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Artificial Intelligence in Auditing: Challenges of Developing Countries

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ABSTRACT

The rapid development of artificial intelligence (AI) is radically transforming auditing activities, ensuring not only the automation of routine processes and the transition to continuous monitoring, but also changing the role of the auditor. Technologies such as big data analysis, machine learning, and Explainable AI (XAI) are becoming more and more commonplace in the audit community. Meanwhile, for developing countries, the process of integrating AI auditing poses a double challenge. On the one hand, technological advances, increasing data volume, and rapid globalization make the integration of AI into human activities not just a desirable improvement, but also a prerequisite for competitiveness. Moreover, AI allows not only to improve productivity, but also to compensate for human resources to some extent. On the other hand, there are a number of systemic limitations to the implementation of AI, which not only slow down the integration process but also make it impossible in some places. All this requires an integrated approach to the application of AI technologies in these countries. The available publications in this area are mostly focused on developed economies, leaving a research gap on a comprehensive model for implementing AI audits in resource-constrained settings. The purpose of this article is to identify key system barriers and develop a practical integrated framework for AI audit readiness in these countries. The study conducted in this article identifies and systematizes the systemic gap between global AI audit models, based mainly on developed infrastructure, and the realities of developing countries. Five interdependent key factors were identified, such as data infrastructure (fragmentation, poor quality, unstable power supply), technological readiness (lack of computing resources, need for new software solutions, weak cybersecurity), human resources (critical shortage of specialists, insufficient adaptation of educational programs), organizational capacity (lack of holistic strategies, informal procedures) and regulatory support (lack of comprehensive laws, non-compliance of internal norms with international standards). To overcome this fragmentation, a practical integrated readiness framework is proposed, which unites all these components and can serve as a tool for diagnosing and planning AI integration. Thus, the study comprehensively analyzed and systematized the key barriers to the implementation of AI in auditing in developing countries, confirming the incompatibility of Western models with their resources. It showed that the successful digital transformation of audit requires not only technological investments but also the parallel strengthening of data infrastructure, staff training, and the creation of a strong regulatory framework. The proposed readiness framework is the basic guide that facilitates this process.

KEYWORDS

artificial intelligence in auditing; AI audit; developing countries; data infrastructure; technological readiness; Explainable AI (XAI); human resources; regulatory support; integrated readiness framework; Digital transformation of auditing.

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Штучний інтелект в аудиті: виклики країн, що розвиваються

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СТАТТЯ

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АНОТАЦІЯ

Стрімкий розвиток штучного інтелекту (ШІ) радикальним чином трансформує аудиторську діяльність, забезпечуючи не тільки автоматизацію рутинних процесів та перехід до безперервного моніторингу, а й змінюючи саму роль аудитора. Такі технології як аналіз великих даних (Big Data), машинне навчання та пояснювальний ШІ стають все більше буденними в аудиторській спільноті. Тим часом, для країн, що розвиваються, процес інтеграції ШІ-аудиту створює подвійний виклик. З одного боку технологічний прогрес, збільшення об'єму даних та швидка глобалізація роблять інтеграцію ШІ в людську діяльність не просто бажаним покращенням, а й необхідною умовою конкурентоздатності. При чому ШІ дозволяє не тільки покращити продуктивність, але й певною мірою компенсувати людські ресурси. З іншого боку існує ряд системних обмежень впровадження ШІ, які не тільки сповільнюють процес інтеграції, але й подекуди роблять його неможливим. Це все вимагає комплексного підходу до застосування ШІ технологій в цих країнах. Наявні публікації в цій сфері здебільшого орієнтовані на розвинені економіки, залишаючи дослідницький розрив щодо комплексної моделі впровадження ШІ-аудиту в умовах обмежених ресурсів. Метою даної статті є визначення ключових системних бар'єрів та розробка практичної інтегрованої рамки готовності до ШІ-аудиту в цих країнах. Дослідженням, проведеним у даній статті, виявлено та систематизовано системний розрив між глобальними моделями ШІ-аудиту, що базуються здебільшого на розвиненій інфраструктурі, та реаліями країн, що розвиваються. Було визначено п'ять взаємозалежних ключових факторів, таких як інфраструктура даних (фрагментарність, низька якість, нестабільне енергопостачання), технологічна готовність (брак обчислювальних ресурсів, необхідність нових програмних рішень, слабка кібербезпека), кадрова спроможність (критичний дефіцит фахівців, недостатня адаптація освітніх програм), організаційна спроможність (відсутність цілісних стратегій, неформалізовані процедури) та регуляторне забезпечення (брак комплексних законів, невідповідність внутрішніх норм міжнародним стандартам). Для подолання цієї фрагментарності запропоновано практичну інтегровану рамку готовності, яка об'єднує усі ці компоненти і може слугувати інструментом діагностики та планування інтеграції ШІ. Отже, проведене дослідження комплексно проаналізувало та систематизувало ключові бар'єри на шляху впровадження ШІ в аудит в країнах, що розвиваються, підтвердивши несумісність західних моделей з їхніми ресурсами. Воно показало, що успішна цифрова трансформація аудиту вимагає не лише технологічних інвестицій, але й паралельного зміцнення інфраструктури даних, підвищення кваліфікації кадрів та створення міцної регуляторної бази. Запропонована рамка готовності є тим базовим путівником, який полегшує цей процес.

