Financial applications of online social networks and media: problems and prospects

Финансовые приложения социальных онлайн-сетей и средств массовой информации: проблемы и перспективы

I. K. Klioutchnikov,
doctor of economic sciences, professor, scientific adviser, department of economics and finance of enterprises and industries, International banking institute n. a. Anatoliy Sobchak
✉ igorkl@list.ru

И. К. Ключников,
д. э. н., профессор, научный руководитель, Автономная некоммерческая организация высшего образования «Международный банковский институт им. Анатолия Собчака»

M. V. Sigova,
doctor of economic sciences, professor, rector, International banking institute n. a. Anatoliy Sobchak
✉ sigovamv@ibispb.ru

М. В. Сигова,
д. э. н., профессор, ректор, Автономная некоммерческая организация высшего образования «Международный банковский институт им. Анатолия Собчака»

A. I. Klioutchnikova,
master's student, Physics and technology school of applied mathematics and informatics (FPMI), Moscow institute of physics and technology (National research university)
✉ anutkakl0002@gmail.com

А. И. Ключникова,
магистрант, Физтех-школа прикладной математики и информатики (ФПМИ), Московский физико-технический институт

I. A. Nikonova,
doctor of economics, professor, department of economics, management and entrepreneurship, International banking institute n. a. Anatoly Sobchak
✉ irina_nikonova@mail.ru

И. А. Никонова,
д. э. н., профессор, кафедра экономики, управления и предпринимательства, Автономная некоммерческая организация высшего образования «Международный банковский институт им. Анатолия Собчака»

A promising direction in the transformation of online social networks and media (OSNEM) is the inclusion of financial services in the scope of their activities by embedding financial applications into them. Such a transition allows social networks, financial intermediaries, and clients to solve a whole range of tasks: increase the scale of OSNEM monetization, retain users in social networks and increase network traffic, provide network users with financial services in the process of network communications «one-stop shop», expand the client base of financial organizations. Recommender systems (RSs) form the backbone of financial applications. The effectiveness of their work largely depends on the collection and optimization of data, as well as the speed and completeness of response to network user requests. The article presents a brief overview of the main ways of solving these problems from the institutional and innovative points of view; new approaches to optimizing recommendations and assessing the creditworthiness of network users are proposed.

Перспективным направлением трансформации социальных онлайн-сетей и средств массовой информации, является включение финансовых сервисов в сферу их деятельности путем внедрения в них финансовых приложений. Такой переход позволяет социальным сетям, финансовым посредникам и клиентам решить целый комплекс задач: увеличить масштабы монетизации деятельности социальных онлайн-сетей и средств массовой информации, удержать пользователей в социальных сетях и увеличить сетевой трафик, предоставить пользователям сети финансовые услуги в процессе сетевых коммуникаций через «единое окно», расширить клиентскую базу финансовых организаций. Рекомендательные системы (РС) составляют основу финансовых приложений. Эффективность их работы во многом зависит от сбора и оптимизации данных, а также скорости и полноты ответа на запросы пользователей сети. В статье представлен краткий обзор основных путей решения этих проблем с институциональной и инновационной точек зрения; предложены новые подходы к оптимизации рекомендаций и оценке кредитоспособности пользователей сети.

Keywords: online social networks and media, financial applications, recommender systems, financial intermediations, optimization data.

Ключевые слова: социальные онлайн-сети и СМИ, финансовые приложения, рекомендательные системы, финансовое посредничество, данные оптимизации.

1. Introduction

Modern online social networks and media (OSNEM) are increasingly offering their users a variety services and products. The September 2022 issue of Social Networks and Media Online [1] notes that they are one of the most disruptive communication platforms with high socio-economic value. Financial applications are rapidly evolving on OSNEM platforms [2]. Thanks to them, network users get the opportunity to buy goods and make financial transactions in a «single window» when communicating on social networks, receiving news content and other information. Thus, financial services are provided regardless of the location of the user and are not limited in time to office work. At the same time, personalization of services takes place considering the interests of network users. Despite the rapid spread of social media financial applications, the prospects for e-financing through online social media are still not entirely clear [3].

