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THE IMPLICATIONS OF UNEXPLAINABILITY IN AI MODELS FOR AUDITING FINANCIAL STATEMENTS

Abstract. *This paper examines the complexity of explainability in AI models. Specifically, the impact this has on AI being adopted in the auditing profession and the implications to stakeholders and auditing professionals. The results indicate that as there is increasingly more data, the models become more complex to understand, making it hard to understand an algorithm's outcomes. This seriously impacts stakeholders and auditing firms when AI tools are used in auditing procedures. Auditors will not be able to justify and validate AI's conclusion. Thus, making it hard for stakeholders to trust the opinions and conclusions provided using AI algorithms.*

Keywords: *artificial intelligence, AI models, audit profession, financial reporting, auditors, algorithms, AI tools.*

Introduction

Financial audits play a crucial role in ensuring the accuracy, reliability, and integrity of the financial statements of corporations. This is important for stakeholders of the firm, especially investors so that they can make informed decisions based on trustworthy financial data. Up to recently "traditional audits" have been conducted manually which included substantial paperwork and time-consuming tasks, e.g. checking off every transaction. However, the big 4 firms are now investing in AI technologies and tools to integrate into the audit work and leverage their platforms to deliver the best work to the stakeholders of the firm. They are using their size and human capital to gain a competitive advantage over all other firms and to change the audit process by digitizing the end-to-end process so that auditors have the best possible tools to use in their work. Auditors have to do a lot of writing and documentation that is required to explain and evidence the work that they perform as part of their auditing. The writing is then also subjected to multiple rounds of reading through various levels of reviews. This calls for major opportunities to accelerate those processes through different types of AI technologies.

With the advent of AI, the auditing process indeed undergoes a significant shift. AI can process and analyze all available data, ensuring that every event is accurately transformed into ledger entries and subsequently reflected in the financial statements. It is critical to understand where AI fits within the workflow and to recognize that AI outputs inherently involve uncertainty due to the lack of an intuitive understanding of how specific prompts lead to certain outputs. This has led to the following research question: “How does the lack of explainability in AI models impact their adoption in auditing financial statements, and what are the implications for various stakeholders?

Explainability of certain AI-generated output is a challenge with certain AI technologies. These models are trained on huge data sets and consist of fully connected neural layers with a large number of parameters (Poon, 2019). These parameters are used to then train an AI system and shape its output. Generally, the higher the number of parameters the better the AI software’s performance and the more complex and nuanced its tasks can be.

The transparency in AI models should come from 2 factors: The inputs and the models that are used to come to a certain output. The inputs in such models are large data sets. How a model then interprets its inputs and generates language depends upon its design, therefore lacking transparency. The complexity of explainability comes into play when AI tools are used in the auditing of financial statements. In a traditional audit, the sampling techniques used to test transactions are a straightforward model. An audit sampling can be defined as a strategy to audit less than 100% of the items within an account balance within an institution's financial statements in making conclusions about the account balance [1]. If the auditor uses a random sampling technique, the rationale behind such a model is straightforward. Random sampling requires the auditor to randomly pick a sample from the population of transactions. Thus, the process can be defined and directly observed. This distinction shows the difference between the complexity and transparency between traditional audits using sampling techniques and the use of AI models that analyze the whole population. The Unexplainability gives rise to the term “Black Box " in AI technologies, suggesting that there is no transparency in AI model. An AI algorithm is declared as a “Black box” if and only if its construction, internal functions, logic and parameters are unreachable for humans and hence they are opaque. This results in implications for the auditing field where having an understanding of the decision-making process is crucial. Without understanding how a model functions, it is difficult to rate an AI’s output.

For ethical matters and supervisory factors, XAI is important when users of AI tools are to comprehend, trust and control the outcomes produced by AI algorithms. XAI, or explainable artificial intelligence, is, in essence, an explainability tool that unlocks different types of information about a model depending on the type of answers that are being sought and the types of modelling approaches used. This programme helps to reveal how a model functions which can facilitate the understanding of how certain variables interact with each other and the relationships between variables. Additionally, XAI can help with the diagnoses of a machine's poor performance, pinpoint certain features or interactions that contribute to biases or errors and reveal where certain sensitive or irrelevant information influences the model’s decision. The techniques are important in making “Black-box” AI models more transparent. Leveraging XAI can help maintain the integrity and effectiveness of adopting AI tools in the auditing of financial statements.