КЛЮЧОВІ СЛОВА

штучний інтелект в аудиті; ШІ-аудит; країни, що розвиваються; інфраструктура даних; технологічна готовність; пояснювальний ШІ (XAI); кадрова спроможність; регуляторне забезпечення; інтегрована рамка готовності; цифрова трансформація аудиту.

1. Introduction

In recent years, there has been a rapid development of artificial intelligence (AI), which has had a significant impact on auditing activities. Thanks to AI, routine processes are automated in auditing and the accuracy of inspections is increased. In addition, the audit made it possible to analyze large amounts of data, which became possible thanks to big data. Leading audit firms are actively implementing machine learning tools into standard procedures, increasingly integrating intelligent audit into their activities [5; 15]. At the same time, in addition to the means of verification, their very logic changes. Data sampling is replaced by continuous monitoring and supervision of risky transactions [5; 15]. Also worth noting is the emergence of Explainable AI (XAI), which makes all decisions of AI models transparent and understandable. This allows the auditor to provide reasonable conclusions to all stakeholders [28].

In parallel with the increase in productivity, new challenges and risks appear, in particular, the need for new competencies [25]. No less important is the issue of control and responsibility for decisions. As the developers of the concept of "internal algorithmic auditing" emphasize, without clearly defined rules for controlling models, old problems will only be transferred to a new environment [24]. Therefore, international organizations in the regulatory sphere are increasingly focusing on the requirements for transparency and accountability, although they are mostly focused on countries with developed economies.

Also, the ability of organizations to use AI depends on the level of readiness of digital infrastructure and human resources and can differ significantly even within the same industry [10]. For developing countries, this forms a double challenge. On the one hand, AI audit allows you to compensate for the lack of human resources and cover large amounts of data. On the other hand, it is these countries that often face a lack of quality data, limited computing capabilities, and a lack of clear regulatory mechanisms.

Despite the large number of publications available, most of them focus either on AI audit implementation technologies or on issues of ethics, trust, transparency, accountability, and control. There is a lack of a comprehensive system analysis that would take into account all these aspects. In addition, there is still not enough research in the literature that takes into account the specific limitations of developing countries.

2. Literature Review

The topic of AI in auditing is currently widely covered on all platforms and has been sufficiently researched in scientific papers. Basic research by D. Appelbaum et al., and others, describe the technological capabilities of AI auditing, changes in audit procedures and the role of the auditor under the influence of automation and big data [5; 11; 13; 15; 25; 26; 27]. In particular, the use of big data stands out as a new type of audit evidence. The authors focus their main attention on the integration of machine learning and data analytics into audit processes and show the transition of audit from random testing to real-time monitoring. C. Zhang et al., in their work, focus on XAI as the main condition for transparency and accountability of model decisions in audit [28]. They emphasize that the lack of explainability is a major obstacle to AI adoption. The authors show that the use of XAI allows auditors to understand the logic of the models and assess the reliability of the analysis. Other authors describe how the integration of AI and blockchain affects the architecture of accounting systems [29]. The ability of AI technologies to significantly expand audit functions to ensure continuous and high-quality data control is emphasized.

R. Libby and P. D. Witz, using the example of an experiment with “mock jurors” in a case of audit negligence, investigate how the use of AI in auditing affects the auditor’s perception of objectivity [19]. They demonstrate that the use of AI reduces assessment bias and increases trust in the audit process. At the same time, it is emphasized that the effective use of AI in auditing requires a deeper understanding of risks, ethical constraints, and the formation of critical thinking, since these factors directly affect the quality of the auditor’s profession.

Other authors show how the professions of auditor and accountant are changing under the influence of the development of AI. In particular, S. Greenman et al. emphasize that AI redistributes the functions of specialists, reducing routine tasks [11]. In turn, they address the ethical challenges associated with the adoption of AI, including job losses and dependence on technology. Review by E. Ahmed and G. Japee demonstrates that in the context of digital transformation, internal audit is gradually shifting from a controlling role to a partner role [2]. L. E. Fotoh and Y. I. Lorentzon emphasize that the impact of AI on auditing will be gradual, and propose a transitional framework for development to ensure the competitiveness of the audit profession [9]. This, in turn, will require the profession to acquire new skills, as well as change the business models themselves.

