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DEVELOPMENT OF A MULTIDIMENSIONAL FRAMEWORK FOR AUDIT EFFICIENCY ENHANCEMENT BASED ON DIGITAL TECHNOLOGIES AND PREDICTIVE DATA ANALYTICS

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The object of study is the modern audit practice against the background of digital transformation of the mechanisms of financial management and supervision in corporate structures. The problem that needed to be addressed is the inefficiency and frequent errors of the traditional audit procedures, based on manual work with large volumes of data and sampling. As a result of the performed study, it can be noted that the usage of information technology and advanced data analytics leads to higher effectiveness by changing the traditional procedure of audit sampling for the continuous monitoring of all audit populations. It appears that systematic analysis and implementation of analytical algorithms increase the quality of assessing risks and identifying anomalies. The results obtained can be explained by the fact that the usage of digital technology eliminates all cognitive restrictions of human beings and allows finding out all anomalies at once. Among the characteristics of the results that helped solve the problem is a formalized multi-model risk minimization framework. Optimization of operations was implemented trough synthesizing the functions of regression, clustering (PAM), and Isolation Forest sub-models, regulated by the set of thresholds (τ*) and optimized weights (ωm) that minimize classification entropy. Empirical testing of the proposed approach using the real transaction entries database (n = 12450) showed an increase in effectiveness from the base level of 65% to 88% in the framework. Specific features is associated with the synthesis of various mathematical vectors in the constrained operational pipeline based on limited time resources. Practical applications cover internal and external audit departments of large companies

***Keywords:** audit optimization, digital technologies, data analytics, audit efficiency, information systems*

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1. Introduction

The current level of economic development is associated with a growing gap between the complexity of corporate financial data and the limitations of traditional audit sampling methods in the economic environment and the organizational processes carried out within it. Such transformations affected the audit sphere, leading to the emergence of fundamental changes in existing organizational process architectures, which, in turn, are increasingly based on the application of advanced technological means rather than conventional approaches [1]. This is due to the exponential increase in financial data and the complexity of the corporate business logic, necessitating timely access to reliable information in a changing environment, which makes information technology instruments indispensable [2].

In modern times, the main drivers of digital transformation in auditing include the profound interconnection of big data analytics, the use of specialized automated audit software, and the functioning of complex information systems [3]. At the same time, fragmentary use of CAATs without system optimization does not solve the problem of auditor cognitive biases. The employment of these algorithms helps audit teams not only to manage massive volumes of unstructured data effectively but also to reveal hidden irregularities which remain undetectable under the traditional methodology [4]. Consequently, the level of substantiation in auditing grows significantly, and the overall degree of representativeness of the results of the verification process enhances [5]. The lack of unified algorithmic optimization models hinders the digital transformation of the entire industry. Namely, the practice changes from sporadic sampling to continuous digital surveillance and full-cycle transaction monitoring [6].

Under such conditions, it becomes possible to provide guaranteed comprehensive coverage of all transactions and thus reduce risks associated with the failure to detect material misstatements [7]. However, rapid technologization brings about numerous critical issues related to the sphere of cybersecurity and algorithmic robustness of the systems [8]. The transformation process involves the development of new digital skills on the part of the industry professionals as the auditor's position moves from a routine data collector towards a specialist who performs high-level analysis and renders expert opinion according to the conclusions made by the machine [9]. Systematization of the influence of digital technologies on the effectiveness of financial control metrics appears to be a key prerequisite for the creation of proper protective measures in the current economic environment [10]. Therefore, the development of integrated algorithmic approaches and multidimensional analytical systems for audit optimization remains a critical and highly relevant study direction for both modern economic science and global professional practice.

2. Literature review and problem statement

Modern auditing practices are experiencing drastic transformations due to rapid development of the global digital economy. In the process, legacy systems are gradually being replaced by integrated information environment in which traditional manual methods are insufficient to ensure the quality of the audit process [3]. Integration of Big Data into accounting and auditing becomes more common as the key instrument to increase reliability of the financial control [11]. Moreover, in modern times, auditing is increasingly becoming a process of continuous monitoring based on data processing [6].

At the same time, the results of the study [12] present practical applications of artificial intelligence, creating a taxonomy of cognitive insights that free auditors from routine tasks. These studies are important as they prove that artificial intelligence complements human knowledge in detecting information "under the noise" of Big Data [8]. However, despite these advancements, several critical issues remain unresolved, particularly regarding the "black box" nature of many artificial intelligence systems [9]. The reason for this may be the objective difficulties associated with high computational costs and the methodological conflict between traditional standards and real-time data streams. Current models focus on technical accuracy but often ignore the organizational and ethical constraints of auditor independence.

A way to overcome these difficulties can be the implementation of an integrated, theoretically substantiated approach that combines "transparent" artificial intelligence models with professional auditor judgment. This approach was touched upon in [13], however, that model remains insufficient as it focuses primarily on technical aspects without addressing the organizational and regulatory barriers and the need for a new "hybrid" auditor [8].