Literature Review

The usage of AI has gained momentum in all areas of our daily lives for example in education, security, banking and accounting processes. The market for AI has been increasing and currently amounts to around 200 billion US dollars in 2023 and is expected to grow well beyond that to 1.3 trillion US dollars by 2033 [2.3]. Goa and Han [3] explore how AI influences audit objectives and how information technology impacts the methods to achieve these objectives e.g. assessing risk, gathering evidence and forming an opinion based on evidence collected. It states that although the advancement of AI will not reduce the demand for audit of financial statements, bringing no change to the auditing purpose, it will bring changes in the auditing objectives1. Goa and Han show how AI influences three key aspects of auditing: the source of auditing evidence, the format of auditing evidence and the auditing judgment.

AI influences the source of auditing evidence as it can go beyond the traditional limitations of auditing which focuses on a specific business entity and sampling methods. Audits without AI typically focus on the specific business activities and transactions within the audited entity. However, AI can enable auditors to gather and analyze data not just from within the entity but also from external sources. Essentially allowing auditing in a broader scope which might include industry trends, economic factors or other types of external data which can essentially impact the firm's financial statements. Additionally, traditionally auditors will often use sampling methods meaning they only examine a representative subset of the data. This is because of the large amounts of transactions and data that are being gathered during the collection of auditing evidence. However, by allowing the use of AI it can help auditors process and analyze the entirety of datasets allowing for a more comprehensive analysis and providing accurate results of the entity's financial health. Concerning the influence of AI on the source of auditing evidence, auditors can use AI with a pre-defined purpose to look for specific types of audit evidence rather than conducting a general review. This is possible because AI can perform an in-depth analysis, deep-mining, of accounting information. According to Goa and Han [4], the analysis is conducted across three dimensions: Space, history of development and the internal structure of accounting information of the companies. Thus, enabling the auditors to focus on specific, high-risk areas within the financial data.

Another key aspect of auditing that is being influenced by AI is the format of auditing evidence [5]. When an audit is conducted manually it relies on the auditors being able to access all necessary information. AI changes this and can allow for a broader range of experts to participate and introduce new methods for collecting evidence. The new circumstances of broader expert engagements and conclusions can therefore be introduced as a new form of evidence for financial statement auditing. Moreover, AI enables professionals in finance, accounting and computing experts to analyze large data sets of accounting information to subsequently use their expertise to extract valuable insights through data mining and issue their opinion of the quality and reliability of accounting information. Auditors can use these experts' conclusions as a new form of evidence in audits removing the limitation of being reliant only on individual capacity. Lastly, Glenn A. Bowen [6] mentioned that AI influences auditing judgment. AI technologies enhance the objectivity and independence of auditors' judgements. Since AI is based on a rationed model rather than subjective human judgements, by relying on these AI models, auditors' judgements might become less subjective.

Research Methodology

This research aims to understand how un-explainability in AI algorithms contributes to the implications of using AI in auditing financial statements. While these models are powerful in identifying patterns and making predictions, they often lack transparency in their decision-making process, making it challenging to justify their outputs. This has important implications, especially in highly regulated and scrutinized fields like auditing. Thus, this study aims to investigate how unexplainability impacts the integration of AI tools for the audit and the effects it has on interested users. To answer this research, question an inductive qualitative method is used. This bottom-up approach tries to develop theories from observations in qualitative studies. Using this approach will help get a deeper understanding of a complex phenomenon through descriptions and observations. In this case, the aim is to get an understanding of how unexplainability affects the adoption of AI in the audit by employing data collection techniques discussed in the next se section.

As part of the data collection online documents, reports and journals were studied. Document analysis is used as a method of accessing data and information in different disciplines [6]. As a research, data collection method, is generally described as the systematic collection, documentation, analysis, interpretation and organization of data. This may be used solely or as a complementary source of data to answer research questions. It involves the process of skimming, thorough reading, examining content and interpretation of documents. Glenn suggests that document analysis involves the 3 following steps: (1) Selecting the relevant documents, (2) extracting the data to draw insights and conclusions about the given concept and finally (3) answering the research question. When selecting the relevant documents a search string was used. Only specific keywords were used that are relevant to the topic. The Keywords that were used in the search query:

- Explainability: “Transparency”, “Interpretability” or “Comprehensibility”
- AI models: “Artificial intelligence”, “Machine learning” or “Neural networks”
- Adoption: “Implementation”, “Acceptance” or “Utilization”
- Auditing procedures: “Auditing”, “Audit procedure”, “financial statement auditing” and “International Audit and Assurance Standards Board”