D. Leocádio et al. propose the concept of integrating AI into audit, which covers all stages of implementation and the role of management and control in it [18]. In turn, D. Kokina et al., based on field data, emphasize the need for a structural approach to management [16]. Their work also notes the importance of reviewing the roles of auditors and adapting all procedures to the practical use of AI in auditing. I. D. Raji et al., in their work on internal algorithmic auditing, they propose a control model that covers the entire cycle of AI implementation, including design, training, deployment, and monitoring [24]. The authors emphasize that algorithms can create risks of bias, opacity, and lack of accountability. To prevent this, they propose the introduction of internal AI audit mechanisms. Similar principles are laid down in the OECD Framework for the Classification of AI Systems, developed by the international organization OECD [23].

At the same time, most studies are based on the examples of countries with developed digital infrastructure, relatively high-quality data, and more mature regulatory institutions. They assume the presence of a sufficient technological base, even at the stage of analyzing the risks of AI implementation and scaling [5; 8; 15; 16; 23; 25; 27]. They also rely on developed human and institutional resources [8; 9; 11; 16; 19; 23, 24]. On the other hand, the issue of limited resources and weak institutions, which is typical for developing countries, remains less researched, even though some works already record critical personnel, economic and institutional barriers [1; 3; 4; 6; 7; 10; 12; 14; 17; 20; 21; 22].

Thus, D. Genaro-Moya et al. in their article show that in Latin America, the potential of AI to increase the effectiveness of public control is quite high [10]. It is recognized by the highest audit institutions, but faces a shortage of personnel, weak infrastructure and frequent delays in the implementation of digital technologies. S. Anomah's study on Ghana also highlights the low level of readiness for AI adoption [4]. Among the influencing factors, the author highlights the lack of resources, competencies and poor quality of management in public audit. Analysis by A. Nyamawe et al. demonstrates that in sub-Saharan Africa, there is a high interest of governments in AI technologies [22]. However, their implementation is hampered by a combination of staffing shortages, unstable digital infrastructure, and uncertain regulatory policies.

Broader cross-regional reviews also confirm the systemic nature of the various limitations faced by AI initiatives. Thus, in the article by M. S. Khan et al. It is emphasized that in low-income countries, one of the key obstacles is the lack of cloud solutions and low data quality [14]. In the study of A. Ateeq et al. note that in South Asian countries, on the one hand, there is a critical shortage of competent personnel in the digital field, and on the other hand, funding for educational programs with AI remains insufficient [6]. Similar conclusions are made by the authors A. O. Aderibigbe et al., who describe the cumulative technological, personnel, and institutional constraints that hinder the development of AI in Africa [1]. In turn, M. Maghsoudi and others. show that in developing countries, unresolved problems of weak infrastructure and low control are superimposed on issues of ethics, risk assessment, and trust in AI algorithms [20].

At the level of private business, the article by S. G. Ayinaddis shows that small and medium-sized enterprises lag significantly behind large companies due to limited digital resources, lack of infrastructure, low level of digital literacy and lack of adequate support from the state and its institutions [7]. The author directly emphasizes that typical models of AI implementation, developed for the conditions of developed countries, do not work in the real conditions of countries, developing. In this way, the incompatibility of the models developed and the socioeconomic environment in which they are used is demonstrated. Research in the field of accounting information systems and business analytics also confirms this gap. In particular, T. H. Y. Nguyen notes in his work that accounting systems in Southeast Asian countries are not ready for AI technologies due to a lack of skills in working with them, low data quality, and weak cybersecurity [21]. Similar conclusions are made by V. Iatsiuta and V. Kobets in their article, which describes the architecture of AI as a Service (AI-as-a-Service) for Ukraine [12]. The authors emphasize that the implementation of such a service is constrained by the lack of unified data and limited IT resources of the business.

In another Ukrainian study, O. Kondratiuk et al. The authors emphasize the indispensability of the human factor due to organizational and technological limitations [17]. While AI can improve the quality of data analysis in audits, its application cannot completely replace the auditor's professional assessment. In turn, the Malaysian researcher M. Akpa proposes a model for evaluating performance in the context of the use of AI. The model proposed by him takes into account human and organizational factors, emphasizing the importance of harmonization of technological and human resources [3].

A literature review shows that despite the high relevance of the topic and the growing number of publications on the use of AI in auditing, most of the available research remains scattered. In addition, they are not sufficiently adapted to the conditions of developing countries. Firstly, there is a clear gap between typical AI audit models, formed mostly in developed countries, and real constraints in low- and middle-income economies. Existing approaches, in particular to risk management and XAI, do not take into account the poor data quality, limited IT infrastructure, and lack of specialists typical of countries with weak economies. Secondly, the existing works do not form a holistic model for implementing AI audits in conditions of limited resources, despite the fact that they cover the issues of infrastructure readiness, social and economic challenges, as well as personnel shortages. Thirdly, the identified need for new roles and skills of the auditor is almost not considered in the context of the regional shortage of personnel and inequality of access to education. Fourthly, modern approaches to ethics, accountability and governance in the field of AI auditing, widely described in the literature, often do not contain practical mechanisms for adapting to the conditions of weak supervisory systems in developing countries.

