable equilibrium after a minor disturbance. The mathematical definition of stability is not suitable for multi-agent financial systems with stochastic characteristics. The stability of multi-agent financial systems is achieved by preserving the basic properties of the system and returning it to its original state after various disturbances and changes in the values of the system parameters, for example, when new agents appear (for example, the creation of new financial institutions, the issue of securities or the elimination of the consequences of bankruptcy or takeover, merger). If a small initial disturbance becomes significant, the system becomes unstable.

A multi-agent financial system is in equilibrium provided that its statistical characteristics remain constant, including when external conditions change that may affect the system (for example, when government regulation changes) [65]. During violations in financial intermediation systems (for example, under the influence of digitalization of finance, implementation of financial recommendation systems, etc.) and in social media systems, the final states of systems change. Multi-agent systems formed in the form of financial inclusions can be represented as a set of agents participating in a multiplayer game. In-game theory, stability is the main property of balance. In this case, the problem of finding equilibrium is reduced to choosing the optimal strategy. Resilience can then be used to describe the characteristics of a set of strategies that are in equilibrium. If each player's strategy is the best response to the strategy of others, and no player has any incentive to deviate from the chosen strategy, then this state is the Nash equilibrium.

The stability of the financial services system in social networks is achieved through the actions performed by all agents of the system. Therefore, the equilibrium point is reached when each agent is in such a state that he does not need further work in the system, that is, the end-user either received the necessary financial service or refused it, which means that he left the system. In this case, the totality of agents' actions leads to stability - the termination of the system. Then each agent acts as if he is coordinating his actions with other agents. At the same time, the crowd effect allows predicting the behavior of agents [66]. The approach to the financial service system in social networks as a multi-agent system allows using the game method to study the behavior of agents and the entire system. In this case, the observed behaviors are considered, not the decisions made by the agents.

VI. CONCLUSIONS

The new "normal" caused by the COVID-19 pandemic has affected netizens and social media functionality. As a result, the transition of social networks to the provision of financial and commercial services to users has accelerated dramatically. For this, various applications have been developed and implemented that can respond to user requests and make recommendations to satisfy them. In turn, the financial sector faced a major challenge to respond to changes in customer behavior, which were largely related to the decline in their economic potential due to COVID-19. All these processes were combined with increased autonomy and isolation of customers, which led to a decrease in the number of customer calls to offices and the transition to online solutions. At the same time, pressure has increased on social media and digital payment, settlement, credit, and trading systems.

Financial and commercial applications were formed through the development of financial and commercial recommender systems in social networks, which was accompanied by an increase in the efficiency and effectiveness of interaction between all participants. As recommender systems become more complex and more in line with the requirements of consumers and financial intermediaries, as well as the conditions provided by social systems, the conditions have been prepared for their integration and institutionalization in social networks. As a result, financial applications continued structural and organizational consolidation and institutionalization within social networks.

In the process of incorporating financial services into social networks, several organizational principles stand out. Among them, the following are especially noticeable: the institutionalization of processes, the absence of time limits, the transition to self-organization and self-government, simplified large-scale replication.

Institutionalization is observed in the formation of financial inclusions in social networks. The course of institutionalization is analyzed using a three-agent model and characteristics of agent behavior. The mechanism of institutionalization can be built according to a three-agent model, and by analyzing the behavior of agents, it is possible to determine the main causal relationships, conditions, and results of its formation. The institutionalization of financial inclusions is based on large databases and new knowledge that comes at the disposal of financial intermediaries.

The institutionalization of financial and commercial processes in social networks is focused on databases. However, this information does not explain organizational changes. Knowledge is not a traditional entity. In addition, each site in its own way solves the problem of the functioning of financial investments. In some cases, it all comes down to simple recommendation systems that social networks provide to financial intermediaries on various terms; in others, social networks are evolving their way of delivering financial services. In the latter case, social networks consider the mechanisms of state regulation. The transition to institutionalization is also associated with the financial culture of society, which can both stimulate and limit its course.

Entities that are process-oriented in terms of execution time are practically unlimited in their work. Deep learning allows recommender systems to replicate skills and expand almost indefinitely as needed throughout the site. Optimization allows you to regulate decision-making processes.

Different roles, interests, and tasks of agents - for example, financial intermediaries determine the demand and supply of network users for financial services, rank the positions of supply and demand - require different sets of methods, tools, and the study of different databases. The most common algorithms use autoregressive tools. They can be coded in different programming languages.

Financial inclusion in social networks, as in other complex digital systems, creates new challenges for experimentation, testing, and widespread use of social, financial, and technical systems. In such systems, autonomous agents interact both locally and remotely with other agents to not only make intelligent choices, but also save time and resources. As a result, the productivity and efficiency of economic and social systems increase.

The accelerated development of the new takes place during the activation of the mechanism of self-organization of the system through the interaction in financial applications with social networks. So, agents in the process of agreeing on the conditions for the consumption of financial services adjust to each other. Although such complex systems are deployed and managed using a centralized infrastructure (financial intermediaries, social networking sites and their processing power), the socio-technical nature of these systems requires new approaches. These approaches should be cost-effective, build trust and enhance transparency, and be consistent with the social values of network users (including privacy, autonomy, fairness, and fairness in choosing and receiving services).

In this article, we define financial investment in social networks as a potential set of financial services that network users receive when using social networks. Financial inclusions are distinct from, but dependent on, and may be an element of traditional financial intermediation and financial start-ups but are (i) embedded in social networks or (ii) financial functions are performed directly by social sites. We consider the first option in connection with the expansion of financial intermediation to social networks - the use of social networks by financial intermediaries to scale their activities; the second option is to expand social networks in the financial sector to retain network users, increase network traffic and monetize network services.

The results of the study of this article can serve as a guide for further study of the evolution of financial and trade services and their integration into social networks as a dynamic process with unexpressed equilibrium points.

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