The monetization of financial applications on social networks is largely dependent on trust — the way trust is transferred between network members, as well as between the social network and financial intermediaries. This problem is largely addressed by the sharing economy [4]. The technical solution to the problem lies in the creation of an appropriate platform architecture for financial applications [5].

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. These applications are especially in demand in mobile communications [6].

Financial applications embedded in social media platforms are based on Web 2.0 technologies. This technology has provided ample opportunities for businesses to connect to social sites [7]. The transition to Web 3.0 greatly enhances the ability of platforms to work with various applications [8] by connecting machine intelligence, which is combined with human intelligence. This creates new ideas and values, as well as new perspectives for solving financial problems within the framework of social communications.

Social mediation, like financial mediation, expands the possibilities of networks, firstly, to provide various additional services; second, to compensate for the negative consequences of rising costs arising in the course of value creation by including additional links in the intermediary chain [9]; thirdly, to unite and multiply the efforts of all participants in the value chain in the context of adding a new element and new functions; fourth, move on to predicting the behavior of network users using artificial intelligence [10].

At the turn of the 20th and 21st centuries, a general approach to value chain analysis in intermediation was proposed by Bakos [11]. The analysis of value-added intermediary services requires an integrated approach that includes optimizing the relationship between the buyer and the seller, finding a price compromise, facilitating transactions and providing the appropriate infrastructure. Social media offered all these elements. The social media platform is fully suited to work in digital commodity and financial markets [12].

Financial and commercial services are becoming a prominent trend in the development of social media [13], financial intermediation [14] and e-commerce. They have no restrictions on the time and place of the provision of services, unlike real offices and shops. Mobility, combined with the flexibility provided by modern recommendation systems embedded in social networks, allow such services to gain the trust of network users [15]. Social distancing and lockdowns caused by the COVID-19 pandemic have accelerated the spread of financial services and social media commerce [16]. As a result, a phenomenon has emerged — financial and trade inclusions in social networks, which serve to implement financial services and trade through social networks.

What new technologies will expand the functions of financial intermediation and combine them with social mediation? Is the expansion of access to financial services and the inclusion of financial services in social networks an epochal event or one of many passing phenomena? The search for answers to these questions in the work was carried out by analyzing new processes for optimizing the main stages of data movement in the system «financial intermediary — social network — network user».

In this article, we define financial inclusions in OSNEMs as a potential set of financial services that netizens receive when using a social site. Financial inclusions are distinct from, but dependent on and part 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 because of the expansion of financial intermediation to OSNEMs — the use of social networks by financial intermediaries to scale their activities; the second option is to expand OSNEMs in the financial sector to retain network users, increase network traffic and monetize network services.

2. Related works and directions

An important tactical area of digital transformation is the rapid development of financial applications in social networks. Financial products, services and consultations in social networks are a new challenge for science and practice. Financial applications on social networks can significantly change the traditional form of financial intermediation and give it an extra boost.

The authors of the article participated in bringing this problem to the forefront of ecoinformatics and began to develop some of its aspects [17, 18]. Despite some development of this topic, today there is still no common understanding of the role and place of the mechanism of financial recommendations in the system of financial intermediation, social communications, and the information sphere, as well as in big data analytics.

Initial advances in social media financial recommendation systems have highlighted some promise for wider adoption and the need to move towards more accurate and personalized recommendations. Further development of financial applications in social networks is associated, first, with the transition to more detailed and multifaceted work with data, with an emphasis on business analytics of user requests. In recent years, business intelligence has increasingly focused on data that is outside the normal distributions and related not only to the heads, but also to their tails. Interest in this topic has especially increased due to the emergence of big data and the development of methods for working with them [19].