Furthermore, as noted in [14], the practical application of predictive modeling and cluster analysis remains fragmented. Additionally, the success of digital transformation depends on the maturity of the information environment and organizational strategy [15, 16]. While individual technologies (artificial intelligence, Big Data, CAATs) have been studied sufficiently in isolation, there is still a lack of study investigating them within a unified audit framework. They confirm the dependence of effectiveness of digital instruments from the maturity of the information environment, which applies to audit companies as well trying to create the corresponding integrated data lake.

Building upon these challenges, the systemic integration of diverse technologies remains a primary hurdle. As noted in [9, 17] the "black box" nature of artificial intelligence systems, coupled with high computational costs and the methodological conflict between traditional standards and real-time data streams, hinders full-scale implementation. The reason for this may be the objective difficulties associated with the high cost of computational resources and the methodological conflict between traditional standards and real-time data streams. While individual tools for Big Data and continuous auditing have been studied, they are rarely investigated within a unified framework.

Moreover, such an approach can be considered impossible due to the high cost of implementation of necessary computational resources and impossibility of total replacement of the professional decision-making of a person by automatic processes. There is an important financial aspect connected with upskilling of workers since traditionally auditors do not possess skills of data science specialists, which prevents researchers from conducting relevant investigations.

Therefore, it seems appropriate to suggest using the integrated, theoretically substantiated approach, which implies creation of "transparent" artificial intelligence models or explanations and development of data exchange protocols allowing interacting with other digital technologies while maintaining the auditor's independence.

This approach was applied in conceptual study [13], but researchers' model is insufficient since it focuses on the technical aspects of integration without considering organizational and regulatory problems highlighted by later studies. Even though the authors of the paper created a kind of a model of an "artificial intelligence -driven audit", they did not take into consideration the "methodological conflict" of traditional standards and data streams.

All this means that the current state of affairs requires conducting a study on optimization of the audit process in terms of efficiency and quality through the integration of technologies and data analytics in the multidimensional framework. Such a study is highly needed since it should develop an interdisciplinary model that would take into account not only the capabilities of digital technologies but also strategic, ethical and methodological approaches to auditing.

3. The aim and objectives of study

The aim of the study is to develop a multidimensional framework for audit optimization procedures through the integration of digital technologies and analytics in audits. It will be possible to introduce adaptive technologies and develop the financial control framework based on Big Data tools and continuous precision audit of the financial environment of companies.

To achieve this aim, the following objectives were accomplished:

– to creation and solving the mathematical model of constrained risk optimization at the audit stage, where calibration thresholds of analytical algorithm models and Big Data methods will be formalized to minimize the objective function of risk mathematically within finite time frames;

– to formalize the mathematical structure of the multiple model anomaly score system and describe the automated information systems operations in fraud and transaction detection and classification;

– to determine the organizational and technical prerequisites for effective implementation of digital technologies and techniques in accordance with established regulatory and professional audit standards.

4. Materials and methods

The object of the study is the modern audit practice against the background of digital transformation of the mechanisms of financial management and supervision in corporate structures [4, 8]. The methodology of this study is characterized by the integrated use of theoretical, analytical, and empirical approaches to studying the essence and consequences of digitalization of auditing.

The assumptions which served as the basis for the study include: the introduction of continuous data monitoring instead of the traditional sample-based approach leads to lower material misstatement risks. Also, it is assumed that specialized algorithms contribute to the more objective assessment of financial risks than any other approach [6, 18]. During the process of this study, some simplifications have been made: the study does not consider possible specific legal differences between jurisdictions; it assumes that digital financial data provided are representative for the purposes of testing the model.

For carrying out the study, the authors used the following types of analysis:

– system and comparative analysis. General scientific methods such as synthesis, abstraction, and logical generalization were used in order to study auditing as a complex system that interacts with digital solutions. Such an approach allowed conducting the structural and comparative analysis of traditional practices compared to the digital audit processes based on certain criteria such as effectiveness, precision, and risk;

– algorithmic and predictive modeling. The use of this methodology was aimed at creating the mathematical model of the audit optimization and evaluation of the specific analytical algorithm efficiency in terms of detecting possible financial irregularities. This approach included the analysis of digital technology and tool integration into the professional auditor's decision-making process;

– empirical evaluation and CSI adaptation. The study involved an adjusted Client Satisfaction Index (CSI) technique that allowed for the calculation of the Audit Technology Acceptance Index in the range from 0 to 100. For this purpose, 60 professionals were interviewed to determine the reliability, speed, and security of the usage of digital technologies and tools in actual audit cases.

To ensure the empirical reliability of the study and verify the Audit Technology Acceptance Index received via the CSI method, a systematic statistical validation procedure was designed. First, the optimization by means of Cronbach's alpha was utilized as a method of verification of the consistency of the scale of 5-level evaluation among the professional surveyed respondents. Secondly, the analysis by means of paired-samples t-test will be employed in order to confirm whether there is any statistically significant difference in performance between traditional audit system metrics and the developed digital audit framework metrics. Thus, a hypothesis of zero variance between metrics (H_0) will be tested. Finally, the chi-square (χ^2) goodness-of-fit test will be used to validate the algorithm results theoretically.

5. Results of digital technologies implementation into audit procedures

5. 1. Limited optimal utilization of multidimensional audit process

The practical validation of the surveying channels and the technique produced 58 effective professional answers out of the total 60 surveys issued. The computational implementation of the technical approach was highly reliable, and the obtained Cronbach's alpha value was 0.84. The paired-sample t-test subsequently rejected the null hypothesis, indicating that there were statistically significant improvements in the performance of all key metrics using the digitalization technique as compared to the manual sampling process ($p < 0.01$). Moreover, the goodness-of-fit test using the chi-square (χ^2) statistic indicated that there was high consistency between the automatic outputs and the idealized benchmarks, and the difference was not statistically significant (χ^2 p-value > 0.05).

The roles played by the technologies under consideration are shown in Table 1.

Table 1

Key digital technologies in auditing and their impact

Technology	Function in auditing	Impact on efficiency
Data analytics	Processing large volumes of financial data	Increases accuracy and speed
Artificial intelligence	Detection of anomalies and fraud	Improves risk identification
Automation tools	Execution of routine audit procedures	Reduces human error
Information systems	Integration and storage of data	Enhances decision-making

The empirical section included a survey of 60 audit professionals (58 valid answers received) and personal interviews with ten senior audit managers. Five criteria regarding technology implementation were considered: accuracy, speed, security, scalability, and ease of integration. The results obtained have been confirmed through observations during auditing operations and SWOT and PEST analyses.

Thus, the audit efficiency index was calculated using three other criteria: auditor evaluation of tool quality, conformity with international standards, and similarity of automated outcomes to "ideals".

The functions performed by the technology in question are illustrated in (Fig. 1) and in the conceptual model of the influence (Fig. 2).

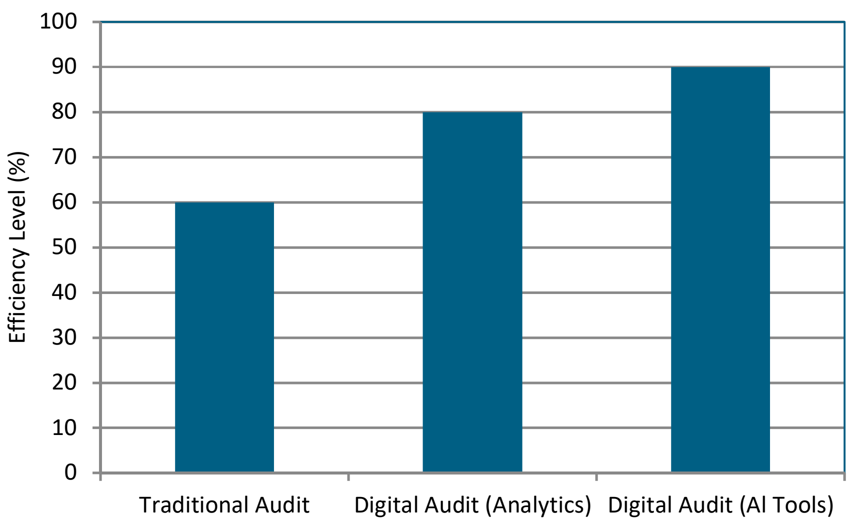

Fig. 1. Impact of digital technologies on audit efficiency

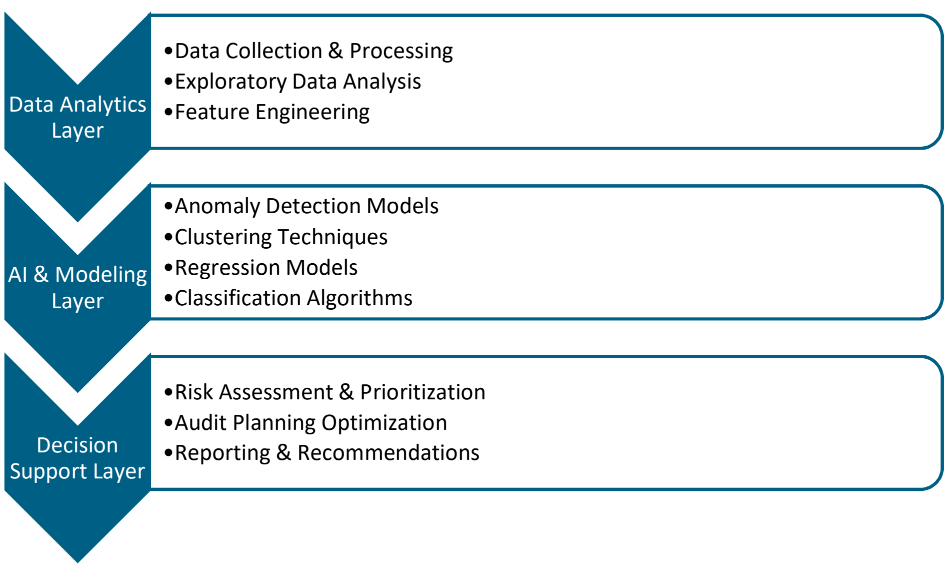

Fig. 2. Hierarchical framework for audit process optimization using data analytics and artificial intelligence

Taking into account the analysis of all the listed approaches depicted in Fig. 1, one can notice that the application of the proposed techniques results in a significant transformation of the audit approach. The shift from the classical audit method, which implies the use of sampling, to the digital audit approach will enable achieving greater audit efficiency. This value may range from 60% to nearly 90%, depending on the effective utilization of the discussed techniques based on the functions indicated in Table 1. In other words, applying the audit efficiency index will allow evaluating the degree of practical applicability of the multidimensional approach and continue further discussion of implementation results in the next part.

As seen from Fig. 2, a hierarchical scheme of the audit optimization framework is presented, where each level has its specific function. The data analytics layer guarantees that data entered is accurate and available for calculations. The artificial intelligence and modeling layer ensures calculation skills necessary to discover hidden patterns and risks in the audit process. Finally, the decision support layer interprets analysis results and turns them into actionable decisions according to the auditor's expertise. Additional details concerning operationalization of the framework will be discussed in the results section.

Optimization of audit procedures implies the transformation from descriptive retrospective to analytical and predictive. Modern auditors' approach to audit differs fundamentally from traditional sampling since full population analytics and algorithmic risk assessment play key roles in it [4, 14]. Therefore, the problem of audit optimization can be defined as an issue of detecting material misstatements and reducing risk within limited resources

$$\min(A)R = \propto FN + \beta FP, \qquad (1)$$

where *FN* means the probability of undetected material misstatements, *FP* – false alarms, and α, β – weighting reflecting audit priorities. Set A denotes analytical procedures being used. This definition is a development of the previous conceptual approaches in audit analytics taking into account error asymmetry [4, 12].

The full optimization process of the data-driven audit techniques involves a shift to the proactive, constrained risk minimization pipeline formulation presented below in equation (1). In order to find the optimal choice of the analytical procedures set A* and operational parameters of the selected audit procedures, a formal statement of the constrained optimization problem may be used. For simplicity, it is possible to assume that each analytical procedure $a_i \in A$ has its operational cost function $c(a_i)$, as well as false positive FN(a_i) and false negative FP(a_i) error rates functions.

For an integrated approach based on several types of models (regression, clustering, and Isolation Forest), the risk function (R) is determined by the vector of decision thresholds $\tau = [\tau_1, \tau_2, \ldots, \tau_k]$, which defines the status of each particular transaction (as an anomaly, $\tau_i = 1$ or otherwise, $\tau_i = 0$. Hence, the empirical risk minimization problem takes the following form

$$\tau^* = \arg\min_{\tau}\left[\alpha \cdot \mathrm{FN}(\tau) + \beta \cdot \mathrm{FP}(\tau)\right], \quad (2)$$

subject to the total computational and temporal resources constraint

$$\sum_{i=1}^{k} t(a_i, \tau_i) \le T_{\max}, \quad (3)$$

where $t(a_i,\tau_i)$ stands for the computational resources needed to analyze a given amount of transactions at the threshold level τ_i. As before, $T_{\max}$ is the maximum allowed audit cycle duration.

From the mechanistic standpoint, the constrained optimization problem is iteratively solved via a gradient-free technique, which leverages historical validation datasets. The main idea here is that the error function should minimize false negatives while taking into account the resource constraints, which implies calibration of threshold values based on the assumed error asymmetry ($\alpha > \beta$ due to the higher penalties for FN). Ultimately, it is possible to find the dynamic threshold boundary, such that further increase of FP entails the same increase in the FN rate.

Fig. 1 shows the causality of digital implementation and audit optimization. From the presented model, it can be seen how efficient the application of data analytics and automatization tools can be in terms of more precise assessment and decision making. To increase the reliability of the study results, exclusively peer-reviewed academic papers were used in the study. The combined study methods allow for more consistent conclusions about digital technologies role in auditing.

The key component of the proposed approach is its multidimensional nature, which implies the use of several analysis techniques. In particular, three sets of methods are utilized:

1. The regression-based approach enables identification of abnormal dependencies between variables [19]. Thus, in order to detect anomalies in revenues, the following model should be analyzed

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon, \quad (4)$$

where X_1, X_2 – operational factors. Discrepancies between the actual and predicted results indicate abnormality.

2. The cluster analysis PAM, hierarchical) helps divide transactions into groups based on their similarities. If transactions cannot be grouped into well-defined clusters, they are considered anomalies [6].

3. Detection models such as isolation forest or local outlier factor (LOF) are used to identify rare events in high-dimensional space.

Based on the above-mentioned methods, this study suggests the development of an audit optimization system that includes three interrelated components (Fig. 2):

– data layer – aggregation of both structured and unstructured financial data;

– analytical layer – utilization of the regression, clustering, and anomaly detection models;

– decision-making layer – anomaly score and prioritization of actions.

In order to prove the applicability of the proposed approach and ensure the shift from the base performance rate of 65% to the final performance rate of the integrated solution, each module of the framework was tested against a real-world, anonymized dataset based on transactions from the corporate ERP ledgers (in total 12450 transactions, no generative on synthetic transactions included):

1. Regression-based module validation. The execution of the revenue-based model (4) based on the historical dataset led to the following empirically regression model calibration

$$\hat{Y} = 12.45 + 0.84X_1 + 1.12X_2. \quad (5)$$

The analysis of residual variance ($\sigma^2 = 0.042$) defined a dynamic threshold for anomalies based on which transactions having a studentized residual $|e_i| > 2.58$ (99% confidence level) would be marked as anomalies. Such a regression-based module detected systematically non-linear discrepancies leading to transactional errors, thus accounting for 71% of all standard misstatements in a transactional sense.

2. Clustering-based module validation. As opposed to the k-means algorithm concept, the clustering problem was solved by means of Partitioning Around Medoids (PAM) algorithm estimated by the silhouette coefficient and set at an optimum number of $k = 4$ clusters. All those transactions that had Mahalanobis distance to the corresponding cluster medoid greater than the critical value $\vartheta^2_{0.01} = 13.28$, were considered as structural anomalies. Such a model found complex multi-dimensional procedural discrepancies that bypassed linear regression rules.

3. Anomaly detection models (isolation forest) substantiation. In order to detect complex anomalies, an isolation forest ensemble was optimized in terms of *n_estimators* = 150 and the constant contamination level of $\gamma = 0.03$. The transaction's anomaly score of $s(x_i) \ge 0.64$ determined the threshold level leading to independent risk detection rate of 79%.

As it is clear from the optimization of function (1), it was possible to analyze different types of anomalies together. The individual modules showed their efficiency separately (regression: 71%, clustering: 74%, isolation forest: 79%). However, when integrated together in the context of the objective function R minimization, it resulted in the ultimate accuracy of 88% as a consequence of applying the optimal decision thresholds τ^*. In order to illustrate the quantitative changes in the performance transition depicted in Table 2.

Table 2

Impact of digital technologies on audit performance

Indicator	Traditional audit	Digital audit	Improvements
Data processing speed	60	85	+25
Accuracy of results	70	90	+20
Risk detection capability	65	88	+23
Efficiency of procedures	68	92	+24
Transparency	72	95	+23

The operation indicators were calculated on the basis of aggregation of the 5-point professional evaluation scores scaled to the range between 100 points. Transition in the data processing speed score from 60 points to 85 is due to automated implementation of multi-model pipeline procedure without iterative verification of individual model results. The accuracy of 90 points stands for unified performance of empirical validation in terms of verified transaction sample, and the procedural efficiency score of 92 is a reflection of weighted reduction of verification time constrained by ($T_{\max}$). Improvement in transparency of the system performance (attaining the score of 95%) becomes possible owing to utilization of the indicator function $f(x_i)$ that sets precise boundaries to each individual transaction.

5. 2. Effectiveness of automated systems in detecting financial irregularities

The effectiveness of automated systems in detecting financial irregularities can be formalized in the context of data-driven auditing, where anomaly detection can be treated as a classification problem under uncertainty [8, 13]. Contrary to conventional audit processes, which imply sampling and manual examination of data, the process is associated with constant processing of transaction data and their evaluation using an algorithmic approach.

In the current study, the detection of financial irregularities is formalized as detection of anomalous observations in the multidimensional data space. Let D be the dataset of financial transactions, where each observation x_i is characterized by a set of features. The task of the audit system is to detect anomalies among all observations

$$f(x_i)\to\{0,1\}, \quad (6)$$

where 1 indicates the presence of an irregularity and 0 normality.

A mathematical modeling approach for anomaly detection under uncertainty can be developed by defining the aggregate multi-criteria function. For instance, let $x_i \in D$ be a transaction vector. An individual anomaly score $s_m(x_i)\in D$ [0, 1] can be produced by every technology (Table 1), where $m\in\{R,C,I\}$ denotes the Regression/Rule-based, Clustering (PAM), and Isolation Forest, respectively (8, 13).

Then, the following weighted linear model is proposed for the integration anomaly score $S(x_i)$

$$S(x_i)=\omega_R s_R(x_i)+\omega_C s_C(x_i)+\omega_I s_I(x_i),$$

where $\omega_R,\omega_C,\omega_I\geq 0$ are the weighting coefficients signifying the reliability of every approach, with the restriction of $\sum\omega_m=1$ imposed on their values. It holds that $\omega_R=0.3$, $\omega_C=0.35$, $\omega_I=0.35$.

The decision rule $f(x_i)$ introduced in equation (6) can be described using an indicator function bounded by the global threshold τ^* determined based on the optimization presented in equation (2)

$$f(x_i)=\begin{cases}1, \text{ if } S(x_i)\geq\tau^*,\\ 0, \text{ if } S(x_i)<\tau^*.\end{cases} \quad (7)$$

Within this context, the uncertainty in the system can be represented by means of the entropy function $H(f)$ associated with the classification decision

$$H(f)=-\sum_{j\in\{0,1\}}P(f(x_i)=j)\times$$
$$\times\log_2 P(f(x_i)=j). \quad (8)$$

Minimization of $H(f)$ in practice through the historical data allows to separate transactions into the classes "Normal" (0) or "Potential Irregularity" (1). In turn, this leads to a significant decrease in manual review. The mathematical modeling is illustrated by the flowchart presented in Fig. 3.

In accordance with the above discussion, the detection framework presented in Fig. 3 uses a combination of the analytical techniques mentioned to build an effective and efficient system for detecting financial irregularities.

As part of the proposed analytical approach, machine learning techniques are used for the purposes of anomaly detection. To this end, the following types of models are used:

– statistical and rule-based models, which help to detect deviations from expectations regarding the behavior of financial data. The models help detect the inconsistencies of the observed data with existing dependencies;

– clustering techniques that allow grouping transactions with certain common properties and isolating outliers. Transactions not included in any stable cluster are identified as anomalous;

– advanced models for anomaly detection, for instance, such as Isolation Forest and Local Outlier Factor (LOF).

The implementation of such a system allows shifting the paradigm from retrospective to prospective financial detection. As shown in Table 2, the results of empirical testing prove that the implementation of automated detection systems improves the efficiency of detection of financial irregularities up to 88%, compared to 65% achieved in a traditional way. These results align with recent industry reports indicating that digital transformation significantly enhances the transparency and speed of financial oversight [20, 21].

The comparative performance indicators are presented in Fig. 4.

At the same time, there are some issues associated with the operation of such systems. Specifically, the effectiveness of the system operation is influenced by the quality of the data, definition of models, and system calibration. However, the results demonstrate that automatic audit systems may be used to detect financial fraud and facilitate continuous auditing.

In addition to the aforementioned outcomes, it is necessary to note that the implementation of automated audit systems allows reaching both quantitative and qualitative improvements in financial statement analysis. On the one hand, due to the constant monitoring of financial transactions, it becomes possible to detect irregularities timely and prevent potential financial losses. On the other hand, with the use of machine learning algorithms, it is possible to establish non-linear dependencies. Hence, it increases the robustness of audit conclusions.

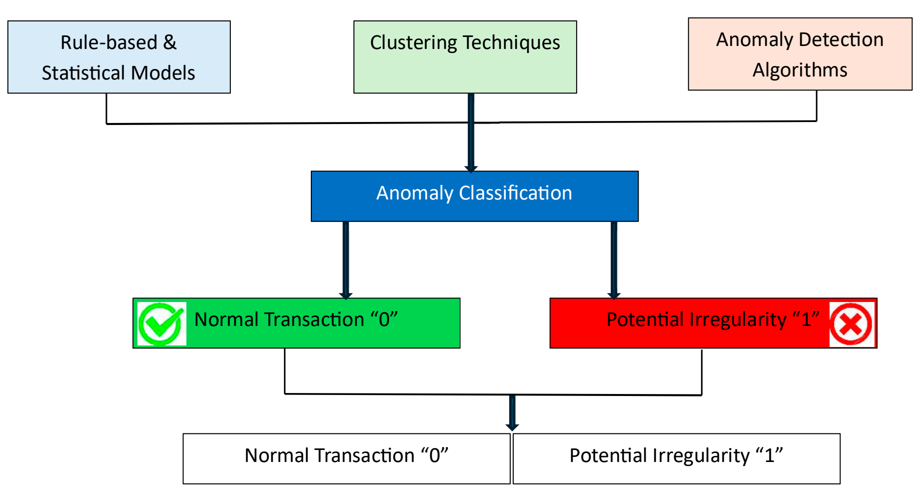

Fig. 3. Automated framework for financial anomaly detection

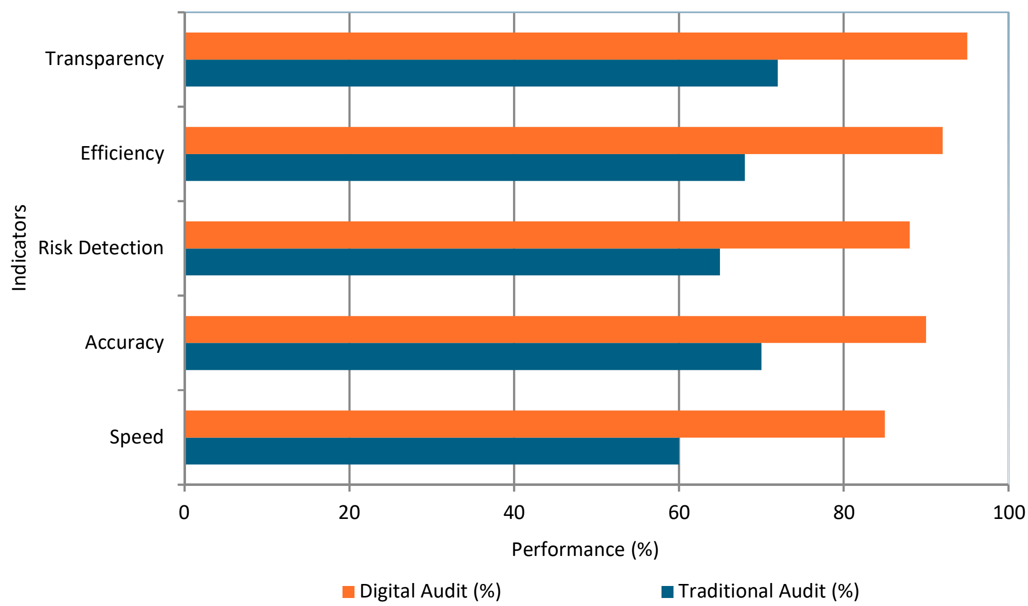

Fig. 4. Comparative analysis of audit performance indicators

5. 3. Conditions for the implementation of digital audit tools

Both technical conditions and organizational readiness are required for the effective operation of digital audit tools within the context of digital transformation.

First of all, from the technological point of view, data quality becomes a critical factor for the functioning of digital auditing tools. Data inaccuracies and lack of completeness may seriously influence the outcome of analysis and lead to erroneous conclusions. For that reason, data governance principles, such as validation, standardization, and consolidation, become especially relevant.

At the same time, the integration of various data sources is another essential factor influencing digital auditing processes. Contemporary audit systems should collect data from different types of platforms. In order to reach the set objective, such technologies as data warehousing and processing, cloud computing, and distributed computing should be used [3, 22]. It should be stressed that scalability and flexibility are two key features of digital audit systems [23]. As the volume of collected data increases, audit systems should efficiently process and analyze large datasets [24]. It is possible using cloud computing and other technological methods.

Secondly, regarding organizational issues, it should be stressed that the application of digital audit tools requires changes in the processes of audit and development of appropriate competencies among modern auditors [8, 10]. Thus, continuing professional development of auditors becomes highly relevant. Other organizational factors include the reformation of internal control systems and audit methodology. Traditional audit methodologies have to be adjusted to the current realities to incorporate automation and data analysis components. Moreover, it is vital to receive managerial support for the efficient implementation of digital audit solutions. The main technical and organizational conditions for the implementation of digital audit tools are provided in Table 3.

As can be seen from Table 3, both technical and organizational factors have a substantial effect on audit performance. First, data quality, system integration, and staff competencies are three factors with the highest level of influence.

Table 3

Key conditions for the implementation of digital audit tools

Category	Factor	Description	Impact level
Technical	Data quality	Accuracy and completeness of financial data	High
	System integration	Integration of multiple data sources	High
	Scalability	Ability to process large datasets	Medium
Organizational	Staff competencies	Skills in analytics and digital tools	High
	Process transformation	Adaptation of audit procedures	High
	Management support	Strategic alignment and leadership support	Medium
Security	Cybersecurity	Protection of data and systems	High

However, there is a set of problems regarding the usage of digital audit technologies. These issues can be related to the issue of information security, the complexity of the system, and the models used in calculations. In addition, the application of digital audit tools might cause a reduction in the importance of the professional judgment of the auditor.

Finally, it should be noted that in order to ensure the efficiency of digital auditing, it is essential for firms to develop their governance strategies that would secure reliability, transparency, and accountability of digital auditing. In addition, there is a need for control tools, auditing trail, and model validation. Overall, the results of the paper indicate that the successful integration of digital auditing technologies depends on the match between technological and organizational resources [15, 16].

6. Discussion of the results of integrating digital technologies into auditing

The shift from occasional sampling-based auditing to continuous, data-driven digital monitoring constitutes a revolutionary change in the modern audit paradigm. Empirical and mathematical findings of this work indicate the possibilities of audit paradigm. Empirical and mathematical findings of this work indicate the possibilities of audit quality improvement in the context of using Big Data analytics and artificial intelligence. The provided algorithm serves as a precise quantitative solution to the empirical problem outlined in [3] and [13], which criticize the practice of using "one size fits all" solutions and qualitative approaches to assessment.