● Financial accounting: “Financial Statements” and “International Financial Reporting Standards”

Additionally, inclusion and exclusion criteria (Table 1) were defined to reduce the noise of including irrelevant data. It should be noted that articles coming from the Journal of Information Systems Engineering and Math are included. The implication for this is that their conclusions are coming from engineering and mathematical expertise. They are not accounting professionals who are experts in accounting standards and procedures. Nevertheless, it is still beneficial to include the conclusion of the paper as it provides viewpoints on the impact technology advancements have on the auditing profession. This is especially important as collaboration between different professions is necessary for the use of AI tools. Moreover, the range of academic articles established is justified by the AI adoption rate in businesses worldwide. AI saw a staggering growth in adoption rate from 2017 to 2018, and it has levelled off significantly since 2019.

Table 1

Inclusion/Exclusion criterion used

	Criteria	References
Inclusion	I.1. Authenticity, Credibility, Representative and Meaning I.2 Relevance to auditing I.3 Academic articles ranging from 2017 to 2024 I.4 Inclusion of another Journal e.g. Mathematical and Engineering Journals	(Morgan, 2022) (Thormundsson, 2024)
Exclusion	E.1 Research that included other innovative technologies other than those defined as “Artificial Intelligence” or “Machine Learning” E.2 Articles that were not in English E.3 Outdated technologies	

From this sample content analysis was conducted to gain an understanding of what the current disclosure is around the AI tools used in the auditing of financial statements, particularly paying attention to the challenges posed by the unexplainability of AI models.

Results

This section discusses the benefits and implications of using AI tools in the auditing of financial statements gathered by the data of online documents. It specifically focuses on the lack of transparency and explainability in AI models and how this has an impact on interested users of financial statements and auditing professionals.

The Benefit of Using AI Tools in the Auditing of Financial Statements

As shown AI technologies and tools will change how financial audits will be conducted. Auditors are required to understand both private and public client information i.e. social media and news articles also need to be reviewed. However, this increasingly becomes more difficult for auditors to do manually due to the information overload. Information is said to increase rapidly at a rate of 10x every 5 years [8].

AI can help the company identify economic events that are not just related to its business (accounting data) but include a broader range of data e.g. from social media posts to customer service comments. This approach is also often referred to as "Data-based auditing", as it leverages AI to analyze all these various types of data to gain a deeper understanding of a company's financial health. As mentioned above traditional audits primarily focus on taking a subsample of accounting information. However, with AI, the scope expands, whereby it cannot just solely obtain evidence by taking a sub-sample of the population. AI can test on 100% of the population, continuously.

Indeed, AI technologies, e.g. machine learning, offer an ever more transformative approach to analyzing audit data. This is true, especially in areas of journal testing where traditional methods have limitations. An AI model can learn from a sample of journal entries to then predict which other entries in the entire population might show anomalies. Unlike rules, e.g. "transactions on weekends should be marked as risky", machine learning models can adapt to understand these subtle differences. For instance, if an overseas processing centre operates at different hours, the models can learn that "Saturday" entries are not necessarily irregular. On the contrary, traditional methods will probably flag journal entries based on such a rule, thus leading to many false positives. Therefore, using AI tools can provide a more in-depth risk assessment due to continuous learning and adaption of new data.

Research done by Patel et al. [9] has shown that the integration of AI technology in financial audits can enhance audit efficiency by increasing its audit quality, risk assessment and decision-making capabilities. AI application in audit planning and risk assessment allows for a more accurate prediction of potential risk areas and reviewing or analyzing vast amounts of different types of data. Being able to use AI to analyze large datasets thereby identifying patterns, allows for auditors to focus their resources on potential high-risk areas more efficiently. Instead of manually conducting tests on samples to reveal errors or fraud cases in transactions, which can be labor-intensive and subject to human error, AI can remove such constraints. Additionally, AI applications for the review of internal control systems allow for continuous monitoring. AI removes the time lag in reviewing and monitoring internal controls. This is done through the continuous gathering of data from various sources and automating the testing of routine internal controls, i.e. segregation of duties or compliance checks, continuously and not periodically. Therefore, generating immediate alerts when anomalies are detected. This concludes that the integration of AI technology in the auditing of financial statements does have the potential to significantly improve its efficiency. Indeed, many research studies have shown that automating manual data analysis and routine tasks can reduce the time and effort required for the audit process. AI tools enable auditors to streamline tasks, improve data processing speed and minimize errors leading to increased efficiency. This allows auditors to focus their resources and efforts on value-added activities such as risk assessment and decision making which enhances the overall audit efficiency [8].

Implications of Implementing AI Tools in the Auditing of Financial Statements

However, the application and integration of AI technologies in the auditing of financial statements cannot be implemented without its implications and challenges. While the impact of AI on the auditing industry has many benefits, such as improved efficiency, it also poses multiple ethical concerns that need to be addressed. There are ethical concerns when it comes to the transparency, fairness and unbiased use of AI algorithms (Patel et al. [9]). Real-world data is continuously fed into AI. This makes it questionable whether or not the data that is being collected and used as an input in the model is used for the purpose intended. A lot of inaccurate data exists which arises due to data characteristics changing due to dynamic environments, which automatically overflows into the algorithms used to create the AI model. This leads to inaccurate algorithms. Patel et al. describe that AI systems indeed learn from existing data, data which may contain biases and prejudices. If there are biases in the data, meaning that the data does not represent the true population due to models being simplified representations of reality, then the algorithm is at risk of making incorrect and unfair decisions. The risk of simplification is that these models might not capture every nuance of the firm's financial activities.

Moreover, transparency and explainability of AI systems are a major ethical implication for auditing firms. As Patel describes, the complexity of major AI technologies and systems makes it difficult for humans to comprehend the basis for the computer's outcomes or decisions. The exact pathways and combination of data points the model uses to arrive at their conclusion may not be clear to auditors. Additionally, unexplainable AI Models often act as modern “computer says no” systems, a phrase popularized by the British comedy series Little Britain [10]. The decisions of such models and systems are often final and irreversible. This leaves the auditors without the initiative to question or understand the outcomes. Thus, creating a term known as “Accountability sink” where the responsibility is deflected from humans to machine algorithms. Therefore, in audits the inability to explain an AIdriven decision shows this “computer says no” scenario where certain outputs and outcomes are not followed by inquiry or justification. This can not only frustrate the auditor but also lacks transparency and effective accountability. Stakeholders, e.g. investors, who read financial statements that are audited using AI tools will have a hard time trusting the output produced. For example, if an AI algorithm marks a certain transaction as suspicious without providing a clear rationale behind it, the auditors are unable to validate or contest the AI’s decision due to the opacity encountered in the model. Thereby putting the auditing firms at risk of jeopardizing their reputation.

The “black-box” nature existing in AI algorithms can make it challenging for auditors to fully trust the model's prediction without understanding its reasoning. This is especially important when it comes to the interested users being in jeopardy. Auditors must look at what are the features that drive the model’s behavior. Their scrutiny may involve addressing several crucial questions e.g.: Are there any influential features that seem implausible? Are there features missing that according to a subject matter expert would be relevant? Does the model behave as expected under different conditions or will it show unexpected patterns? And are there any spikes in the model’s response? [11]. The complexity of AI models resulting in the unexplainability of algorithms used in the models leads to undefendable decisions. Users of AI that rely wholly on the system and do not pursue reasonableness tests of the AI output are then at risk of several issues such as accuracy and reliability, biased outcomes, loss of critical thinking and decision-making skills, ethical and legal risks and erosion of accountability. Auditors should therefore not solely rely on these AI algorithms without validating their outputs.

Minimizing the Unexplainability Problem in AI models

As technological advancement increases, tools for validating AI outputs are being developed. There needs to be techniques available to increase the transparency and transform these models away from their “black-box” nature. An example of such a technique is the XAI model mentioned beforehand. This technique combats the explainability issue. Overall, the main goal of XAI is to help users of AI models to understand which variables affect the model predictions and the steps that the model has taken to reach a certain decision [12]. Thus, removing the limitation of how users of AI tools cannot comprehend how a certain prompt has led to a certain output. Moreover, another important crucial factor of XAI is that XAI processes should show how outcomes will be used by an organization [12].

In the context of auditing, as it can be seen, indeed explainability influences the adoption of AI. Auditors must be able to comprehend, justify and rely on outputs produced by AI to ensure that they comply with regulatory standards and ethical requirements. Without sufficiently being able to explain an AI-generated insight, auditors will be reluctant to rely on such systems as they are unable to justify the decision that the AI model took. Therefore, it can be said that using XAI is important for the adoption of AI tools into the auditing process thus building confidence for auditors and stakeholders.