The literature on both informational and socio-economic aspects of online social networks is very diverse [20, 21]. There is a wide range of research on innovative social media solutions, including recommender systems as well as financial applications. It is difficult, if not impossible, to give even a superficial overview of even the basic issues involved in developing applications for online social networking. Nevertheless, the topic of financial inclusions — problems and prospects for their development in OSNEM has not been sufficiently developed. This article attempts to consider the main problems associated with the optimization of the central element of financial applications — recommender systems (RS).

3. Tasks/problems of recommender systems

Thanks in large part to social media finance applications, finance as a stand-alone product and service is rapidly evolving into finance as a lifestyle [22].

Embedded in social media, RSs have made it easier for new entrants and third-party vendors to enter the market, as well as facilitating the spread of various types of partnerships and market initiatives. For RSs, ways to collect data and improve the quality of recommendations are associated with an increase in the efficiency of their implementation, which is a fundamental problem and determines the direction of development of financial applications. An optimization mechanism is used to select the best solutions to problems.

3.1. Data collection

The way data is collected and processed is the basis of all RSs. The results of the recommendations depend on it.

Many PCs reduce problem solving, firstly, to minimizing the frequency of data exchange, and secondly, to reducing the number and length of recommendation messages, since short recommendations are more understandable and easier to remember. Therefore, making a recommendation as short as possible based on a thorough analysis of user behavior and demand becomes an important task for recommender systems.

To increase the reliability of the assessment of user behavior and demand, it is necessary to increase the exchange of data and expand the scope of their search. To improve the reliability of the assessment of user behavior and demand, it is necessary to increase the exchange of data and expand the scope of their search. In this regard, RSs are increasingly moving towards using the concept of long tails, that is, when developing recommendations, they consider the wider distribution of user search queries in browsers.

3.2. Recommendations quality

Improving the effectiveness of RSs depends primarily on the accuracy and speed of response to consumer requests [23]. This requires solving several complex and important tasks related to (i) profiling user behavior and patterns, (ii) developing methods that will allow RSs to adapt to constantly changing conditions and user behavior patterns, (iii) selecting representative data. Solving these problems will allow RSs to move towards predicting user intent based on both direct and contextual information. A positive result can be achieved by storing the user's intentions as nodes embedded in an n-dimensional vector space. The number of dimensions (n) corresponds to the number of context parameters considered.

Financial inclusions are based on the exchange of information between the financial institution and the network user. Therefore, it is very important to quantify how effectively agents interact within the system. Various options for evaluating efficiency are possible. A physically based estimate of flow efficiency, valid for any network, regardless of scale, nature of weights, and metadata, will allow comparison of disparate systems. At the same time, the level of network congestion/sparseness is not a criterion for its effectiveness [24]. This indicates its popularity, but not the effectiveness of the recommendations.

4. Interaction optimization

Optimization is present at all stages of PCs, from data collection to solution preparation [25]. A lot of research is devoted to the latest developments in the field of optimization of various applied problems [26].

There is no universal exact solution for optimization in multidimensional Euclidean space. Most often, in combinatorial optimization problems, the number of options grows exponentially depending on the size of the initial data, which leads to a corresponding increase in the complexity of the algorithms. For their relative simplification, gradient descent is more often used.

4.1. Gradient descent algorithms

There are various variants of gradient descent algorithms. Among them are the traditional ones such as Batch Gradient Descent, Mini Batch Gradient Descent, Nesterov Accelerated Gradient and Stochastic Gradient Descent [27]. Recently, optimizers based on visualization methods and small parameters have become widespread. Among them, for example, stand out Gray Wolf Optimizer and its modified, hybridized, and parallel versions [25], as well as evolutionary optimization methods [28] with their latest versions [29, 30]. Each optimization algorithm has its pros and cons and serves different purposes. At the same time, target optimizers are used for various financial applications.