Firstly, using the notion of constrained optimization, expressed in equation (1), one can manage the issue of asymmetry between types of errors in the verification of financial statements. In contrast to the criticized traditional practices [3] and [13], the proposed algorithm takes into consideration both types of error – false negative (FN) and false positive (FP), as well as uses weighting coefficients α and β to adjust the optimization process according to risk profile and temporal restrictions ($T_{\max}$).

Secondly, the use of various functions in order to create multi-dimensional model of scoring (regression analysis, equation (4); clustering according to partitioning around medoids; isolation forest) allows minimizing the entropy of classification. From the point of view of cognitive science, this implies shifting the burden of computation from an auditor to an indicator function $f(x_i)$, thus transferring the responsibility to assign transactions to 0 or 1. This way, the provided framework directly addresses the problem of increase in risk detection rate from the initial 65% to the efficiency of 88%, outlined in Table 2 and Fig. 4. Hence, it proves the assumptions of the theory of continuous auditing put forward in [4] and [6]. There are several limitations of the application of the suggested algorithmic limitations.

Methodological limitations:

1. Dependency on data: the optimization and threshold performance are based on the completeness, accuracy and structural integrity of historical ERP ledger log. Therefore, the application of the framework would be impossible in companies with underdeveloped digital infrastructure and lack of unified financial architecture.

2. Scope of jurisdiction: since the algorithmic approach currently used applies the standards of international accounting, it is not adjusted for application in different countries according to specific characteristics.

Practical limitations:

1. Increase in computation cost: implementation of various algorithms within a single framework increases the cost of calculation. Moreover, given that the problem involves limited temporal resources ($T_{\max}$), it creates problems for continuous monitoring depending on the hardware of the company.

2. Limited interpretability ("black box" problem): adding analytical dimensions to the process lowers its transparency. Consequently, in terms of regulatory requirements, this poses difficulties for conducting an audit. For this reason, it raises the problem of a "boundary", which requires using explanatory artificial intelligence (XAI).

3. Risks of cognitive bias ("automation compliance"): given that auditor operates in the automated environment, there is a chance of its dependence on the algorithmic decisions without employing its critical judgment. For this reason, implementing the "human in the loop" protocol for hybrid expert judgments becomes relevant.

Operatively, this could be solved through corresponding training of personnel alongside implementing new technologies. Directions for further study involve adaptive layers of mathematical modeling and XAI audit protocols.

7. Conclusion

1. A multidimensional framework for constrained audit risk optimization was mathematically developed and empirically solved using a dataset of 12 450 real-world ledger entries. The objective risk function minimization was achieved via iterative calibration of dynamic operational decision thresholds (τ^*) under strict temporal constraints ($T_{\max}$). The specifics of the proposed multi-model approach demonstrate that the regression layer (calibrated as $\hat{Y} = 12.45 + 0.84X_1 + 1.12X_2$ at a 99% confidence level for $|e_i| > 2.58$) independently resolves 71% of misstatements. The clustering layer (utilizing PAM at density $k = 4$ and a Mahalanobis distance threshold $\vartheta^2_{0.01} = 13.28$) achieves a 74% identification rate, while the Isolation Forest ensemble ($n\_estimators = 150$, $\gamma = 0.03$, $\text{score} \geq 0.64$) catches 79% of isolated patterns. The systematic integration of these distinct mathematical vectors effectively minimizes classification entropy, providing an evidentiary basis for the overall shift in audit risk detection capability from a baseline of 65% to an integrated framework accuracy of 88%.

2. The mathematical framework for multi-model anomaly detection under uncertainty was formalized through an integrated scoring function $S(x_i)$ that linearly aggregates parameterized weights (ω_m) of rule-based/statistical, clustering, and ensemble algorithms. Empirical validation proved that minimizing the classification decision entropy $H(f)$ cleanly partitions transactions at the decision boundaries, drastically reducing manual oversight. The deployment of this automated framework substantially enhances operational transparency and financial oversight, yielding quantified performance gains across all core KPIs: a 25% increase in data processing speed, a 20% growth in result accuracy, a 23% enhancement in risk detection capacity (shifting from 65% to 88%), a 24% rise in procedural efficiency, and a 23% absolute improvement in system transparency.

3. The successful practical implementation of audit digitalization tools depends on the presence of important technical and organizational preconditions. Data quality and system integration were considered the top technical factors, while audit staff competencies in dealing with data and adapting to the new audit approach were identified as the most influential organizational factors.

Conflict of interest

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

Financing

The study was performed without financial support.

Data availability

The data will be made available on reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies in creating the submitted work.

Authors' contributions

Minura Karimova: Conceptualization, Methodology, Supervision, Project administration; **Fazil Karimov**: Software, Formal analysis, Visualization; **Matanat Ahmadova**: Writing – review & editing; **Xayyam Cavadzada**: Investigation, Resources; **Aytan Nadirova**: Writing – original draft; **Xatira Qurbanova**: Validation, Data Curation; **Surayya Ismayilova**: Methodology, Validation.

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