Conclusion

This research has explored the potential impacts that unexplainability in AI models has on the financial audit. The major findings of this research indicated that the amount of depth that can be provided with the audit opinion becomes deeper because of the broader available data and analytics that will be used. Additionally, by leveraging AI tools auditors can now allocate their resources more effectively. Standardized tasks involving automation processes will need less supervision. The time spent manually on such standardized tasks, being very labor-intensive, will now be removed. Instead, auditors can focus their time on critical activities such as risk assessments and decision-making. However, explainability issues in AI models remain an issue as we continue to have technological advancement. As more and more data is fed into models, more parameters and variables are used to construct variables and relations, making it harder to justify if the outputs produced are indeed correct. Nonetheless, the more research and implementation is done towards AI tools there are also ways in which we can mitigate such risks. An example mentioned was “XAI”, a program facilitating the understanding of relationships between variables and how the model has reached a certain decision. Looking ahead, there are areas of opportunities for AI technologies used in the audit. AI tools used in the audit should take a “white-box” approach rather than a “Black-box” approach thereby creating more understanding and thus explainable models. This is where the hierarchy of understanding comes into play - “Who needs to understand what?”. What kind of expectation do we need to give the engagement partner who is signing the audit? Is it a reasonable expectation for them to understand how the algorithm was developed, how the system is being trained and the overall working of it? Indeed, an engaging party in the audit engagement should have a knowledge and understanding of the model’s algorithm through the help of the central specialist who developed those tools. An auditor using AI tools in its audits needs to understand what the tools do and it needs to be able to justify the use of the tool. Is the certain AI technology that is being used applied to the right context? Do the auditors have the right kind of data and is the data presented in the right kind of format?

Regulators should therefore call for model and input transparency and experts at these companies need to collaborate with regulators. The 2022 White House blueprint for an AI bill of rights states that “You should know that an automated system is being used and understand how and why it contributes to outcomes that impact you” (The White House, 2023). Designers, developers and deployers of automated systems should provide generally accessible plain language documentation including clear descriptions of the overall system functioning and the role automation plays, notice that such systems are in use, the individuals or organization responsible for the system and explanations of outcomes that are clear, timely and accessible.

The conclusions of this research therefore allow for several recommendations to improve the limitation that explainability in AI models has on the adoption of AI tools in the auditing of financial statements. AI is expected to complement existing audit technologies. Therefore, it becomes more important for auditors to work with mathematical and engineering experts. This can be facilitated through the combination of hiring, e.g. IT talents, and training auditors to work with such new technologies. Thus, ensuring that a diverse team of experts is leveraged to address the complexity of AI explainability. Moreover, it is also important to integrate explainable artificial intelligence techniques, XAI, to provide insights into how AI models make decisions. This may lead to more accurate and reliable audit conclusions. XAI facilitating transparency will help gain trust among stakeholders because auditors may be able to explain AI-generated conclusions. Overall, it is important to balance the benefits of automation with the value of a human auditor performing tasks. While in the future AI might be able to automate the entire auditing procedures, it will not be able to provide the judgment and ethical consideration that a human auditor would have.

REFERENCES

1. Hayes, R., Wallage, P. and Gortemaker, H. (2014), Principles of Auditing: An Introduction to International Standards on Auditing, 3rd ed., Pearson Higher Education, London, ISBN: 13- 9780273768173.

2. Thormundsson, B. (2024, February 16). Artificial intelligence (AI) worldwide - statistics & facts. Statista. Retrieved June 17, 2024, from https://www.statista.com/topics/3104/artificial-intelligence-ai-worldwide/#topicOverview.

3.Thormundsson, B. AI adoption rate in businesses worldwide 2017-2022. Statista. https://www.statista.com/statistics/1368935/ai-adoption-rate-worldwide/#:~:text=While%20artificial%20intelligence%20(AI)%20saw,its%20adoption%20rate%20in%2020.

4. Gao, Y., & Han, L. (2021). Implications of artificial intelligence on the objectives of auditing financial statements and ways to achieve them. Microprocessors and Microsystems, 104036.

5.Ding, W., Abdel-Basset, M., Hawash, H., & Ali, A. M. (2022). Explainability of artificial intelligence methods, applications and challenges: A comprehensive survey. Information Sciences, 615, 238–292. https://doi.org/10.1016/j.ins.2022.10.013.

6. Glenn A. Bowen, (2009),"Document Analysis as a Qualitative Research Method", Qualitative Research Journal, Vol. 9 Iss 2 pp. 27 – 40.

