Cybernetic cognitive model for describing the financial health of it gaming company

Olena Kryvoruchko[1,†], Alona Desiatko[1,*,†], Ihor Karpunin[1,†], Svitlana Symonenko[2,†] and Olena Furman[3,†]

[1] State University of Trade and Economics, 19A Kyoto str., 02156 Kyiv, Ukraine
[2] Dmytro Motornyi Tavria State Agrotechnoligical University, 66 Zhukovskyi str., 69063 Zaporizhzhia, Ukraine
[3] Kremenets Regional Humanitarian and Pedagogical Academy named after Taras Shevchenko, 1 Litseyna str., 47003 Kremenets, Ukraine

Abstract

A software implementation of a cognitive model in Python using the popular NetworkX and Matplotlib libraries is proposed. This software implementation allows visualizing the influence graphs of different concepts, as well as building histograms showing the strength and direction of these influences. Thus, the software provides a convenient and visual tool for analysts and managers of the company, allowing them to promptly assess the financial condition of the company and forecast its future changes based on iterative data analysis and model updates. The analysis of the obtained histograms shows the distribution of the strength of influence of different concepts in the model. These histograms demonstrate both positive and negative relationships between concepts, as well as the frequency of their manifestation within the developed model. It was found that the use of cognitive modeling taking into account weakly structured concepts contributes to a deeper understanding of economic processes related to the financial condition of the company. This approach makes it possible to identify hidden relationships and trends that can have a significant impact on the financial performance of the company in the long term.

Keywords

cognitive model, cybernetic modeling, concept, algorithmic language, Python

1. Introduction

Analysis of the financial condition (FC) of business entities (hereinafter referred to as BE, i.e. enterprises, companies, organizations, etc.) plays a key role in the modern business and economy of Ukraine. The management of a BE needs to have an accurate understanding of its FC to make informed strategic decisions, which may relate to investment projects, business expansion, changes in operations, and other important aspects of management.

Understanding a BE's current FC will allow management to assess its resilience to various economic shocks, such as economic crises, changes in market conditions, or internal problems, which is particularly important for identifying potential risks and developing mitigating measures. Investors, creditors, suppliers, and other stakeholders rely on financial reports and analyses to assess the creditworthiness and reliability of an enterprise by monitoring its financial performance indicators (FPI) and other markers.

Accurate and reliable FPIs, as well as other data, are necessary to attract investment, obtain credit from banks, and establish long-term partnerships. Analysis of the FC and FPI of BE allows to identify of weaknesses and strengths in financial management, which helps to improve financial planning, optimize costs, and improve the overall performance of BE. In most countries, companies are required to provide regular financial statements by established standards, and analyzing FC and FPI helps businesses not only to comply with these requirements but also to identify possible areas for improvement in internal control and auditing.

Early diagnosis of financial problems, including leveraging the potential of cyber modeling, and timely remedial action can prevent bankruptcy and minimize the negative impact on BE. Comprehensive analyses of BE's FC and FPI will allow the timely identification of signs of financial instability and the taking of necessary actions.

IT gaming companies operate in a rapidly changing environment where innovation and user experience play a key role and this creates an excellent environment for the application of cognitive modeling, as many interrelated factors need to be considered. In the gaming industry, there are different revenue sources such as game sales, in-game purchases, advertising revenue, and others, which will allow us to build a multidimensional model with a variety of concepts and make our analysis more comprehensive and interesting. Note that it is important for a game company to

CPITS-II 2024: Workshop on Cybersecurity Providing in Information and Telecommunication Systems II, October 26, 2024, Kyiv, Ukraine
* Corresponding author.
† These authors contributed equally.
olena_909@ukr.net (O. Kryvoruchko); desyatko@gmail.com (A. Desiatko); i.karpunin@knute.edu.ua (I. Karpunin); svitlana.symonenko@tsatu.edu.ua (S. Symonenko); ramskaoa@meta.ua (O. Furman)
0000-0002-7661-9227 (O. Kryvoruchko); 0000-0002-2284-3418 (A. Desiatko); 0000-0002-6442-3446 (I. Karpunin); 0000-0003-0599-3999 (S. Symonenko); 0000-0002-3175-1814 (O. Furman)

consider not only financial metrics, but also factors such as player engagement, customer satisfaction, and development speed.

These metrics directly affect the financial health of the company and need to be analyzed carefully. It is important to note that the gaming industry is at the forefront of technological innovation, making it ideal for testing and implementing advanced data analytics and cognitive modeling techniques, and in turn, this will allow us to demonstrate the potential of our methods in environments where a high degree of adaptability and predictive power is required.

Additionally, we note that the gaming industry is highly competitive, making it important to analyze the impact of the competitive environment on a company's financial health. This reinforces the need to use cognitive modeling for a more accurate and informative analysis. IT gaming companies have a lot of data about users, their behavior, sales, and marketing campaigns, therefore, this will provide excellent opportunities for data collection and analysis, as well as for building models based on this data.

In the gaming industry, constant development and changing conditions require the use of complex models to analyze and forecast the financial health of a company. The diverse revenue sources in the gaming industry allow for a more multi-dimensional and comprehensive model, which helps to more accurately assess a company's financial condition (FC).

Factors affecting customer satisfaction and engagement have a direct impact on the revenue and overall financial stability of a company, making them important to analyze. The gaming industry is at the forefront of using new technologies, making it ideal for testing and implementing new methods of data analysis.

2. Analysis of recent studies and publications

As was shown [1–6] cognitive models allow for visualizing and analyzing complex relationships between different variables and indicators, which is especially relevant for the tasks of assessing the company's FC. The use of cybernetic modeling and object-oriented programming (hereinafter OOP) provides additional advantages for the construction and application of such models [4].

Cybernetics, as the science of control and communication in complex systems, offers a methodology for the analysis and modeling of systems with feedback. In the context of financial analysis, cybernetic modeling helps to solve a wide range of theoretical and applied problems, which are already reworked [7–18].

In particular, in financial systems, many variables are interrelated through feedback loops (e.g., investments affect profits, which in turn affect future investments). Cybernetic modeling can accurately account for such relationships. In addition, financial indicators and company conditions change over time, which is especially relevant at the present moment, when Russia's aggression against Ukraine continues unabated and the financial condition of many companies has deteriorated for objective reasons. Cybernetic modeling will allow building dynamic models that take into account time delays and non-linear effects in the system.

3. The purpose of the paper

The purpose of the paper is to develop a cybernetic model of cognitive modeling for the analysis of the financial condition and BE indicators for more accurate prediction and assessment of the impact of various factors on financial results in the example of an IT gaming company.

4. Methods and models

Consider implementing the cognitive model in the form of a directed graph in Python, which allows us to visualize the relationships between financial indicators and conduct simulation modeling to predict various scenarios. This approach will potentially help management to make informed management decisions and improve the financial health of the company. A cognitive model is a network of concepts and links between them that reflect cause-effect relationships and interrelationships. To realize such a model in the form of a graph would require:

- Nodes—represent concepts or variables such as financial performance indicators, external factors, etc.
- Edges—directed links between nodes that show the influence of one concept on another.

This approach will allow:

- Visualize and analyze the relationships between various financial indicators and external factors.
- Use graph theory methods to analyze the structure and behavior of a model.

Also with this kind of cybernetic modeling, it is quite easy to modify and extend the model by adding new nodes and links.

At the final stages of the research and to adapt the proposed model to a specific object (IT gaming company) we will need to: identify company-specific FPIs, external factors, and other parameters; update the nodes and links in the cognitive map by the peculiarities of the IT gaming company; test and validate the model on the company's historical data.

The development of a software product architecture (hereinafter referred to as PA) for cognitive modeling of the FC and evaluation of its FPI requires a thorough analysis of various aspects, including the choice of programming language. Below we present a brief analysis of the architecture and justification of the potential of using different programming languages for this task, see Fig. 1. The analysis of the software product architecture is shown conceptually in Fig. 1. A brief description is given below.

1. Cognitive modeling module: graph visualization (creating and displaying a cognitive map); analysis and simulation (algorithms for analysis and simulation based on the cognitive model).
2. Data module: data collection (integration with external data sources (financial reports, and

market data); data warehouse (database for storing historical data and modeling results).

3. Data processing module: data cleaning and preprocessing (preparing data for analysis); data analysis (applying machine learning (ML) and statistical techniques to analyze financial performance).
4. Reporting and visualization module: report generation (creating reports based on modeling results); data visualization (interfaces for interactive visualization of data and analysis results).
5. User interface (UI): web interface (access to the system functionality via web browser); mobile application (access to the system functionality via mobile devices).

The proposed architecture, see Fig. 1, is a flexible framework that can be enhanced and adapted to a company's specific requirements and business processes. Different companies may operate in different industries, each with its unique characteristics and requirements.

For example, an IT Gaming Company may require more flexible and faster data analysis to assess financial health in a dynamically changing market environment. A manufacturing company may require more detailed cost analysis and supply chain management, as well as consideration of long production cycles, while a financial institution needs more regulatory compliance and financial risk analysis.

In addition to the above, note that different companies may use different data sources and proprietary systems to manage their operations. Consequently, at the implementation stage of a particular system, it will be necessary to adapt the architecture to interact with specific ERP systems such as SAP, Oracle, and Microsoft Dynamics. In addition, it is important to consider the specifics of data sources, which will require customizing the architecture to handle different types of data (structured, unstructured, semi-structured data) and volumes. Such aspects of development as scalability and performance of such a system are also extremely important, as different companies may have different requirements for the scalability and performance of the system for FC monitoring and FPI modeling.

For example, small businesses can do this with minimal computing power and simple analytical tools. Large businesses may already require high-performance and scalable solutions for processing large amounts of data and complex analytical tasks. Also important is such an aspect of the problem as data security and confidentiality, which is especially relevant in the conditions of martial law and military aggression unleashed by the Russian Federation against Ukraine. Different companies in such a situation may have different requirements for data security and confidentiality. For example, financial companies may require more stringent security measures and compliance with regulatory standards (e.g. GDPR, PCI DSS) at the stage of development and implementation of such a PA. At the same time, technology companies may focus in parallel on protecting intellectual property and customer data in terms of reference.

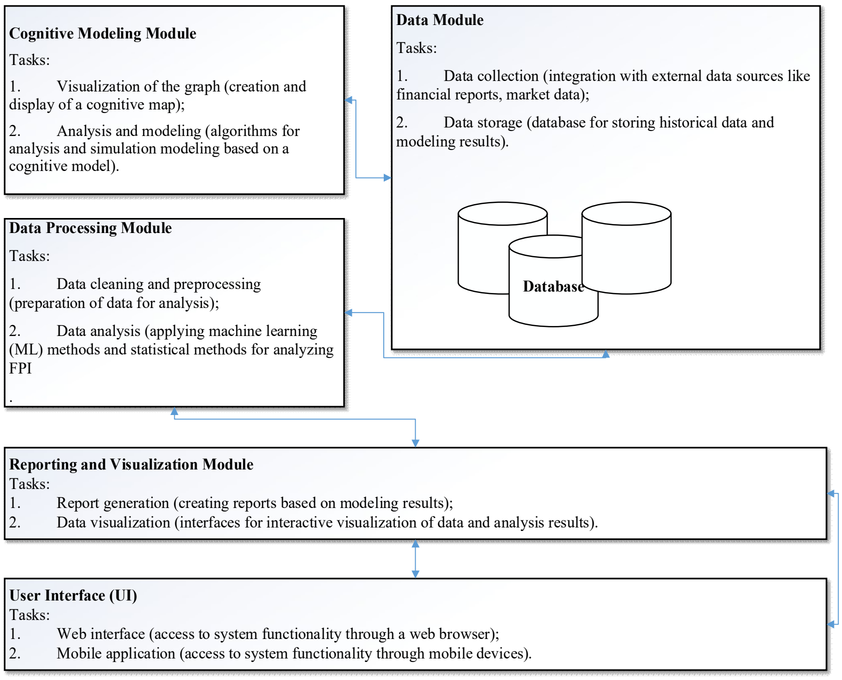


Figure 1: Conceptual scheme of the developed PA

The specifics of business processes will a priori affect the module that implements the user interface. For example, an intuitive interface for employees may be a primary requirement for companies with non-technically savvy users, while a customizable interface may be a priority for companies with unique workflows and user experience needs, such as game designers or core developers of such software.

The general architecture, shown in the form of modules in Fig. 1, allows only laying down the basic principles and approaches to the creation of such a system, which can be adapted to the specific needs of the company. This ensures flexibility, modularity, reusability, etc.

Although this is beyond the scope of the tasks to be solved in this paper, we will nevertheless note some possible improvements to such a system. Firstly, these are possible additional modules, the introduction of which is conditioned by the specific tasks of the company. For example, these may be modules related to risk management or supply chain analysis. Secondly, the improvements may concern the task of integration with new data sources, since setting up integration with new management systems and data sources used in the company is important for the subsequent correct modeling of the FPI and assessment of the company's FC as a whole. Thirdly, it may be necessary to optimize performance and tune the system to cope with high load levels and large data volumes. Finally, possible improvements may concern the security settings of such a PA, i.e. implementation of additional security measures and verification of compliance with regulatory requirements for information security.

After building the cognitive model, the next step is to develop a simulation model that will allow us to analyze various scenarios of changes in the financial condition of the company. For this purpose, we will use data analysis and machine learning methods available in Python.

Cognitive technologies such as cognitive maps and cognitive modeling provide a new way to represent and analyze complex systems. As shown in [2–4], traditional financial analysis techniques are often limited in their ability to handle loosely structured problems. Cognitive modeling based on cybernetic tools will allow us to account for fuzzy and uncertain relationships between financial ratios. For example, cognitive maps will allow visualization and deeper analysis of causal relationships between different financial metrics, which will improve the understanding of financial health dynamics. OOP and modern Python libraries (e.g. NetworkX for graphs and Scikit-learn for machine learning) provide powerful tools for implementing cognitive models. Thus the OOP methodology allows cognitive models to be structured as classes and objects, which simplifies their development, testing, and modification. Modern Python libraries, which we will use during the implementation of our project, will allow us to automate the process of data analysis and forecasting, making cognitive models more efficient and accurate. Summarising all of the above, it is not difficult to see that the development and implementation of cognitive models for BE FC assessment contributes to both the theoretical and practical part of computer science, as it extends the existing theories and methods of cognitive modeling, the scope of their application to new areas, such as financial analysis, and the development of new algorithms, among others. The creation of new tools and systems for business, which can improve management and decision-making processes, will be able to improve the financial stability and competitiveness of enterprises, given the situation in which the Ukrainian economy is at war with RF. Thus, the connection between cognitive modeling and BE FC evaluation is a new and promising approach in computer science, and the integration of cognitive technologies and modern programming methods opens new opportunities for the analysis and forecasting of FC, improvement of management processes, and creation of intelligent information systems. These aspects not only contribute to scientific progress but also offer practical solutions for businesses that can significantly improve their efficiency and sustainability.

The first step is to build a cognitive model that will represent the main FPIs and their relationships (let us illustrate this with a simple example). For this purpose, we use an oriented graph, where the vertices (nodes) will represent concepts such as revenues, expenses, profits, assets, and liabilities, and the edges will represent the links between these concepts, see Fig. 2.

The code illustrating the creation of such a graph is shown below.

```
#Import the required libraries
import networkx as nx
import matplotlib.pyplot as plt

#Create an empty oriented graph
G=nx.DiGraph()

#Add nodes (financial concepts)
nodes=[“Income”, “Costs”, “Profit”, “Assets”,
“Obligations”]
G.add_nodes_from(nodes)

#Add edges (links between concepts)
edges=[(“Income”, “Profit”), (“Costs”, “Profit”),
(“Profit”, “Assets”), (“Assets”, “Obligations”)]
G.add_edges_from(edges)

#Visualise the graph
plt.figure(figsize=(10, 7))
pos=nx.spring_layout(G)
nx.draw(G, pos, with_labels=True,
node_colour=“lightblue”, node_size=3000, font_size=12,
font_weight=“bold”, arrows=True)
plt.title(“Cognitive model of financial status”)
plt.show()
```

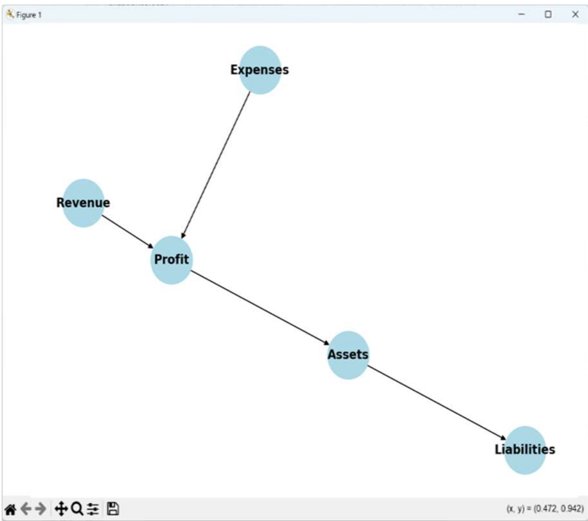


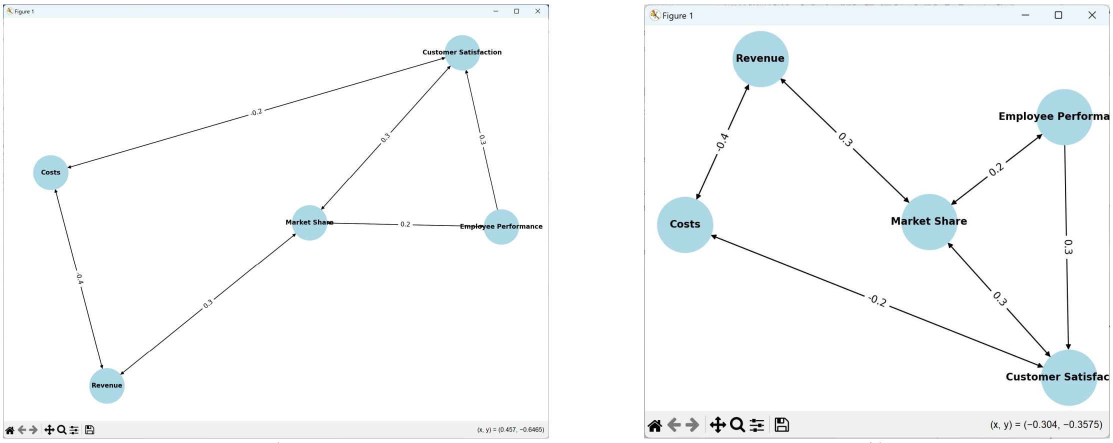
Figure 2: A cognitive model that will represent the main FPIs and their relationships in the form of a directed graph (implementation in PyCharm)

For a complete code, in order to account for the changing influence of concepts on each other, we will use influence matrices for the illustration below. These matrices will contain weighting coefficients that actually determine the strength of the connection between concepts. The matplotlib library can be used to visualise the change in the degree of influence.

The above small example illustrates how changing the weighting of concept influence affects the structure of the cognitive model, and visualizes this using histograms.

In histogram 4(a), it can be seen that most of the weight values are between 0 and 0.4, and some negative weights are also present, indicating a negative impact.

The histograms, see Fig. 4 a), b) c) show the distributions of the weights of the links between concepts in the cognitive model.



a) b)

Figure 3: Examples of a) and b) structures of a cognitive model that takes into account the influence of concepts on each other in the format of different values of weights (implementation in PyCharm)

Fig. 4 b) shows the Strong Influence Strength Histogram. Histogram in Fig. 4 c) shows a narrower distribution of values, indicating that all relationships between concepts are weakened.

Let's consider the meaning of concepts in more detail.

The concept Revenue affects Market Share with a weight of 0.2 and also affects Costs with a weight of -0.4.

The concept Costs affects Customer Satisfaction with a weight of -0.2.

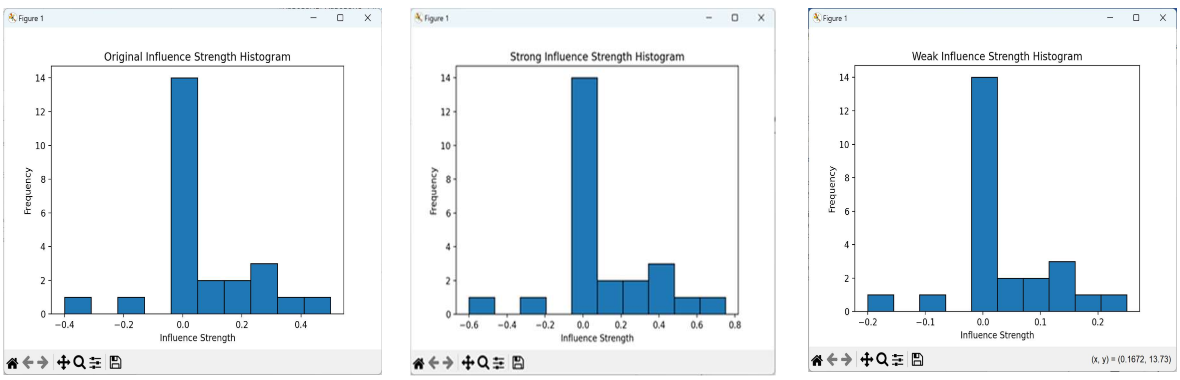
The Market Share concept affects Revenue with a weight of 0.3.

The concept affects Customer Satisfaction with a weight of 0.4.

The concept affects Employee Performance with a weight of 0.1.

Positive Weights indicate the positive impact of one concept on another. For example, an increase in Market Share has a positive impact on Revenue.

Negative Weights indicate a negative impact, e.g. an increase in Costs harms Customer Satisfaction.



a) b) c)

Figure 4: Distribution of weights of links between concepts in the cognitive model

Changes in concept weights can be easily traced by comparing histograms, while graphs and visualization of the concept network help to understand the structure and intensity of influence between concepts. Thus, even with such simple examples implemented in the PyCharm environment, we can conclude that the use of histograms allows us to visualize how the weights of links between concepts change when the influence is strengthened or weakened. This will help system analysts and researchers understand which concepts have the greatest influence on a cognitive model and how changes in one part of the system can affect other parts.

In our view, the implementation of a cognitive model to assess an enterprise's FC in the form of a decision support system (DSS) or an intelligent system (IS) offers many advantages. Cognitive models can predict future PEs based on current data and historical trends, which in turn will allow companies to make more informed decisions and develop risk management strategies. In addition, the integration of a cognitive model into an IPS will allow real-time monitoring of an enterprise's FPs, identifying deviations and potential threats, and taking timely corrective action. Cognitive models must be able to take into account many factors affecting the financial state of the enterprise, which is especially important for complex and multi-component business processes of IT gaming companies. The developed SPPR with a cognitive model should be interactive, allowing users to modify input data and observe the results, which will help in analyzing "what-if" scenarios. Such a system will also be able to adapt to changes in the external and internal environment of the enterprise. Note that automating FC analysis and forecasting will reduce the likelihood of human error and subjectivity in decision-making.

The above methodology allows repeating experiments with changing initial conditions and model parameters, which provides flexibility and adaptability to the analysis. This is especially important for assessing the impact of new concepts and changes in the company's business processes.

5. Conclusions

The main findings of the research were as follows and the following conclusions were drawn.

1. We developed a software implementation of the cognitive model in Python using NetworkX and Matplotlib libraries. This software implementation allows visualizing graphs and histograms of concept influences, as well as iterative data analysis and model updating. The software provides a convenient and visual tool for analysts and managers of the company, allowing them to promptly assess the financial condition and forecast future changes.
2. Histograms showing the distribution of the strength of influence of different concepts in the model were obtained. The histograms show both positive and negative relationships, as well as the frequency of their manifestation in the model.
3. It is shown that the use of cognitive modeling taking into account weakly structured concepts contributes to a better understanding of economic processes related to the financial condition of the company and allows to identify of hidden relationships and trends.

References

[1] L. Guryanova, T. Klebanova, T. Trunova, Modeling the Financial Strategy of the Enterprise in an Unstable Environment, Economic Studies, 26(3) (2017).

[2] L. M. Malyarets, et al., The Modeling of Multi-Criteria Assessment Activity in Enterprise Management (2019).

[3] O. Chukurna, et al., Formation of Methodical Foundations for Assessing the Innovative Development Potential of an Industrial Enterprise, Naukovyi Visnyk Natsionalnoho Hirnychoho Universytetu, 4 (2020) 146–151.

[4] O. Sosnovska, M. Zhytar, Financial Architecture as the Base of the Financial Safety of the Enterprise, Baltic J. Econom. Stud., 4(4) (2018) 334–340.

[5] V. Tkachenko, et al., Development and Effectiveness of Financial Potential Management of Enterprises in Modern Conditions, Financial and Credit Activity Problems of Theory and Practice, 3(30) (2019) 85–94.

[6] Y. Y. Varlanov, O. Y. Varlanov, Modeling the Financial Condition of Enterprises: An Essential Approach to Integrated Assessment, J. Econom. Sci. (59) (2012) 139–146.

[7] N. Mazur, et al., Improvement of Controlling in the Financial Management of Enterprises, TEM J. 10(4) (2021).

[8] L. Ogiela, M. R. Ogiela, Cognitive Systems for Intelligent Business Information Management in Cognitive Economy, Int. J. Inf. Manag. 34(6) (2014) 751–760.

[9] L. Ogiela, Towards Cognitive Economy, Soft Comput. 18 (2014) 1675–1683 (2014). doi: 10.1007/s00500-014-1230-z.

[10] H. O. Aifuwa, M. Saidu, Board Cognitive Diversity and Firm Performance Nexus: Evidence from Nigeria, Int. J. Manag. Innov. Entrepreneurial Res. 6(2) (2020) 88–99.

[11] B. Zyznarska-Dworczak, Sustainability Accounting—Cognitive and Conceptual Approach, Sustainability, 12(23) (2020) 9936.

[12] M. Petrova, I. Buzko, Y. Dyachenko, Cognitive, Intelligence Technologies and Economic Foundations of Teaching of International Economic Relations and Tourism, Engineering for Rural Development, 17 (2018) 1102–1106.

[13] N. Morozko, V. Didenko, Financial Management of Small Organizations based on a Cognitive Approach (2018).

[14] H. Wang, et al., The Effect of Digital Transformation Strategy on Performance: The Moderating Role of Cognitive Conflict, Int. J. Conflict Manag. 31(3) (2020) 441–462.

[15] R. K. Reger, A. S. Huff, Strategic Groups: A Cognitive Perspective, Strategic Manag. J. 14(2) (1993) 103–123.

[16] O. Kryvoruchko, et al., Cognitive Modeling and Formation of the Knowledge Base of the Information System for Assessing the Rating of Enterprises, Int. J. Electron. Telecommun. (2023) 697–705.

[17] M. Chyzhevska, et al., Dual Impact of Crypto Industry Technologies on the Energy Poverty, in: n Cybersecurity Providing in Information and Telecommunication Systems, vol. 3421 (2023) 293–299.

[18] V. Lakhno, et al., Allocation of Organizational and Financial Resources of the Information Protection Side using a Genetic Algorithm, Informatics and Cybernetics in Intelligent Systems, CSOC 2021, LNNS, 228 (2021). doi: 10.1007/978-3-030-77448-6_5.