Summarizing the results of the literature review, we can say that modern research does not form a holistic and practically applicable model for the implementation of AI audit in developing countries. This emphasizes the relevance of the research aimed at systematizing existing approaches, identifying key challenges and forming recommendations for minimizing risks and increasing trust in AI.

3. Problem Statement

This article aims to determine to which the implementation of AI in auditing is possible in the real constraints of developing countries. Most of the existing approaches to AI auditing are formed in countries with developed digital infrastructure, high economic indicators, high-quality data, and extensive human resources. On the other hand, in Africa, Latin America, Asia and Eastern Europe, there is a shortage of qualified personnel, inconsistency of information systems, limited budgets and uncertainty of the regulatory framework, which often makes it impossible to implement Western models. The research conducted in the article is aimed at solving three key tasks: to identify and systematize the key barriers to the implementation of AI auditing, as well as to show their interdependence; to bridge the research gap on a comprehensive model of AI adoption in resource-constrained settings; develop a practical integration framework for the audit environment that can serve as a tool for planning and implementing AI audits in developing countries.

The object of this study is the process of integrating AI into audit and financial control, which is considered a complex system that includes technological, organizational, personnel and regulatory components. The subject of the study is the limiting factors that affect this process.

4. Methods and Materials

The methodological basis of the study of the implementation of AI audit in developing countries is based on a systematic analysis of scientific publications, analytical reports, regulatory documents and reports of leading industry specialists. This approach ensures transparency, impartiality and reproducibility of research results, as well as allows for a comprehensive assessment of key aspects of the research process.

5. Results and Discussion

5.1. The Gap Between Global Models and the Reality of Developing Countries

A literature review revealed a significant imbalance between conceptual AI models and the conditions in which they are implemented. On the one hand, we have the technological potential of machine learning, big data, XAI, and various digital platforms [5; 13; 15; 26; 27; 28; 29]. On the other hand, empirical studies conducted in developing countries demonstrate various limitations that significantly narrow the possibilities of implementing and scaling such technologies [1; 4; 6; 10; 14; 20; 22]. The authors emphasize that weak infrastructure, lack of quality data, computing resources, and skilled personnel limit the use of AI in key sectors of the economy and public administration [1; 6; 14].

There is also a significant inequality in the participation of developing countries in the global development of AI. They have a rather small share in the volume of scientific publications, which is why their needs remain underrepresented [14; 20; 22].

In addition, there is a difference in the priorities of countries with different levels of development. For developing countries, access to basic services and technological infrastructure is one of the central issues, while the interests of countries with higher economies may lie elsewhere (e.g., regulation and ethics of AI) [1; 4; 6; 7; 10; 14; 16; 17; 20; 22].

In this way, we can see that this gap is systemic and multidimensional. For developing countries, this means that any framework for the introduction of AI, in particular in the field of auditing, should be based not only on global models, but also on the limitations recorded in studies [4; 6; 10; 14; 20; 22].

5.2. Key Challenges of AI Audit Implementation in Developing Countries

5.2.1. Data infrastructure

Most AI audit models developed in developed countries are based on the availability of standardized information flows, developed data infrastructure, relatively high-quality data, and unified recording formats [5; 12; 13; 15; 16; 25; 29]. They are considered as a reliable basis for the deployment of algorithms for monitoring transactions, analyzing financial flows, detecting anomalies and generating analytical reports [12; 13; 16; 29].

On the other hand, for developing countries, a different situation is quite typical. In the public sector of Latin America, information systems are still scattered, and integration between databases is limited [10]. In Africa and South Asia, incomplete or inaccurate data are common, and there are no uniform standards for their collection, analysis and coding [1; 6; 14; 22]. For example, in the public sector in sub-Saharan Africa, the prevalence of unbalanced, biased, and low-quality data hinders the deployment of machine learning models [22].

An additional complicating factor is periodic interruptions in power supply and Internet connection, which are typical, in particular, for African countries [1; 22]. For example, as of 2022, 43% of Africa's population still did not have access to electricity [22]. This makes data transmission not only unreliable and fragmented but often impossible.

Under such conditions, even relatively simple machine learning models are sensitive to errors, which in turn affects the accuracy of their work [10; 16; 21; 22]. Auditors often distrust AI recommendations and conclusions due to a clear inconsistency with their experience with manual audits [10]. This often leads to the fact that AI solutions remain at the stage of pilot projects without further scaling and operation [10; 14; 20; 22].

Thus, the data infrastructure in developing countries is a critical bottleneck that determines not only the effectiveness of AI audit models but also the very possibility of their practical application in these countries.

5.2.2. Technological readiness

Modern AI audit models perform many complex tasks, such as automated transaction monitoring, analysis of large amounts of data, the use of blockchain to confirm audit evidence, and the support of continuous control [5; 13; 15; 16; 17; 25; 26; 28; 29]. An important condition for trust in these models is not only the accuracy of the results obtained, but also the auditor's ability to interpret the results [5; 9; 16; 17; 18; 19; 24; 28]. This reinforces the role of XAI, which provides transparency of models and allows you to understand the logic of decision-making [12; 15; 16; 24; 28]. All these technologies form a solid foundation for the implementation of AI in auditing.

In developing countries, the implementation of such solutions faces a number of technological challenges, which are reflected in regional studies. In Ukraine, there is an increase in the amount of data received from customers, which is why there is a need for high-quality AI-based solutions. But to use AI in auditing, new software is needed [17]. Often, in the process of developing AI solutions, there are problems in optimization, limitations in support of multiple sources, and potential security vulnerabilities [12]. Therefore, AI integration requires addressing key issues, including cybersecurity [17].

The example of Vietnam shows that companies face significant challenges in adapting to new technologies. Overcoming them requires not only methodological support, but also serious investments in technological infrastructure [18; 21]. In the public sector of Ghana, there is also a need to adapt technological resources to the changes associated with the use of AI [4]. Similar conclusions are drawn for Latin American countries, emphasizing that supreme audit institutions must respond to technological advances. They should ensure the openness of data and expand the possibilities of using analytics in auditing [10]. This will allow auditors to improve the quality of control, reduce the risks of errors and increase the transparency of conclusions.

In the broader context of developing countries, there is a lack of reliable computing resources and access to high-speed Internet [1; 4; 6; 14; 20; 22]. Common challenges in AI adoption include insufficient technical capacity and limitations in data management [10]. There is often a lack of modern formalized procedures that would turn the results of AI models into a real tool that helps in decision-making. Policies related to documentation, review, verification, transfer to a higher level, etc., often remain informal and fragmented [1; 6; 20]. Without this, the work of AI becomes an incomprehensible and uncontrollable process.

Technological readiness is closely related to financial resources and IT infrastructure, which is especially important for small and medium-sized enterprises, as they often face high barriers to access the necessary infrastructure [7].

As a result of all the above factors, even where such approaches as XAI could theoretically increase the credibility of AI audits, their large-scale implementation is hampered by technological unpreparedness [1; 4; 10; 20; 21; 22].

5.2.3. Lack of skills

The role of the auditor is gradually changing from classical sample analysis to analytical work with data [2; 18; 25]. This requires an increasingly higher level of professionalism and the acquisition of new skills that combine technical and auditing knowledge [13; 17; 18]. The auditor must not only be able to apply modern technologies in practical work, but also critically evaluate, interpret and question the recommendations of models [13; 16; 17]. This, in turn, requires changes in the requirements for auditor training and adaptation of training programs to modern challenges [13; 25].

Studies conducted for developing countries describe the key factors that determine the industry's readiness to implement AI in accounting and auditing processes. An analysis of the impact of AI on the profession of auditors and accountants conducted in Ghana showed the difficulty of transitioning to new technological approaches, in particular due to the insufficient qualification of personnel [4]. There is also a need for skilled personnel with AI skills in Vietnam, as traditional training programs often do not provide these competencies. [18; 21]. The lack of qualified personnel is also one of the barriers to integrating AI into auditing in Nigeria [21]. Due to the lack of personnel, audit bodies often involve international specialists for the implementation of projects, which further increases the costs of their implementation [10].

As we can see, having a skilled workforce with AI skills is critical for developing countries. These countries are significantly lagging in the adoption of AI, in particular due to the lack of specialists in the field of machine learning, data science, and AI engineering [1; 4; 6; 14; 20; 22]. According to a Ukrainian study, 30% of representatives of the financial sector have only heard the term "machine learning", without having a real idea of its mechanisms [17]. This creates a need for the systematic development of technical literacy of specialists, which is one of the key factors in the integration of AI into auditing [2; 4; 9; 10; 13; 15; 16; 17; 25].

Despite the urgent need, there is an insufficiency of local educational programs in developing countries, which causes or deepens the structural personnel shortage [1; 4; 6; 14; 20; 22; 27]. In addition, there are a number of other factors that affect personnel training. In African countries, for example, the integration of AI into educational programs is complicated by financial constraints and the need for proper teacher training [14]. In a broader context, educational institutions often work with limited digital infrastructure and do not have access to modern analytical tools [1; 4; 6; 14; 22]. Systems of retraining of current employees of state institutions are often isolated and limited [1; 10; 14; 17; 20; 22; 27].

Thus, the lack of qualified personnel becomes the main obstacle to the successful implementation of AI, especially in those areas where AI could theoretically compensate for human deficits [1; 4; 6; 7; 10; 11; 13; 14; 17; 22]. This requires the development of training programs and serious investment in technical education and training of personnel [1–9; 10; 11; 13; 14; 17; 18; 21; 22; 25; 27; 29].

5.2.4. Organizational capacity

The scientific literature on audit and accounting information systems describes modern approaches to the creation of special bodies and roles, the development of policies that help integrate AI into existing control systems [5; 13; 15; 16; 24; 25; 26; 28]. This helps developed countries to ensure that new initiatives really work, and not remain only on paper.