Goh, C., Pan, G., Sun, S. P., Lee, B., & Yong, M. (2019). Charting the future of accountancy with AI. CPA Australia, 74.

7. Kayesa, N. K., & Shung-King, M. (2021). The role of document analysis in health policy analysis studies in low and middle-income countries: Lessons for HPA researchers from a qualitative systematic review. Health Policy OPEN, 2, 100024–100024. https://doi.org/10.1016/j.hpopen.2020.100024.

8. Khan, N., Yaqoob, I., Hashem, I. A. T., Inayat, Z., Mahmoud Ali, W. K., Alam, M., Shiraz, M., & Gani, A. (2014). Big Data: Survey, Technologies, Opportunities, and Challenges. The Scientific World, 2014, 712826–18. https://doi.org/10.1155/2014/712826

9. Patel, Rajesh, Fatima, Silva, Buddhika, Shaturaev, & Jakhongir. (2024, January 6). Unleashing the Potential of Artificial Intelligence in Auditing: A Comprehensive Exploration of its Multifaceted Impact. Munich Personal RePEc Archive. Retrieved June 17, 2024.

10. Harford, T. (2024, June 14). Who's responsible for our accountability problem? Financial Times. Retrieved June 17, 2024, from.
https://www.ft.com/content/2e1042d5-5e89-4fb6-bbee-de605a534172

11.Surkov, A., Srinivas, V., & Gregorie, J. (2022, July 25). Explainable AI Unleashes the Power of Machine Learning in Banking. The Wall Street Journal. Retrieved June 18, 2024, from https://deloitte.wsj.com/cio/explainable-ai-unleashes-the-power-of-machine-learning-i n-banking-01658775295.

12.Spichiger, R., & Ardouin, J.-N. (2021, September 6). The importance of explainable AI and AI-based process transparency in financial services. EY. Retrieved June 18, 2024, from https://www.ey.com/en_ch/ai/the-importance-of-explainable-ai-and-ai-based-process-t ransparency-in-financial-services.

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ҚАРЖЫ ЕСЕПТІЛІГІНІҢ АУДИТІНІҢ ЖИ МОДЕЛЬДЕРІНДЕГІ ТҮСІНІКТЕГІЛІКТІҢ САЛДАРЫ

Аңдатпа. *Бұл құжат ЖИ үлгілеріндегі түсіндірудің күрделілігін қарастырады. Атап айтқанда, мұның аудиторлық кәсіпте ЖИ-ты қабылдауға әсері және мүдделі тараптар мен аудиторлық мамандар үшін салдары. Нәтижелер деректер көлемі ұлғайған сайын модельдерді түсіну қиындап, алгоритм нәтижелерін түсіну қиындайтынын көрсетеді. Бұл аудит процедураларында ЖИ құралдарын пайдаланған кезде мүдделі тараптар мен аудиторлық фирмалар үшін елеулі салдарларға ие.*

Аудиторлар ЖИ қорытындысын негіздей және растай алмайды. Бұл мүдделі тараптардың ЖИ алгоритмдері арқылы алынған пікірлер мен қорытындыларға сенуін қиындатады.

Түйін сөздер: *жасанды интеллект, AI модельдері, аудиторлық кәсіп, қаржылық есеп беру, аудиторлар, алгоритмдер, AI құралдары.*

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ПОСЛЕДСТВИЯ НЕОБЪЯСНИМОСТИ В МОДЕЛЯХ ИИ ДЛЯ АУДИТА ФИНАНСОВОЙ ОТЧЕТНОСТИ

Аннотация. *В этой статье рассматривается сложность объяснимости в моделях ИИ. В частности, влияние, которое оно оказывает на внедрение ИИ в аудиторскую профессию, и последствия для заинтересованных сторон и аудиторских специалистов. Результаты показывают, что по мере увеличения объема данных модели становятся более сложными для понимания, что затрудняет понимание результатов алгоритма. Это серьезно влияет на заинтересованных сторон и аудиторские фирмы, когда инструменты ИИ используются в аудиторских процедурах. Аудиторы не смогут обосновать и подтвердить заключение ИИ. Таким образом, заинтересованным сторонам будет сложно доверять мнениям и выводам, полученным с использованием алгоритмов ИИ.*

Ключевые слова: *искусственный интеллект, модели ИИ, аудиторская профессия, финансовая отчетность, аудиторы, алгоритмы, инструменты ИИ.*