

Anna Karmańska

University of Economics in Katowice

e-mail: anna.karmanska@ue.katowice.pl

ORCID: 0000-0001-5883-1243

ARTIFICIAL INTELLIGENCE IN AUDIT

DOI: 10.15611/pn.2022.4.06

JEL Classification: O33, M42, J24

© 2022 Anna Karmańska

This work is licensed under the Creative Commons Attribution-ShareAlike 4.0 International License. To view a copy of this license, visit <http://creativecommons.org/licenses/by-sa/4.0/>

Quote as: Karmańska, A. (2022). Artificial Intelligence in audit. *Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu*, 66(4).

Abstract: The main objective of this paper is to identify the benefits of applying the Artificial Intelligence (AI) in the audit sector. The study employed a questionnaire for a research sample including 206 auditing and accounting practitioners and students. Data were collected via an online survey. A principal axis factor analysis with the Promax rotation was conducted to assess the underlying structure for the points of the questionnaire. The research outcomes indicate that, in the opinion of the respondents, AI adoption increases audit efficiency, and enhances client communication and service. Finally, AI can also automate time-consuming and routine tasks. The three indicated factors account for 62.223% variance. The findings reveal the advantages of AI adoption and could support managers in deploying new technology in their organizations. The research limitation concerns the fact that this study focused only on respondents from Poland.

Keywords: audit, Artificial Intelligence, machine learning.

1. Introduction

Artificial Intelligence (AI) is gaining significant momentum and shows enormous potential to revolutionise every model of business, including the accounting and audit sector. Gartner defines AI as applying advanced analysis and logic-based techniques, including machine learning (ML), to interpret events, support and automate decisions, and take actions (Panetta, 2019).

Audit firms are investing billions of dollars to develop AI systems to help auditors execute their tasks (Commerford, Dennis, Joe, and Ulla 2022). For example, PwC plans to spend \$12 billion and hire 100,000 new people in areas such as artificial intelligence and cybersecurity by 2026 (Maurer, 2021).

Moreover, the work-from-home strategy, due to the COVID-19 pandemic, also had an impact on increasing investment of audit firms in digital programs, including artificial intelligence, blockchain, network security, and data function development (Albitar, Gerged, Kikhia, and Hussainey, 2021).

The main objective of this study was to identify the benefits of the usage of AI in financial audits.

The paper focused on addressing the following research question: what are the benefits of AI adoption in audits? According to the literature review, there is still an existing gap in the academic papers on this topic, especially in Poland. The literature search, which was performed with the terms “artificial intelligence” and “audit” in the subject area: business economics in the bibliographic databases: Emerald Management (11 studies) and the ISI Web of Knowledge in the area of business management and accounting (90 papers), clearly confirms the research gap.

The research employed a questionnaire, and the final sample included 206 respondents. The data were collected through the use of an online survey. A principal axis factor analysis with the Promax rotation is conducted to assess the underlying structure for the points of the questionnaire. The findings examined the benefits of AI adoption in audit processes and support in deploying new technology.

2. Audit of financial statements

A financial statement audit can be defined as the examination of an entity’s financial statements by an independent auditor. Based on Directive 2014/56/EU2 amending Directive 2006/43/EC3 on statutory audits, and Regulation (EU) No 537/2014, EU Member States require audit firms to carry out statutory audits in compliance with the international auditing standards (ISA) adopted by the Commission. International standards for auditing are issued by the International Federation of Accountants (IFAC) through the International Auditing and Assurance Standards Board (IAASB).

The purpose of an audit is to enhance the degree of confidence of the intended users of the financial statements (ISA 200.3). The output of the audit process is the auditor’s report, which contains an opinion on whether the financial statements are prepared, in all material respects, in accordance with the applicable financial reporting framework (Karmańska, 2020). In planning and performing an audit of financial statements the auditor exercises professional skepticism and judgment (ISA.200.15-16). Skepticism is defined as an attitude that includes a questioning mind, being alert to conditions that may indicate possible misstatement due to error or fraud, and a critical assessment of evidence (ISA200.13).

The auditor should design and perform audit procedures that are appropriate for obtaining the sufficient relevant audit evidence which is necessary to reduce audit risk to an acceptably low level (ISA.315.2), and support the auditor's opinion (ISA.500.6). In light of the increasing use of emerging technologies in performing audit procedures, the revised ISA 315 focuses on different aspects of automated tools and techniques (ATT). IAASB defines artificial intelligence techniques as the machine learning technology trained to recognize patterns in vast volumes of data, including unstructured data such as emails, social media, contracts, invoices, images, and conference call audio files. AI can be useful in gathering information from various sources to assist the auditor in identifying risks of material misstatement (IAASB, 2020).

There are three methods available to the auditor for selecting items, such as accounting vouchers and balances to test (ISA.500.A52). The first method is selecting all items (100% examination). This laborious and costly approach may be appropriate when the population constitutes a small number of large value items or due to significant risk other means do not provide sufficient appropriate audit evidence (ISA.500.A53). The second method is selecting specific items based on the auditor's professional judgment and intuition. For example, the auditor can choose items of high value or suspicious unusual entries like credit balances of receivables. The third method is audit sampling, which is the application of audit procedures to less than 100% of items within a population of audit relevance such that all sampling units have a chance of selection to provide the auditor with a reasonable basis on which to conclude the entire population (ISA.530.5a). Statistical sampling has the following characteristics: random selection of the sample items and the use of probability theory to evaluate sample results, including measurement of sampling risk (ISA.530.5g). Statistical sampling is usually used because it allows for the replacement of biased methods based on the auditor's intuition (Hołda, 2010), and the sampling risk of a statistical plan can be measured and controlled by an auditor.

The Polish Audit Oversight Agency (PANA), an independent public body, performs the public oversight of statutory auditors and audit firms by the Act of 11 May 2017 on Statutory Auditors, Audit Firms and Public Oversight (published under item 1089 in the Polish Journal of Laws of 6 June 2017). PANA performed analyses on a sample of about 30 thousand audits for the year 2020 completed by 2257 auditors from 1062 audit firms. The average number of audits per person was 13.08, but taking into account audit firms from the list of the TOP 11, the average was 27.07 per auditor (Polska Agencja Nadzoru Audytowego, 2021). The above data indicate the excessive workload of auditors. Taking into account tightened time constraints, the implementation of information systems and emerging technologies are considered to be of most importance for increasing productivity in the audit sector.

3. Literature review

Implementing emerging technologies is based on the technology acceptance model (TAM) proposed by Davis. This model indicates two main factors, in particular an individual's perceived usefulness as to the degree to which the user believes that using the technology will enhance the performance, and the perceived ease of use – the degree to which the user believes that using the technology will be free of effort (Davis, 1985).

Computer Assisted Audit Tools and Techniques (CAATs) can be described as any use of technology to support the completion of an audit (Pedrosa, Costa, and Aparicio, 2020). Commonly used CAATs comprise specialised audit software (Statistical Software, Test Data, Database SQLSearch, Parallel Simulation Software, Embedded Audit Modules), spreadsheets, word processors, and program languages to gain access to and manipulate the data (Serpeninova, Makarenko, and Litvinova, 2020).

By using CAATs, auditors can schedule and document the audit, classify, summarise and match, sample the data, make statistical analyses and identify anomalies (Aksoy and Gurol, 2021). Concurrent with new technological developments, the scope of CAATs' use is also advancing (Aksoy and Gurol, 2021).

Machine learning (ML) is a subset of AI (Hoogduin, 2019). This is a broad discipline that has designed learning algorithms that can discover hidden regularities in growing volumes of data (Bertomeu, Cheynel, Floyd, and Pan, 2021). ML involves a series of statistical techniques, such as mathematical modelling, data visualisation, and pattern recognition, to conduct self-learning activities, to predict and understand trends and patterns (Zhang, Xiong, Xie, Fan, and Gu, 2020).

Hoogduin provides examples of machine-learning techniques in the audit (Hoogduin, 2019). One of them is regression analysis, which uses the presumed relationship between some variable of interest (the 'dependent'), typically a financial statement account that the auditor wants to examine, and a set of predictors, financial or non-financial data that the auditor believes has a plausible relationship with the dependent variable, which is 'trained' on historical data. The regression analysis can help auditors identify outliers and observations that are unexpected. The regression analysis applications may be deployed among others in the analysis of depreciation charged against the historical cost of fixed assets, interest expense against the balance of long-term debt, or a margin analysis between revenue and cost of sales (Hoogduin, 2019).

AI implementation faces barriers including a lack of organizational capabilities related to data, and individual competencies related specifically to AI (Bérubé, Giannelia, and Vial, 2021). However, the Big Four: Deloitte, EY (Ernst&Young), KPMG, and, PwC (PricewaterhouseCoopers) can overcome the barriers and all of them are reporting usage of AI applications in areas such as audit planning risk assessments, tests of transactions, analytics, and the preparation of audit work-papers (Munoko, Brown-Libur, and Vasarhelyi, 2020).

For example, PwC in cooperation with H2O.ai – a leading Silicon Valley company built a bot that used AI and machine learning based on algorithms trained to replicate the thinking and decision-making of experts (Zemankova, 2019; Zhang et al., 2020). The bot, GL.ai, can examine every uploaded transaction by every user and every amount on every account in the general ledger. Due to the analysis of billions of data points in milliseconds the bot can find unusual transactions and detect anomalies indicating potential errors or fraud without bias or variability. According to PwC, GL.ai speeds up the audit process, generates insights that boost efficiency, and provides comfort that attention is being focused on areas of true risk (PwC, n.d.). In another example, EY uses AI techniques to analyse and extract data from unstructured data such as contracts, invoices, and images to gain audit evidence (EY, 2019). Moreover, AI is used for large sets of data to help identify, assess and respond to the risks of material misstatement due to fraud.

According to EY, adopting AI in audit increases confidence and trust due to the elimination of human error and reasoning, replacing it with high precision, objectivity, and accuracy. Moreover, due to the analysis of larger samples, the quality is higher, which brings increased value for customers. EY also uses drones in inventory counting to autonomously scan bar codes, QR codes, and other labels and transmit that data to an online auditing platform (Vein and Sidhu, 2018). This solution makes audits faster, more accurate and more seamless. According to research (Christ, Emett, Summers, and Wood, 2021), drone-enabled inventory audit procedures can decrease count time from 681 h to 19 h at the same time, eliminating error rates from 0.15% to 0.03% compared to manual work.

Nevertheless, the investment and development of emerging technologies in the BIG Four poses a threat for small audit firms. Due to the global domination of the largest firms, the BIG 4 have an impact on competition, choice, price, and quality in the audit industry.

Apart from the BIG-4 companies, researchers also highlight the benefits of embracing AI in the audit industry. The potential advantages from the use of AI in the audit process from previous studies are presented in Table 1.

Table 1. Benefits of AI adoption in audit

	Benefits	Author(s), year
B1	advances the communications techniques with those charged with governance	(Albawwat and Frijat, 2021)
B2	analysis and extraction of information from semi and unstructured data	(Deloitte, 2018; EY, 2019; Kokina and Davenport, 2017; Ucoglu, 2020)
B3	automation of time-consuming, process-heavy, routine, and redundant work	(Tiron-Tudor and Deliu, 2021; Zhang, 2019; Kokina and Davenport, 2017)
B4	better user experience, new and improved interface for human interaction	(Tiron-Tudor and Deliu, 2021)

B5	elimination of human errors	(Christ et al., 2021; Tiron-Tudor and Deliu, 2021; Commerford et al., 2022; Zemankova, 2019; EY, 2019; Ucoglu, 2020)
B6	enhances predictive analytics	(Zhang, 2019)
B7	enhances the process of detecting material misstatements	(Albawwat and Frijat, 2021)
B8	enhanced client service	(Munoko Brown-Liburd, and Vasarhelyi, 2020; EY, 2019; Bhalerao, Kumar, Kumar, and Pujari, 2022)
B9	generates a better understanding of the client's operations and the associated risks, more in-depth insight into business processes	(Albawwat and Frijat, 2021; Munoko et al., 2020)
B10	higher audit quality	(Law and Shen, 2021; Commerford et al., 2022; EY, 2019)
B11	improved audit documentation	(Christ et al., 2021; Tiron-Tudor and Deliu, 2021)
B12	increased audit effectiveness and efficiency	(Christ et al., 2021; Zemankova, 2019; Zhang, 2019; Munoko et al., 2020; Hasan, 2022; Puthukulam, Ravikumar, