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Dmytro BARANIEI, Tetiana FILIMONCHUK

Kharkiv National University of Radio Electronics, Kharkiv, Ukraine

ANALYSIS OF APPROACHES TO EXPLAINABLE SEMANTIC VERIFICATION OF FINANCIAL DATA MINING RESULTS

*The **study examines** methods of explainability and semantic verification for financial data mining outcomes in computer decision support systems, particularly in high-risk industries such as aerospace. The **purpose** of the article is to analyze modern explainability methods and approaches to verifying the results of intelligent systems within a financial context, identify their limitations, and justify an approach to explainable semantic verification based on a combination of xAI methods, ontological knowledge representation, and formal verification procedures. **Tasks** include: analyzing modern methods of explainability and approaches to verifying the functioning of intelligent systems; identifying the limitations of existing solutions in ensuring the logical admissibility, semantic consistency, and reliability of data mining, results; and developing an approach to explainable semantic verification specifically for financial data. The study employs **methods** of analyzing and generalizing scientific sources, systemic and comparative analysis, and approaches to ontological modeling and the semantic interpretation of machine learning results. The findings indicate that modern xAI approaches provide interpretations of machine learning outputs, but do not guarantee their logical admissibility, semantic consistency, or regulatory acceptability in the financial sphere. The feasibility of integrating xAI methods with ontological knowledge models and formal verification procedures is substantiated, allowing for expanded quality control of analytical conclusions. The proposed approach involves the sequential implementation of analytical result formation, explanation generation, semantic mapping, logical verification, and result reliability assessment. **Conclusions**. The scientific novelty of the obtained results lies in the justification of the proposed approach to explainable semantic verification of financial data mining results. Unlike existing methods, this approach provides not only a meaningful interpretation of the output, but also its logical verification and semantic consistency with domain-specific knowledge and industry constraints.*

***Keywords**: financial intelligent systems; explainable verification; explainable artificial intelligence; ontological models; semantic mapping; information technology; algorithmic accountability.*

1. Introduction

The financial sector is one of the most technologically advanced segments of the modern digital economy. The problems of transparency, validity and verification of the results of intelligent analysis of financial data are important not only for banking and fintech applications, but also for computer decision support systems, information technologies for managing enterprises, programs and projects in high-risk industries, in particular in the aerospace sector. Active digitalization of financial and economic processes, the development of intelligent information systems and the widespread implementation of artificial intelligence technologies have led to a significant transformation of approaches to data processing, risk assessment and support for management decisions in the financial sector and high-risk industries, in particular in the aerospace sector. In such conditions, modern information systems increasingly use machine learning algorithms to automate data analysis, risk forecasting, anomaly detection and justification of decisions in financial management, project management and resource planning tasks [1, 2].

The use of machine learning models allows financial organizations to analyze large volumes of data and identify complex statistical patterns, which significantly increases the efficiency of financial operations [3]. However, the increase in the complexity of artificial intelligence algorithms is accompanied by the emergence of new challenges related to the transparency and interpretability of algorithmic solutions. A significant part of modern machine learning models, in particular deep neural networks, function as so-called “black boxes”, the internal logic of which is difficult to analyze even for system developers [1, 2].

In the financial sector, such opacity of algorithms creates serious risks. Decisions made by intelligent systems can directly affect customers’ access to financial resources, the level of credit risk, or the classification of transactions as suspicious [4]. In the event of an algorithm error or incorrect justification of a decision, financial institutions can suffer significant economic losses or legal sanctions.

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The growing regulatory requirements for the use of artificial intelligence systems in the financial sector also increase the relevance of the issue of transparency of algorithmic decisions. In particular, modern European Union regulations, such as the Artificial Intelligence Act [5] and the General Data Protection Regulation (GDPR) [6], provide for the need to ensure algorithmic accountability and the ability to explain automated decisions.

In response to these challenges, the scientific direction of Explainable Artificial Intelligence (xAI) was formed, aimed at developing methods for interpreting the results of machine learning models [1, 3]. However, most modern xAI approaches provide only a descriptive analysis of the factors that affect the forecasting result and do not allow for formal verification of the logical correctness of the generated analytical results.

In this regard, there is a need to develop new methodological approaches that combine the interpretation of machine learning results with mechanisms for their formal verification. One of the promising directions for solving this problem is the use of ontological knowledge models, which allow formalizing the subject area and providing logical verification of the results of data mining [7, 8].

1.1. Motivation

Despite significant progress in the application of artificial intelligence in the financial sector, in practice there remains a contradiction between the high predictive efficiency of machine learning models and the insufficient level of validity of their results in critical tasks. For financial institutions, it is important not only to obtain an accurate forecast, but also to be able to prove that this forecast is formed on the basis of correct, stable and meaningfully acceptable dependencies [2, 9].

Existing xAI approaches largely address the problem of interpreting individual decisions, but they are mostly focused on explaining the influence of features rather than on checking the admissibility of the result itself from the standpoint of the subject domain. As a result, a gap arises between the statistical explanation of the model and the normative-semantic justification of the financial decision, which is especially critical in the tasks of scoring, risk analysis, and anomaly detection [10].

An additional motivation is that modern financial intelligence systems operate in an environment where decisions must comply not only with data but also with regulatory requirements, internal rules of the institution, and formalized knowledge about the subject area [11]. In such conditions, it is not enough to know what factors influenced the result; it is also necessary to establish whether it does not contradict the logic of financial rules, the semantics of concepts, and the requirements of algorithmic accountability.

That is why there is a need for an approach that combines explainability tools with ontological knowledge models and formal verification tools [8, 12]. This approach allows us to move from descriptive analysis of model behavior to explained semantic verification of its results, which is a necessary condition for increasing the reliability, transparency and practical applicability of financial intelligent systems. This is especially important in computer decision support systems for managing complex enterprises, programs and projects, in particular in the aerospace industry, where errors in analytical conclusions can have significant economic and organizational consequences.

1.2. Publication Analysis

The issue of transparency of artificial intelligence algorithms and interpretability of machine learning results has become one of the central research areas in the field of intelligent information systems over the past decade. A significant amount of work has been devoted to developing methods for explaining the decisions of machine learning algorithms that function as “black boxes”, as well as to developing a conceptual framework for the responsible and accountable use of artificial intelligence.

The first group consists of review and conceptual works devoted to the classification of xAI methods, their evolution and evaluation. In [13], one of the most well-known generalized taxonomies of xAI is proposed and the main challenges of responsible AI are outlined. In [14], the authors systematized the methods of explaining black boxes according to the criteria of model dependence, scale of explanation and type of interpretation. In [15], the authors developed these ideas in the concept of xAI 2.0, focusing on open problems, interdisciplinarity, causality, assessment of the quality of explanations and the need to move to practically meaningful and testable explanations. In [16] and [17], the authors show that the modern development of xAI is increasingly shifting from simple explanation of prediction to issues of stability, user-oriented design, assessment of the quality of explanations and the formation of standardized application frameworks. Therefore, the reviewed works focus on the general methodological development of xAI, but the issues of formal verification of solutions in high-risk industries remain only partially addressed in them.

The second group consists of works focused on applied methods for explaining machine learning models. The authors [18] proposed the LIME method, which is based on building a local approximation of a complex model by a simpler interpreted model in the vicinity of the object under study. Lundberg and Lee [19] developed the SHAP approach, which uses the Shapley value to determine the contribution of each feature to the formation of the model result. In financial applications, these approaches have become the basic tools for explaining solutions in scoring, risk analysis, and fraud detection problems [20]. At the same time, the issues of stability of explanations, their repeatability under minor data changes, and the lack of a connection between numerical attributions and the semantics of the subject domain remain unresolved.

The third group consists of studies where xAI is combined with semantic technologies, knowledge graphs and ontological structures. The authors of [21] consider the knowledge graph as a universal means of integrating knowledge, data and relationships in a formalized space. In [22], a knowledge graph-oriented architecture of xAI is proposed, in which explanations are enriched with semantic context and related facts of the subject area. The authors of [23] showed that knowledge graphs can act as an infrastructure for auditing AI systems, providing collection, integration and analysis of audit trails in a semantically consistent format. These works are particularly important for the proposed topic, since they bring xAI closer to logical verification and accountability. However, even in this group of studies, formal verification of the analytical result of a financial model through ontological rules, coherence metrics and semantic matching criteria has not yet received a complete methodological design.

A separate group consists of works directly related to the financial context. The authors of [24] showed the practical significance of explainability in financial services and at the same time drew attention to the limitations of traditional interpretative tools. In [20], the authors analyzed 138 publications on xAI in finance and found that xAI is most often used in credit management, price forecasting and fraud detection, and the dominant methods remain SHAP, feature importance and rule-based approaches. At the same time, the authors directly point out the presence of unresolved problems related to the assessment of the quality of explanations, industry specifics and the requirement for more reliable mechanisms for proving the correctness of decisions.

Thus, the analysis of sources shows that modern research has provided significant progress in the development of methods for explaining the decisions of machine learning models, and also outlined the possibilities of using semantic technologies to enrich such explanations. At the same time, the scientific and applied problem of developing a holistic approach to the explanatory verification of the results of the functioning of financial intelligent systems remains unresolved, which would combine the interpretation of the model result, its semantic coordination with formalized knowledge of the subject area and formal verification of the logical correctness of the conclusion obtained. It is the absence of such an integrated approach, capable of ensuring not only clarity, but also evidentiary validity, reliability and normative acceptability of decisions, currently limits the practical use of intelligent financial systems in tasks critical to errors and regulatory requirements.

1.3. State of the Art

Despite significant progress in the development of machine learning technologies, modern financial intelligent systems face a number of fundamental problems related to ensuring the transparency and reliability of the results of data mining [20, 23]. One of the key problems is the lack of formalized mechanisms for verifying the logical validity of the results generated by machine learning algorithms. Most modern models operate on the basis of statistical dependencies between variables, which does not allow directly checking the compliance of the obtained results with the regulatory rules of the subject area [13, 15].

At the technical level, the problem is related to the complexity of modern machine learning algorithms. At the semantic level, there is a gap between the numerical parameters of the models and the conceptual apparatus of the financial subject area. At the regulatory level, the problem is the need to ensure algorithmic accountability, when financial institutions must prove that the decisions generated by intelligent systems are justified and do not violate regulatory requirements [19].

The presence of these problems indicates the existence of a critical gap between explainability methods and methods of formal verification of data mining results. Modern xAI approaches allow mainly to interpret the results, but do not provide mechanisms for checking their logical correctness. In this regard, there is a need to develop new approaches that integrate the results of machine learning model interpretation with formalized knowledge structures of the subject area.

1.4. Objectives and Tasks

The **purpose** of the article is to analyze the possibilities of applying existing methods of explained verification of the results of the functioning of financial intelligent systems, as well as to substantiate the approach to building explained semantic verification based on the integration of xAI methods, ontological knowledge models and logical verification procedures. This approach allows not only to interpret the results obtained, but also to assess their semantic consistency, logical correctness and suitability for use in conditions of increased requirements for transparency and algorithmic accountability of financial systems. The practical interest in this approach is also due to its potential suitability for information technologies to support decision-making in high-risk industries, in particular in the management of aerospace enterprises,

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programs and projects.

To achieve the goal, within the framework of this publication it is necessary to solve the following **tasks**:

1. To analyze modern methods of explainability and approaches to verifying the results of the functioning of intelligent systems, in particular in the financial context.
2. To identify the limitations of existing solutions in ensuring logical admissibility, semantic consistency and reliability of the results of data mining.
3. To develop an approach to explainable semantic verification of the results of financial data mining based on a combination of AI methods, ontological knowledge representation and formal verification procedures.

2. Analysis of Xai Methods and Semantic Approaches to Verifying Data Mining Results

One of the key prerequisites for building explainable verification of data mining results is the use of methods that make the decision-making process of machine learning models more transparent. In modern intelligent systems, in particular in the financial sector, high accuracy of models is often combined with a low level of their interpretability, which complicates the analysis of the reasons for the result obtained. In this regard, xAI methods have developed significantly, designed to identify factors that most affect the model's output, as well as to increase confidence in automated decisions.

Within the framework of the modern direction of xAI, several classes of approaches have been formed, differing in the level of dependence on the model, the scale of explanation and the method of forming the interpretation. From the point of view of practical application, the greatest interest is of methods that can explain the results of complex models without the need to change their internal structure. That is why model-agnostic post-hoc approaches have become widespread in the problems of applied data analysis, which allow analyzing the already obtained result and establishing the importance of individual features in its formation.

The most well-known methods of this type are LIME (Local Interpretable Model-agnostic Explanations) [18], which is based on building a local approximation of a complex model by a simpler interpreted model in the vicinity of the object under study. This approach allows us to form an explanation for a specific forecast, focusing on the nearest region of the feature space. Formally, this can be presented as a problem of minimizing the deviation between the original model and its local interpreted approximation:

$$\xi(x) = \arg\min_{g \in G} L(f, g, \pi_x) + \Omega(g), \qquad (1)$$

where f is the initial machine learning model;

g is interpreted model;

L is loss function;

π_x is proximity weight function;

$\Omega(g)$ is a measure of the explanatory model complexity.

Another widely used method is SHAP, proposed by Lundberg and Lee [19]. This approach is based on cooperative game theory and uses Shapley values to determine the contribution of each feature to the model output. SHAP values are defined as coefficients of the explanatory model g, which is a linear function of the binary variables:

$$g(z') = \phi_0 + \sum_{i=1}^{M} \phi_i z'_i, \qquad (2)$$

where M is the number of features;

$z' \in \{0,1\}^M$; $\phi_i \in R$;

z'_i is indicates the presence of this feature i;

ϕ_i is relative contribution to the prediction of the trait model i.

Since the model $g(x')$ is a local explanation of the forecast $f(x)$, generated by the model for the feature vector x, which means that a unique explanatory model can be generated for any given x:

$$\phi_i(f, x) = \sum_{z' \subset x'} \frac{|z'|!(M - |z'| - 1)!}{M!} [f_x(z') - f_x(z' \setminus i)], \qquad (3)$$

where $|z'|$ is the number of nonzero entries in z';

$z' \subseteq x'$ represents all z' vectors, where the nonzero elements are a subset of the nonzero elements in x'.

This approach is the standard for banking scoring systems because it guarantees additivity and local accuracy. However, the computational complexity (2^n) limits its application in real-time systems without the use of approximations (TreeSHAP).

Despite the practical value of xAI methods, their use in financial analysis tasks has a number of fundamental limitations. First, the explanations generated by such methods can be unstable, that is, they can change even with a slight modification of the input data. This is critical for financial systems, since the results must not only be understandable, but also reproducible and stable. Second, xAI explanations mostly remain at the level of numerical attributions and do not contain the semantic context necessary for interpreting the result in terms of the subject domain [25]. Therefore, the mere fact that a certain feature significantly influenced the model solution does not yet indicate the substantive or normative correctness of such a solution.

To overcome this limitation, it is advisable to use knowledge representation tools, primarily ontological models. Ontologies provide a formalized description of the subject area in the form of a system of concepts, relationships, and rules, which allows you to move from a numerical description of the result to its meaningful interpretation. In financial systems, ontological structures can be used to formalize terms and categories, represent business rules, describe economic processes, and integrate knowledge from various data sources [26]. This creates the basis for checking the results of intellectual analysis not only in terms of the statistical significance of the features, but also from the standpoint of semantic and logical consistency.

A promising direction in this context is the neuro-symbolic approach, which combines the ability of machine learning models to detect complex patterns in large data sets with the capabilities of symbolic representation of knowledge and logical inference [27]. Within the framework of such an approach, the statistical result of the model can be associated with formalized structures of the subject domain, which opens up the possibility of further substantive verification of the conclusions obtained. Thus, semantic technologies do not replace xAI methods, but complement them, transferring explanations from the level of feature attribution to the level of conceptually consistent analysis.

Thus, modern xAI methods provide a toolkit for interpreting the results of machine learning models, and ontological and neuro-symbolic tools create the prerequisites for their meaningful alignment with the subject area. However, these components are not yet sufficiently integrated into a single procedure that would allow not only to explain the result, but also to verify its logical admissibility, semantic compliance and suitability for use in financial systems. This indicates the need to develop new approaches to ensuring explainable verification of data mining results that combine methods for interpreting machine learning models with formalized knowledge structures.

3. An Approach to Explained Semantic Verification of Financial Data Mining Results

The limitations of modern XAI methods and semantic knowledge representation tools identified in the previous section indicate the feasibility of their integration within a single approach focused on solving the problem of explained verification of the results of the functioning of financial intelligent systems. Unlike traditional interpretive solutions that focus mainly on establishing the influence of individual features on the model result, the proposed approach is aimed at combining explanation, semantic coordination and formal verification of the obtained conclusion. This allows us to consider the result of machine learning not only as a statistically substantiated forecast, but also as an object of logical analysis in the context of formalized knowledge of the financial subject area.

The conceptual basis of the proposed approach is that explainability and verification should be considered as interrelated stages of analyzing the results of the functioning of an intelligent system. If explainability answers the question of what factors influenced the result of the model, then verification makes it possible to establish whether this result is logically permissible, semantically consistent and acceptable for use in the conditions of a specific subject area. For financial systems, this is of fundamental importance, since their results must be not only accurate, but also justified from the standpoint of business rules, regulatory requirements and expert knowledge.

The proposed approach to explainable semantic verification is based on the integration of three interrelated components:

– machine learning models that generate analytical results;

– explainable artificial intelligence (xAI) methods that provide interpretation of results;

– ontological knowledge models that allow for formal verification of the logical correctness of results.

Within this approach, the result of data mining is considered as a multi-level object. At the first level, it is the output of a machine learning model. At the second level, it is an object of explanation for which influence factors are determined. At the third level, it is an element of the semantic space of the subject area, which correlates with the concepts, relationships and rules of the ontological model. It is this sequence that allows us to move from statistical interpretation to meaningful verification of the result.

Unlike existing approaches, the proposed solution involves not only generating an explanation, but also further semantic processing of the result in order to establish its correspondence with formalized knowledge of the subject area. Thus, data processing is transformed from a purely statistical process into a hybrid neuro-symbolic process, within which the results of machine learning are consistent with deterministic knowledge structures. This creates the prerequisites for building intelligent financial systems that are capable not only of forming forecasts, but also of providing a reasonable check of their admissibility.

The implementation of the proposed approach is carried out in the form of a sequence of interconnected stages.

Stage 1 – formation of analytical results. The first stage is the processing of the input data using a machine

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learning model. The result of this stage is a prediction or classification decision:

$$y = f_{ML}(x), \tag{4}$$

where x is input feature vector,

f_{ML} is machine learning model,

y is the result of the analysis.

At this stage, the system generates an initial result, which subsequently serves as the object of explanation and verification.

Stage 2 – generating an explanation of the result. In the second stage, xAI methods are applied to identify the factors that influenced the result obtained.

The result is presented as a feature importance vector:

$$e = f_{xAI}(x, y) = \left[w_1, w_2, ..., w_n\right], \tag{5}$$

where w_i – contribution of feature i to the result.

The purpose of this stage is not to verify the correctness of the conclusion, but to establish its internal structure of influences, that is, to determine which parameters were decisive for the formation of the result.

Stage 3 – semantic feature mapping. In the third stage, the numerical parameters of the explanation are translated into concepts of the ontological model of the subject domain. This process can be formalized as a mapping:

$$\mu : F \to O, \tag{6}$$

where F is a set of signs,

O is a set of ontology concepts.

The stage provides a transition from statistical parameters to semantic categories that correspond to domain knowledge, that is, a transition from a numerical level of description to a meaningful interpretation of the result in terms of financial concepts, risk categories, regulatory restrictions, or business rules.

Stage 4 – logical verification of the result. At the fourth stage, the compliance of the obtained result with the rules and restrictions defined in the ontological knowledge base is checked. Logical rules can be represented in the form of products:

$$\text{IF condition} \Rightarrow \text{conclusion.} \tag{7}$$

If a contradiction is detected between the model result and the domain rules, a logical inconsistency is recorded. This allows the system to not only explain decisions, but also to detect cases in which a statistically plausible conclusion is inconsistent with the formalized domain logic.

Stage 5 – assessing the reliability of the result. At the final stage, the reliability of the obtained result is quantitatively assessed using a system of metrics that characterize various aspects of the quality of the explained verification.

Stability metric explanation:

$$M_{stab} = 1 - \left\| E(x) - E(x + \delta) \right\|, \tag{8}$$

where δ is a small disruptive change in input data.

This metric reflects how robust the explanation is to small changes in the input information.

Ontological coherence metric:

$$M_{coh} = \frac{\left|C_{valid}\right|}{C_{total}}, \tag{9}$$

where C_{valid} is the number of concepts and relationships that are consistent with the ontological model;

C_{total} is total number of items checked.

It characterizes the degree of logical consistency of the result with formalized knowledge.

Semantic relevance metric:

$$M_{rel} = \sum w_i \cdot \text{relevance}(c_i), \tag{10}$$

where relevance(c_i) is concept relevance function c_i to the subject area.

This metric allows us to assess how much the obtained explanation is related to the meaningful aspects of the financial decision.

Taken together, these metrics enable the transition from a qualitative interpretation of results to their quantitative assessment in terms of stability, logical consistency, and semantic relevance. This is especially important for financial intelligent systems, where decisions must be not only understandable but also reliable, reproducible, and verifiable.

Thus, the proposed approach (Fig. 1) allows us to move from descriptive explanation of machine learning model results to their explanatory semantic verification. Its application creates the prerequisites for increasing algorithmic accountability, reducing the risk of using incorrect or semantically inconsistent solutions, and forming a new generation of intelligent financial systems focused on combining accuracy, transparency, and logical validity.

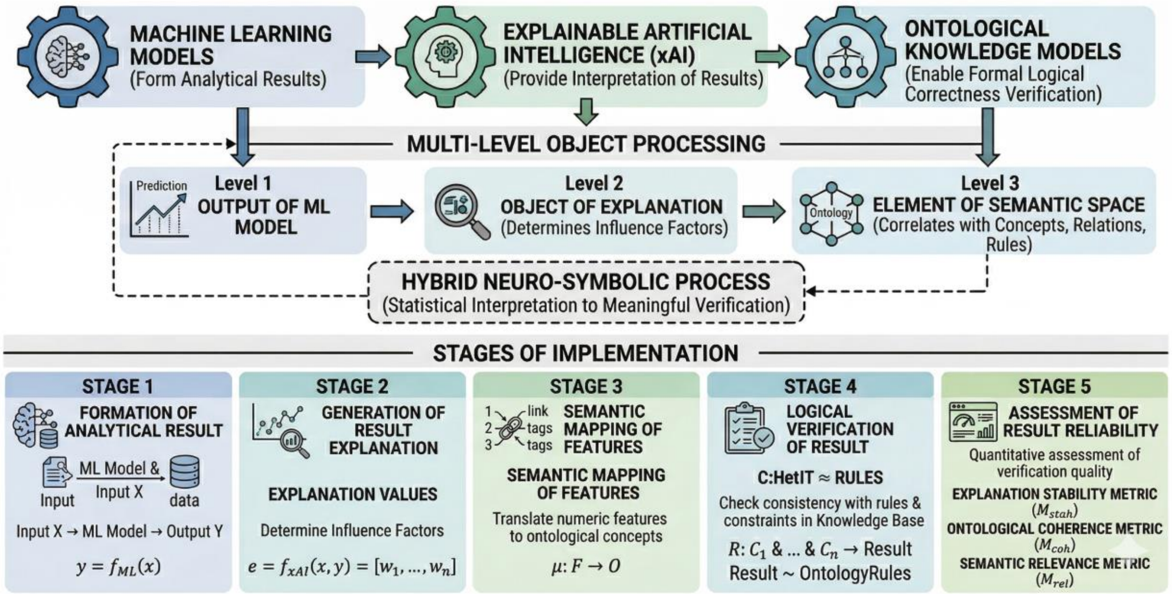

Fig. 1. Approach to explained semantic verification of financial data mining results

3. Results and Discussion

The analysis shows that modern methods of explainable artificial intelligence provide a significant increase in the transparency of the functioning of machine learning models, but their capabilities are mainly limited to interpreting the influence of individual features on the result obtained. For financial intelligent systems, this is not enough, since in such systems not only the accuracy of the forecast and the clarity of the explanation are important, but also the logical admissibility, semantic consistency and normative acceptability of the formed conclusion. This confirms that there is a conceptual gap between descriptive explainability and formal verification of decisions, which is not eliminated by traditional xAI tools.

The main result of the work is the justification of the approach to the explained semantic verification of the results of financial intelligent systems, which integrates three components: a machine learning model, xAI tools and an ontological model of knowledge of the subject area. Unlike existing solutions, the proposed approach is focused not only on establishing the factors influencing the result, but also on further semantic mapping of the explanation and logical verification of the obtained conclusion for compliance with formalized knowledge. Due to this, the result of the model is considered not only as a statistical forecast, but as an object of substantive control.

The practical significance of the proposed approach lies in the fact that it creates a basis for building financial intelligent systems capable of combining analytical efficiency with accountability and verifiability. In particular, in the tasks of credit scoring, risk assessment, detection of fraudulent transactions or support of investment decisions, this approach allows to identify situations in which the result of the model is statistically plausible, but does not comply with business rules, regulatory restrictions or semantics of the subject area. This expands the possibilities of quality control of decisions and reduces the risk of using incorrect conclusions in critical financial processes. In addition, the proposed approach can be adapted to decision support systems in the tasks of financial and economic support of aerospace enterprises and programs, where the validity, verifiability and accountability of analytical conclusions are of particular importance.

An important result is also the proposed structure of stages of explained semantic verification, which includes: formation of an analytical result, generation of an explanation, semantic mapping, logical verification and assessment of the reliability of the result. Such a sequence allows us to move from the analysis of the features that influenced the forecast to checking its compliance with the formalized knowledge of the subject area. The proposed metrics of explanation stability, ontological coherence and semantic compliance allow us to assess the result not only qualitatively, but also quantitatively, which is important for further formalization of control procedures.

It should be noted that the proposed approach is conceptual in nature and at the current stage is a methodological basis for further development of applied information technology. Its practical implementation requires solving a number of additional tasks, in particular, building or adapting ontological models of the financial subject area, formalizing logical verification rules, choosing methods of semantic mapping between model features and ontology concepts, as well as experimental testing of the proposed metrics on real financial data.

Therefore, the obtained results confirm the feasibility of transitioning from traditional explainability to explainable semantic verification as a new level of control over the results of the functioning of financial intelligent systems. The proposed approach allows combining the statistical capabilities of machine learning models with formalized knowledge of the subject area, which creates the prerequisites for increasing the reliability, transparency and validity of intelligent financial decisions.

4. Conclusions

The article considers the problem of ensuring transparency, validity and verifiability of the results of financial data intelligence analysis in the context of increasing complexity of machine learning models and increasing requirements for algorithmic accountability. It is shown that for the financial sector, it is not enough to simply obtain an accurate forecast or its interpretation, since the practical use of intelligent systems also requires verification of the logical admissibility, semantic consistency and regulatory acceptability of the generated results. This makes it advisable to move from traditional explainability to explainable semantic verification.

Within the framework of solving the first task, modern methods of explainability and approaches to verifying the results of the functioning of intelligent systems, in particular in the financial context, were analyzed. It was found that the most common xAI methods, in particular LIME and SHAP, provide interpretation of the results of machine learning models by determining the weight of individual features, and semantic and neuro-symbolic approaches create the basis for meaningful coordination of such results with the subject area. At the same time, it is shown that existing solutions are mainly focused either on explaining the result or on partial use of formalized knowledge, without providing a holistic procedure for its verification.

Within the framework of solving the second task, limitations of existing solutions in ensuring logical admissibility, semantic consistency and reliability of data mining results were identified. It was determined that modern xAI approaches are characterized by instability of explanations, dependence on changes in input data, lack of sufficient semantic context and limited suitability for checking the compliance of the obtained results with business rules, regulatory requirements and formalized knowledge of the subject area. It is substantiated that these limitations prevent the use of traditional explainability methods as a sufficient tool for high-risk financial tasks.

Within the framework of the third task, an approach to the explained semantic verification of the results of the intellectual analysis of financial data was developed based on a combination of XAI methods, ontological knowledge representation and formal verification procedures. It is shown that the proposed approach involves the sequential implementation of the stages of analytical result formation, explanation generation, semantic mapping, logical verification and reliability assessment. This allows us to move from a descriptive explanation of the result to its substantively substantiated verification in the context of formalized knowledge of the financial subject area and creates the prerequisites for increasing the transparency, reliability and algorithmic accountability of financial intellectual systems.

Prospects for further research should be associated with the development of applied information technology for implementing the proposed approach, the formalization of ontological models for individual financial tasks, the improvement of semantic mapping methods between model features and subject area concepts, as well as experimental testing of the proposed metrics on real financial data sets. Special attention should be paid to testing the efficiency of the approach in credit scoring tasks, risk assessment and detection of fraudulent transactions, as well as its adaptation to computer decision support systems in the financial and economic support of aerospace enterprises, programs and projects.

Contributions of authors: conceptualization, methodology – **Tetiana Filimonchuk;** formulation of research goals and objectives – **Dmytro Baraniei, Tetiana Filimonchuk;** conducting research on the current state – **Dmytro Baraniei;** interpretation of results – **Dmytro Baraniei, Tetiana Filimonchuk.**

Conflict of Interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, author ship or otherwise, that could affect the research and its results presented in this paper.

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Data Availability

The work has associated data in the data repository.

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence methods while creating the presented work.

All the authors have read and agreed to the published version of this manuscript.

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АНАЛІЗ ПІДХОДІВ ДО ПОЯСНЮВАНОЇ СЕМАНТИЧНОЇ ВЕРИФІКАЦІЇ РЕЗУЛЬТАТІВ ІНТЕЛЕКТУАЛЬНОГО АНАЛІЗУ ФІНАНСОВИХ ДАНИХ

Д. І. Баранєй, Т. В. Філімончук

Предметом дослідження є методи пояснюваності та семантичної верифікації результатів інтелектуального аналізу фінансових даних у комп’ютерних системах підтримки прийняття рішень, зокрема для високоризикових галузей, включаючи авіаційно-космічну. **Метою** статті є аналіз сучасних методів пояснюваності та підходів до верифікації результатів функціонування інтелектуальних систем у фінансовому контексті, виявлення їх обмежень та обґрунтування підходу до пояснюваної семантичної верифікації. **Завдання**: проаналізувати сучасні методи пояснюваності та підходи до верифікації результатів функціонування інтелектуальних систем; виявити обмеження існуючих рішень щодо забезпечення логічної допустимості, семантичної узгодженості та достовірності результатів інтелектуального аналізу даних; розробити підхід до пояснюваної семантичної верифікації результатів інтелектуального аналізу фінансових даних. У ході дослідження застосовано **методи** аналізу та узагальнення наукових джерел, системного й порівняльного аналізу, а також підходи онтологічного моделювання та семантичної інтерпретації результатів машинного навчання. У **результаті** встановлено, що сучасні xAI-підходи забезпечують інтерпретацію результатів моделей машинного навчання, проте не гарантують їх логічної допустимості, семантичної узгодженості та нормативної прийнятності. Обґрунтовано доцільність інтеграції методів xAI з онтологічними моделями знань і процедурами формальної перевірки. Запропоновано підхід, що передбачає послідовну реалізацію етапів формування аналітичного результату, генерації пояснення, семантичного мапінгування, логічної верифікації та оцінювання достовірності результату. **Висновки.** Наукова новизна отриманих результатів полягає в обґрунтуванні підходу до пояснюваної семантичної верифікації результатів інтелектуального аналізу фінансових даних, що, на відміну від існуючих підходів, забезпечує не лише змістовну інтерпретацію результату, а й його логічну перевірку та семантичну узгодженість із знаннями предметної області та галузевими обмеженнями.

Ключові слова: фінансові інтелектуальні системи; пояснювана верифікація; explainable artificial intelligence; онтологічні моделі; семантичний мапінг; інформаційні технології; алгоритмічна підзвітність.

Баранєй Дмитро Ігорович – асп. каф. електронних обчислювальних машин, Харківський національний університет радіоелектроніки, Харків, Україна.

Філімончук Тетяна Володимирівна – канд. техн. наук, доц., доц. каф. електронних обчислювальних машин, Харківський національний університет радіоелектроніки, Харків, Україна.

Dmytro Baraniei – PhD Student at the Department of Electronic Computers, Kharkiv National University of Radio Electronics, Kharkiv, Ukraine,
e-mail: dmytro.baraniei@nure.ua, ORCID: 0009-0009-4229-774X

Tetiana Filimonchuk – Candidate of Technical Sciences, Associate Professor, Associate Professor at the Department of Electronic Computers, Kharkiv National University of Radio Electronics, Kharkiv, Ukraine,
e-mail: tetiana.filimonchuk@nure.ua, ORCID: 0000-0002-4380-504X