4.2. Solvency thresholds and financial interests of users

Hyman Minsky [31] identified three types of income-debt relationships for firms: hedging, speculative financing, and financial rewards. This study finds transition thresholds between each state proposed by Minsky's hypothesis and classifies the actual state of the firm. This study goes far beyond calculating the probability of bankruptcy and relationships between firms. It proposes extending the actual threshold value of the Minsky hypothesis to social networks and their financial transactions. It can be used to check the status of financial inclusions in social networks. For example, it can serve as a conceptual framework for optimizing the financial condition of a network user to assess its creditworthiness and stable/unstable financial position based on interests and activity in a social network.

Typically, Merton's corporate default models are used to calculate the probability of customer default. Typically, the dynamics of the operating cash flow of company V over time is described by a stochastic diffusion process, where d_z is the Brownian motion:

$$dV = V\,dt + \sigma\, V\,dz.$$

The cash flow must be sufficient for each period to cover at least the repayment of the debt, C; this means that we are interested in the section of the distribution in which $V_t > C_t$.

However, this method is not applicable to assessing the state of network use, since it is based on balance data and strict reporting information and does not provide an opportunity to analyze the past state of the user based on his current social activity.

Diversity of interests is an important distinguishing feature of network users. However, in such conditions, the optimization of financial interests is a difficult task. To solve it, new optimization techniques have recently been resorted to. A competitive strategy and measurement of entropy, known from thermodynamics and information theory, is used to control the convergence operator, considering the maintenance of diversity [32]. An important aspect of the quality of such optimization is the ability to generalize unexpected behavior of users and interests that fall out of their normal distribution and belong to the tail parts.

In machine/deep learning terminology, optimizing both financial needs and financial behavior refers to the problem of minimizing the cost/loss function $J\ (\theta)$ parameterized by model parameters $\theta \in \mathbb{R}^d$, by updating the parameters in the opposite direction of the gradient objective function $\nabla_\theta J(\theta)$ relative to the parameters. The learning rate η determines the size of the steps that are taken to reach a (local) minimum.

Recommendations are often first optimized based on nearest neighbor (kNN) algorithms [33] and hierarchical optimization [34]. These algorithms also solve the cold start problem. From a computational point of view, they are simple, efficient, and easy to interpret. They can be run locally on various devices and used to protect data. In addition, kNN is easy to implement and debug.

Standard optimization of interests and requests of network users can be defined as an intelligent system with two phases: speed (or volume) and. With the growth of data volumes and high speeds of their receipt, the algorithm focuses on diversification; with data reduction and negligible speeds, the current solution focuses on amplification. In such cases, the standard approach is the following: the best solutions are stored as pBest. The optimization algorithm regulates the movement of data in two vectors: velocity (volume) — $V_i = \langle v_i^1, v_i^2, ..., v_i^D \rangle$ and position — $X_i = \langle x_i^1, x_i^2, ..., x_i^D \rangle$, where vi and xpi are the speed and position of, for example, a network user's request for a service.

In this case, the interests of network users are randomly placed in a D-dimensional heuristic space with random values of the rate and time of occurrence. As it evolves, each query updates its value with the equation:

$$v_i^1 = \varpi v_i^d + c_1 \phi_1^d\ (p\mathrm{Best}_i^d - x_i^d) - c_2 \phi_2^d\ (g\mathrm{Best}^d - x_i^d)$$

and positions according to the equation:

$$x_i^d = x_i^d + v_i^d,$$

where {1, 2 ,. . ., D} represents the size of the problem; positive constants ω, c_1 and c_2 — coefficients of data volume acceleration or growth; ϕ_1 и $\phi_2 \in [0, 1]$ — two uniformly distributed random numbers in the range [0, 1]; c_1 and c_2 — acceleration coefficients. There are three components on the right side of the velocity update equation: inertia (preserves its own property), whose weight is controlled by w using the named inertia weight; cognitive component — an evaluation criterion (problem assessment) — the quality of demand or behavior of a social user or an assessment of the state of the environment (for example, the site's technological platform) in which social users are located; social component (data structure, their reaction). The cognitive and social components simplify the customization process. They direct the data to a better position. At the same time, $p\mathrm{Best}_i$ is the best recommendation achieved during the i-th review of the data; and gBest, the global best recommendation in a review of all behavior and all interests of a web user.

5. Conclusions

The design of financial applications in OSNEM is related to several organizational principles. Among them, the following are especially noticeable: institutionalization, the absence of temporal and spatial restrictions, the transition to self-organization and self-government, large-scale replication, and optimization of processes.

The institutionalization of processes is observed within the system of financial inclusion in social networks. In future studies, the authors plan to analyze institutionalization using a three-agent model that will determine the behavior of agents at the micro level, which will provide a projection for moving on to subsequent macro studies of the problem. The mechanism of institutionalization can be designed according to the three-agent model and based on the analysis of the behavior of agents, the main cause-and-effect relationships, conditions, and results of its formation can be determined.

Deep learning allows RSs to replicate skills and expand as needed almost indefinitely within OSNEM. Optimizations allow you to regulate decision-making processes.

Financial inclusions in social networks, like other complex digital systems, pose new challenges for experimentation, testing and large-scale 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, productivity improves, and the efficiency of economic and social systems increases.

The mechanism of self-organization is activated through interaction in the system of financial accessibility. So, agents in the process of agreeing on the conditions for the consumption of financial resources adjust to each other. Although such complex systems are deployed and operated using a centralized infrastructure (financial intermediaries, social networking sites and their computing power), the socio-technical nature of these systems requires new approaches. These approaches should be cost-sensitive, build trust, enhance transparency, and be consistent with the social values of network users (including privacy, autonomy, equity, transparency, and fairness in choosing and receiving a service).

References

1. OSNEM. Online Social networks and Media. 2022. 31 p.
2. T. C. Nelms, B. Maurer, L. Swartz, S. Mainwaring. Social Payments: Innovation, Trust, Bitcoin, and the Sharing Economy//Theory, Culture & Society. 2018. № 35 (3), 13-33.
3. A. Bharadwaj, O. A. El Sawy, P. A. Pavlou, N. Venkatraman. Digital business strategy: Toward a next generation of insights//MIS Quarterly. 2013. № 37 (2). 471-482.
4. J. Ralanen, A. Ojala, T. Tuovinen. Building Trust in the Sharing Economy: Current Approaches and Future Considerations//Journal of Cleaner Production. 2020. № 279 (37). 123724. doi: 10.1016/j.jclepro.2020.123724.
5. G. G. Parker, M. W. Van Alstyne, S. P. Choudary. Platform Revolution: How Networked Markets Are Transforming the Economy and How to Make Them Work for You. W. W. Norton. New York. 2016.
6. J. Hawley. Big Tech's «Innovations» That Aren't//The Wall Street Journal. Aug 28, 2019.
7. D. Kreps, K. Kimppa Theorising Web 3.0: ICTs in a changing society//Information Technology & People. 2015. № 28 (4). P. 726-741. https://doi.org/10.1108/ITP-09-2015-0223.
8. H. K. Aggerholm, S. E. Andersen. Social Media Recruitment 3.0: Toward a new paradigm of strategic recruitment communication//Journal of Communication Management. 2018. № 22 (2). P. 122-137. https://doi.org/10.1108/JCOM-11-2017-0131.
9. G. M. Giaglis, S. Klein, R. M. O'Keefe. The Role of Intermediaries in Electronic Marketplaces: Developing a Contingency Model//Information Systems Journal. 2002. № 12 (3). P. 231-246.
10. T. Pavlovic, Flávio Azevedo, Marina Maglić et al. Predicting attitudinal and behavioural responses to COVID-19 pandemic using machine learning//PNAS Nexus. 2022. Vol. 1. Iss. 3. https://doi.org/10.1093/pnasnexus/pgac093.
11. Y. Bakos. The Emerging Role of Electronic Marketplaces on the Internet//Communications of the ACM. 1998. № 41 (8). P. 35-42.
12. E. Turban, D. King, J. Lee et al. Electronic Commerce. In A Managerial Perspective (2nd Edition). Prentice Hall, 2002.
13. Social Media. 2021 Social Media Industry Benchmark Report. Rival IQ. February 16, 2021. https://www.rivaliq.com/blog/social-media-industry-benchmark-report.
14. T. Bick, Y. C. Park. Fostering FinTech for financial transformation: The Case of South Korea//CEPR and Korea Institute of Finance. 16 September 2021.
15. D. Chaffey. Financial Services marketing trends for 2021. Smart Insights. 15 Mart, 2021. https://www.smartinsights.com/digital-marketing-strategy/financial-services-marketing.
16. T. Mahoney. How the Global Pandemic Will Disrupt the Future of Human Ethos//Medium. Jul 8, 2020.
17. I. K. Klioutchnikov, A. I. Klioutchnikova. Long-Tail Distribution Financial Recommender Systems Embedded into Social Networks//Communications of the IBIMA. 2022. Article ID 165496. doi: 10.5171/2022.165496.
18. I. K. Klioutchnikov, O. I. Kliuchnikov, O. A. Molchanova. Alliance of Commerce and Financial Intermediation with Social Networks: Problems and Prospects//Journal of Internet and e-Business Studies. 2020. Article ID 704163. doi: 10.5171/2020.704163.
19. P. Mikalef, I. Pappas, J. Krogstie, P. Pavlou. Big Data and baseness analytics: research agenda for realizing business value//Information & Management. November 2019.
20. J. E. Teixeira, A. T. Tavares-Lehmann. Industry 4.0 in the European union: Policies and national strategies//Technological Forecasting and Social Change. 2022. № 180. 121664.
21. J. Scott, F. N. Stokman. Social Networks. In International Encyclopedia of the Social & Behavioral Sciences. Second Edition. Elsevier. 2015. P. 473-477.
22. Embedded Finance. Embedded Finance — A Universal Business Theme: Focus on Europe, Latin America, and Asia Pacific, Everest Group. 2022.
23. B. M. Changmai, D. Nagaraju, D. P. Mohanty et al. On-device User Intent Prediction for Contest and Sequence Aware Recommendation//CARS-2019: Context-Aware Recommender Systems Workshop. September 20, 2019. Copenhagen, Denmark. ACM, New York, NY, USA, 8 p. arXiv:1909.12756v1 [cs.IR] 18 Sep 2019.
24. G. Bertagnolli, R. Gallotti, M. D. Domenico. Quantifying efficient information exchange in real network flows//Communications Physics. 2021. 4 (1). doi:10.1038/s42005-021-00612-5.
25. H. Faris, I. Aljarah, M. A. Al-Betar et al. Grey wolf optimizer: a review of recent variants and applications//Neural Computing and Applications. 2018. 30(22). doi: 10.1007/s00521-017-3272-5.
26. L. Amodeo, E-g. Talbi, F. Yalaoui. Recent Developments in Metaheuristics. Springer. 2018. 496 p.
27. S. Ruder. An overview of gradient descent optimization algorithms. Cornell University. 15 Jun 2017. arXiv.org > cs > arXiv:1609.04747.
28. T. Back, D. B. Fogel, Z. Michalewicz. Handbook of evolutionary computation. Oxford University Press, New York. 1997.
29. Y. Zhou, S. Zhang, Q Luo et al. CCEO: cultural cognitive evolution optimization algorithm//Soft Computing. 2019. 23 (4). December 2019. doi: 10.1007/s00500-019-03806-w.
30. N. Javaid. Differential Evolution: An Updated Survey//Conference: 12-th International Conference on Complex, Intelligent, and Software Intensive Systems (CISIS-2018). May 2018.
31. H. P. Minsky. The Financial Instability Hypothesis 4//The Jerome Levy Economics Institute Working Paper № 74. 1992. https://ssrn.com/abstract=161024.
32. W. Guo, L. Zhu, L. Wang et al. An Entropy-Assisted Particle Swarm Optimizer for Large-Scale Optimization Problem//Mathematics. 2019. № 7, 414. P. 1-12.
33. D. A. Subramanian. Simple Introduction to K-Nearest Neighbors Algorithm//Towards Data Science. 2019, Jun 8.
34. V. Thambawita, R. Ragel, D. Elkaduwe. An optimized Parallel Failure-less Aho-Corasick algorithm for DNA sequence matching//Conference: 2016 IEEE International Conference on Information and Automation for Sustainability (ICIAfS). December 2016. doi:10.1109/ICIAFS.2016.7946533.

Список использованных источников

1. OSNEM. Online Social networks and Media. 2022. 31 p.
2. T. C. Nelms, B. Maurer, L. Swartz, S. Mainwaring. Social Payments: Innovation, Trust, Bitcoin, and the Sharing Economy//Theory, Culture & Society. 2018. № 35 (3), 13-33.
3. A. Bharadwaj, O. A. El Sawy, P. A. Pavlou, N. Venkatraman. Digital business strategy: Toward a next generation of insights//MIS Quarterly. 2013. № 37 (2). 471-482.
4. J. Ralanen, A. Ojala, T. Tuovinen. Building Trust in the Sharing Economy: Current Approaches and Future Considerations//Journal of Cleaner Production. 2020. № 279 (37). 123724. doi: 10.1016/j.jclepro.2020.123724.
5. G. G. Parker, M. W. Van Alstyne, S. P. Choudary. Platform Revolution: How Networked Markets Are Transforming the Economy and How to Make Them Work for You. W. W. Norton. New York. 2016.
6. J. Hawley. Big Tech's «Innovations» That Aren't//The Wall Street Journal. Aug 28, 2019.
7. D. Kreps, K. Kimppa Theorising Web 3.0: ICTs in a changing society//Information Technology & People. 2015. № 28 (4). P. 726-741. https://doi.org/10.1108/ITP-09-2015-0223.
8. H. K. Aggerholm, S. E. Andersen. Social Media Recruitment 3.0: Toward a new paradigm of strategic recruitment communication//Journal of Communication Management. 2018. № 22 (2). P. 122-137. https://doi.org/10.1108/JCOM-11-2017-0131.
9. G. M. Giaglis, S. Klein, R. M. O'Keefe. The Role of Intermediaries in Electronic Marketplaces: Developing a Contingency Model//Information Systems Journal. 2002. № 12 (3). P. 231-246.
10. T. Pavlovic, Flávio Azevedo, Marina Maglić et al. Predicting attitudinal and behavioural responses to COVID-19 pandemic using machine learning//PNAS Nexus. 2022. Vol. 1. Iss. 3. https://doi.org/10.1093/pnasnexus/pgac093.
11. Y. Bakos. The Emerging Role of Electronic Marketplaces on the Internet//Communications of the ACM. 1998. № 41 (8). P. 35-42.
12. E. Turban, D. King, J. Lee et al. Electronic Commerce. In A Managerial Perspective (2nd Edition). Prentice Hall, 2002.
13. Social Media. 2021 Social Media Industry Benchmark Report. Rival IQ. February 16, 2021. https://www.rivaliq.com/blog/social-media-industry-benchmark-report.
14. T. Bick, Y. C. Park. Fostering FinTech for financial transformation: The Case of South Korea//CEPR and Korea Institute of Finance. 16 September 2021.
15. D. Chaffey. Financial Services marketing trends for 2021. Smart Insights. 15 Mart, 2021. https://www.smartinsights.com/digital-marketing-strategy/financial-services-marketing.
16. T. Mahoney. How the Global Pandemic Will Disrupt the Future of Human Ethos//Medium. Jul 8, 2020.
17. I. K. Klioutchnikov, A. I. Klioutchnikova. Long-Tail Distribution Financial Recommender Systems Embedded into Social Networks//Communications of the IBIMA. 2022. Article ID 165496. doi: 10.5171/2022.165496.
18. I. K. Klioutchnikov, O. I. Kliuchnikov, O. A. Molchanova. Alliance of Commerce and Financial Intermediation with Social Networks: Problems and Prospects//Journal of Internet and e-Business Studies. 2020. Article ID 704163. doi: 10.5171/2020.704163.
19. P. Mikalef, I. Pappas, J. Krogstie, P. Pavlou. Big Data and baseness analytics: research agenda for realizing business value//Information & Management. November 2019.

20. J. E. Teixeira, A. T. Tavares-Lehmann. Industry 4.0 in the European union: Policies and national strategies//Technological Forecasting and Social Change. 2022. № 180. 121664.
21. J. Scott, F. N. Stokman. Social Networks. In International Encyclopedia of the Social & Behavioral Sciences. Second Edition. Elsevier. 2015. P. 473-477.
22. Embedded Finance. Embedded Finance — A Universal Business Theme: Focus on Europe, Latin America, and Asia Pacific, Everest Group. 2022.
23. B. M. Changmai, D. Nagaraju, D. P. Mohanty et al. On-device User Intent Prediction for Contest and Sequence Aware Recommendation//CARS-2019: Context-Aware Recommender Systems Workshop. September 20, 2019. Copenhagen, Denmark. ACM, New York, NY, USA, 8 p. arXiv:1909.12756v1 [cs.IR] 18 Sep 2019.
24. G. Bertagnolli, R. Gallotti, M. D. Domenico. Quantifying efficient information exchange in real network flows//Communications Physics. 2021. 4 (1). doi:10.1038/s42005-021-00612-5.
25. H. Faris, I. Aljarah, M. A. Al-Betar et al. Grey wolf optimizer: a review of recent variants and applications//Neural Computing and Applications. 2018. 30(22). doi: 10.1007/s00521-017-3272-5.
26. L. Amodeo, E-g. Talbi, F. Yalaoui. Recent Developments in Metaheuristics. Springer. 2018. 496 p.
27. S. Ruder. An overview of gradient descent optimization algorithms. Cornell University. 15 Jun 2017. arXiv.org > cs > arXiv:1609.04747.
28. T. Back, D. B. Fogel, Z. Michalewicz. Handbook of evolutionary computation. Oxford University Press, New York. 1997.
29. Y. Zhou, S. Zhang, Q Luo et al. CCEO: cultural cognitive evolution optimization algorithm//Soft Computing. 2019. 23 (4). December 2019. doi: 10.1007/s00500-019-03806-w.
30. N. Javaid. Differential Evolution: An Updated Survey//Conference: 12-th International Conference on Complex, Intelligent, and Software Intensive Systems (CISIS-2018). May 2018.
31. H. P. Minsky. The Financial Instability Hypothesis 4//The Jerome Levy Economics Institute Working Paper № 74. 1992. https://ssrn.com/abstract=161024.
32. W. Guo, L. Zhu, L. Wang et al. An Entropy-Assisted Particle Swarm Optimizer for Large-Scale Optimization Problem//Mathematics. 2019. № 7, 414. P. 1-12.
33. D. A. Subramanian. Simple Introduction to K-Nearest Neighbors Algorithm//Towards Data Science. 2019, Jun 8.
34. V. Thambawita, R. Ragel, D. Elkaduwe. An optimized Parallel Failure-less Aho-Corasick algorithm for DNA sequence matching//Conference: 2016 IEEE International Conference on Information and Automation for Sustainability (ICIAfS). December 2016. doi:10.1109/ICIAFS.2016.7946533.