The Ukrainian example shows the importance of the country's government facilitating the implementation of AI initiatives. The country has established an Expert Committee on the Development of AI under the Ministry of Digital Transformation, which presented a draft concept of this development for public discussion [17]. Thus, the state demonstrates its readiness for the further implementation of AI and forms a stable institutional foundation for this.

However, developing countries are mostly characterized by limited readiness to implement complex technologies in the field of AI. Studies show that governments in low-income African countries are at the lowest levels of AI readiness rankings [14; 22]. These countries, as well as Latin American countries, are characterized by weak digital reforms, low integration of information systems, uneven infrastructure development and insufficient strategic planning [1; 4; 10; 22]. Part of this problem is the lack of clearly defined procedures, roles, and tools that would support the systematic implementation of AI [1; 4; 6].

A study in Ghana showed that despite the existence of initiatives, the readiness of audit institutions to implement AI remains limited due to the lack of a holistic strategy, uneven support for reforms, and a lack of skilled workers [4]. In Latin America, there is a problem with the consistency of information standards and risk assessment when using algorithms [10]. Such conditions inhibit the further development and scaling of AI projects [1; 4; 22]. In turn, this requires additional efforts and measures from countries with limited resources to increase their readiness for AI initiatives.

In addition to readiness for new technologies, comprehensive interaction between government agencies, educational institutions, IT companies and international organizations is necessary. Such forms of interaction contribute to the exchange of experience, the formation of standards and the strengthening of human resources, which are key conditions for the successful implementation of AI in audit [1; 4; 10; 20; 22].

5.2.5. Regulatory restrictions

The international AI regulatory environment shows significant unevenness, which is particularly acute for developing countries. The world's first EU AI Act has been created in the EU countries, which establishes risk classification, conformity assessment mechanisms, requirements for transparency, data management, model security, and post-implementation monitoring [8]. EU countries have followed the path of regulatory policy, which, on the one hand, lays a solid foundation for the further development of AI, and on the other hand, can slow down the development of AI technologies and investment in the industry. The United States has followed the path of market expediency, in which innovation and billions of dollars in investments in them dominate preventive regulation. There are industry regulations (FTC, FDA, HUD, etc.) and a set of recommendations NIST AI RMF (AI Risk Management Framework from the US National Institute of Standards and Technology). Already at this level, there is a gap between the regulatory European model and the American market model.

In developing countries, there is a lack of comprehensive laws and mandatory AI regulations. Instead of special laws, the most common format is codes of ethics, general IT strategies and principles of responsibility, which do not have the legal force of law [1; 4; 20; 22]. Some countries, including Latin American regions, take the EU AI Act as a guideline, but the status of adoption of similar acts in individual countries is not determined [10; 14; 18; 20].

As a result, a triple regulatory gap is formed for these countries:

- between the EU and the USA, where there are fundamentally different regulatory models;
- between developed and developing countries in the context of access to quality standards and regulations;

- within the countries themselves, where the state often faces difficulties in implementing even basic norms for the responsible use of AI [1; 4; 10; 14; 20; 22; 24].

For the field of financial audit, the discrepancy between internal regulations and external regulations is especially critical, because, according to the EU AI Act, this area belongs to the high-risk category. In practice, for developing countries, this means that any organizations that interact with European counterparties (audit outsourcing, financial analytics, internal control, etc.) actually face the requirements laid down in this act. In the absence of mature infrastructure and quality data in these countries, the EU AI Act becomes an indirect external regulatory pressure on them. They have to adapt to European standards under the influence of external requirements, which often do not take into account their real capacity.

5.3. Integrated AI Audit Readiness Framework in Developing Countries

A generalization of the literature review shows that considering all aspects separately does not allow for fully assessing the readiness of developing countries to implement AI audits. Most modern approaches are based on selective solutions to problems, while these countries are forced to work with all constraints together, while overcoming fragmentation in research.

To overcome this fragmentation, an integrated preparedness framework is proposed, which consists of five interrelated components: infrastructure readiness; technological readiness and XAI; human resources; institutional architecture; regulatory framework and governance. This framework is aimed at low- and middle-income countries and can be used as a tool to diagnose problem areas in specific sectors of the economy. It can also be considered as a methodological basis for the systematic implementation of AI audit.

5.3.1. Infrastructure readiness

For developing countries, infrastructure readiness first of all means step-by-step structuring of data, and only then the gradual complication of models. It includes, first of all, the availability and quality of data, the availability of basic computing resources and minimum data management standards. Also, the level of integration of accounting systems is no less important. Data structuring can be divided into two stages.

At the first stage, uniform rules are established for key data elements. Such accounts as dates, currencies, account codes, counterparty identifiers, etc., are brought to a single format. A minimum set of required fields for each operation is defined. It can include the date, amount, type of transaction, counterparty, comment, etc. Then a register of data sources and routes of their movement is built, namely: where data is generated and stored, and how it is transmitted between systems. At the end, the rules of inspections are established.

In the second stage, all key sources are connected to a single intermediate storage using simple ETL (Extract-Transform-Load) processes. In practice, this means setting up systematic uploading of data from the accounting system, banking services, and tax reporting to a single repository. Thanks to the preliminary unification, all data can be combined with shared keys and brought to the agreed format. Next, ETL processes clean the data from duplicates, bring all indicators to a single unit of measurement, check if all fields are filled in, and upload the results to a shared repository. For organizations with limited resources, it can be a separate server or an inexpensive cloud database, and the integration with AI models is carried out using scripts or available solutions.

Such data preparation not only reduces the risks of skewed training of Sh-algorithms, but also builds a solid foundation for further gradual increase in their complexity.

5.3.2. Technology Readiness and XAI

The ability of organizations to select and adapt AI models that provide a basic explanatory layer and are resilient to low-quality data defines the second component. Developed countries tend to opt for the latest and most sophisticated algorithms, but this approach cannot be mechanically transferred to developing countries. Here, too, it is advisable to move in stages. It is recommended to start with algorithms that are least sensitive to omissions and noise. Such models include systems of classification of operations by risk level (decision trees and rule-based), simple statistical methods for determining anomalies, and regression models.

With improvements in infrastructure and data quality, it becomes possible to move to more complex models. Organizations can use ensemble methods (Random Forest, Gradient Boosting, AdaBoost) that combine many simple models into one, as well as apply deep neural networks to solve specific problems.

XAI deserves special attention, since its implementation is also advisable to carry out from simple to complex. At the minimum level, basic explanations are carried out in the form of simple tables and histograms, and key risk factors are listed. At the intermediate level, tools such as LIME (Local Interpretable Model-agnostic Explanations) are used to explain individual decisions in a format understandable to the auditor. And finally, at an advanced level, interactive dashboards are integrated into workflows.

This step-by-step approach allows you to give preference to understandable models over opaque algorithms and gradually increase complexity without losing control.

5.3.3. Personnel capacity

The third component of the framework combines auditing and technical knowledge, as well as educational programs. There is quite a significant inequality here. For developed countries is simply improving the level of skills and acquiring additional skills; for many developing countries can mean learning from scratch. Therefore, education in these countries requires not only targeted investments but also the implementation of a whole action plan.

At the university level, AI and analytics modules should be included in educational programs. Educational institutions should form partnerships with international universities. The focus of training should be on practical cases, not on the mathematical details of algorithms. In parallel, short (3–6 months) refresher courses for auditors already working in the private and public sectors should be introduced. In addition, the most trained specialists can act as trainers for their colleagues during training programs. This reduces dependence on the participation of international consultants.

And finally, most importantly, any form of training should be aimed at the formation and development of critical thinking in auditors. Because it is important for them to be able to check the quality of data, detect biases in algorithms, understand situations in which the model can make a mistake, and not take all AI recommendations as truth without verification.

5.3.4. Institutional architecture

The fourth component of the framework is the presence of structures that are responsible for managing AI. This includes committees, working groups, and centers of competence. It also includes management procedures and coordination mechanisms between financial, audit and IT departments.

For developing countries, a two-tier approach is advisable. At the first level, small functional groups (3–5 people) are created, which act as a center. They coordinate all pilot projects and summarize the experiences of different institutions, determining which conditions affect implementation, what typical errors occur during launch, and which budgets are realistic. They also develop standard policies and templates, which include documenting the operation of models, test procedures, reporting formats, etc. In addition, they act as intermediaries between technical suppliers, regulators, and end users. The effectiveness of such focal points increases significantly if they are embedded in the system of public-private, regional and global partnerships, which avoids their isolation and overload.

The second level is strategic. In parallel with the creation of coordination groups, a written strategy for the implementation of AI audits should be developed with a defined time frame in years. It defines the distribution of responsibility, mechanisms of communication within the organization and with stakeholders. In addition, a plan for managing personnel, technical and other risks is drawn up.

5.3.5. Regulatory framework

The last component consists of a set of rules and procedures for documenting models, fixing their decisions, defining accountability, and ensuring transparency to stakeholders. Obviously, a full framework like the EU AI Act is difficult to implement right away, so it is advisable to apply a minimum package of management policies.

To begin with, a simple register of AI models must be compiled, which records the name of the model, its purpose, the data used, the developer, the person responsible, the date of the last check, etc. Before implementation, the model must be tested on historical data and on well-known cases. All model recommendations should be recorded along with an explanation. This will create a basis for further analysis and correct operation. For each model, a person or a separate unit is assigned who is responsible for supervision, control, notification of failures, as well as regular updates. In case of incorrect operation of the model or doubts about its decisions, there should be a clear procedure for contacting the specialists of the IT department and temporarily limiting the operation of the model.

Generalized practical steps and tools of the integrated AI audit readiness framework are presented in Table 1.

Table 1. Integrated AI Audit Readiness Framework

Component	Practical steps	Tools
Infrastructure readiness	Approve a single data standard (dates, currencies, accounts, counterparties, minimum set of fields); compile a register of all systems and data sources with responsible persons; set up regular automatic data transfer to a single repository with clearing duplicates and unifying formats; launch regular quality checks; organize backup and control access to storage.	A document that describes the standards; a tabular register of data sources (Excel or a simple database); ETL scripts or processing (SQL, Python, BAS, etc.); intermediate storage (SQL server or cloud database); a set of data quality control rules; backup and access policy.
Institutional architecture	Create a coordination group or AI audit center (3–5 people) and formally approve its competencies; describe the distribution of roles and responsibilities (audit, IT, finance, management); maintain a register of pilot AI audit projects with fixation of results; hold regular coordination meetings; Establish 1-2 partnerships with universities or professional associations.	Order or regulation on the AI audit center; tabular register of projects (Excel, project management system); template of minutes of coordination meetings; cooperation agreements with partners; internal portal or knowledge base of the organization.
Technology readiness and XAI	Select 2–3 simple tasks to start with (risky operations, anomalies, basic forecasts); implement simple models based on rules and threshold statistical tests and simple regressions; for each model, issue a short card (purpose, data, restrictions, owner); test on historical data and compare with manual audit; provide minimal explanatory XAI in the form of a list of risk factors and simple tables or graphs for users.	Model catalog in the form of a table; model card template for 1–2 pages; SQL, Python, BAS, or other scripts to implement rules and tests; a test environment with historical data; standard reporting forms (tables, histograms, simple panels); a documented procedure for checking the correctness and quality of models and a log of its decisions.
Staffing capacity	Draw up a competency matrix for auditors, IT professionals and analysts (data, models, XAI, ethics, etc.); conduct a quick assessment of skills through surveys or tests and highlight critical gaps; update the curricula of universities and internal courses with an emphasis on practical cases of AI audit; launch short practical trainings for current auditors; form a group of trainers and a community to share experiences.	Competency table; online or offline tests and questionnaires for skills assessment; updated work programs of academic disciplines, presentations, practical tasks; schedule of trainings and training sessions; regulations on trainers; internal chats or forums for discussion.
Regulatory framework	Adopt a short audit policy (model scopes, approval procedure, periodic review, prohibited practices, etc.); create a registry of AI models with purpose, data, owner, risk level, and status; define rules for documenting model decisions and explanations; response procedure (response to errors, complaints, the possibility of temporarily shutting down the model, etc.); schedule regular review or audit of models.	Document "Policy on the use of AI in auditing"; standardized pattern of entry in the model registry; regulations for documenting results and explanations; response instructions with a description of actions and forms of reports; checklist or program for independent audit of models; References to relevant auditing standards and data protection legislation.

Source: Developed by the author.

5.4 Research Limitations and Future Prospects

The study carried out has a number of limitations. It is based on the analysis of scientific publications, analytical reports and regulations, and does not include the verification of the proposed framework in real projects. In addition, AI regulation regulations are constantly changing, and this may require individual proposals to be updated in the medium term. Another limitation is that the focus has been on the public sector and supreme audit institutions, while private companies in developing countries may face other constraints and have different opportunities.

Given these limitations, it is advisable to direct further research to test the proposed framework in practice in several selected countries. At the same time, it is necessary to cover both the public and private sectors. It is also important to compare how the management and control of the use of AI are organized in different structures, and how these approaches are suitable for the conditions of limited resources. In addition, it is necessary to analyze how the implementation of AI audits in these structures is influenced by global regulatory policies, and what mechanisms can be to adapt to them without undue pressure. A separate area concerns the development of a system of indicators for the effectiveness of an AI audit and the analysis of the level of trust in it by auditors. Finally, the development and implementation of local educational programs for auditors of public and private companies with further assessment of their effectiveness in practice is promising.

6. Conclusions

The study shows the complexity of integrating AI into the audit of developing countries and highlights various obstacles that arise along the way. The gap between global AI audit models and the real capabilities of countries with weak economies is manifested through systemic constraints in data infrastructure, organizational capacity, technological readiness, human resources, and regulatory environment. The presence of these limitations confirms that the implementation of AI is a complex task, and must cover different sectors and levels of government.

The proposed integrated readiness framework demonstrates that successful implementation requires not only consistency, but also simultaneous interaction and strengthening of all its components. Countries need to simultaneously unify data, build governance institutions, choose affordable technological solutions, develop human resources competencies, and develop regulatory mechanisms. In this context, the framework acts as a diagnostic and planning tool that allows organizations to identify their weaknesses and work systematically to eliminate them.

The practical content of the framework is that it allows you to build an AI audit in stages, from simple to complex, without trying to immediately reproduce Western samples. Case studies from different regions show that starting with simple models, basic tools, minimal documentation, and small coordination structures provides more sustainable results and increases the level of trust in AI solutions. This is especially important in countries where the external regulatory framework is developing faster than the local infrastructure, because these countries are forced to adapt to international standards without sufficient resources. This, in turn, requires the development of flexible adaptation mechanisms and further empirical research on how the proposed framework works in various areas of the economy.

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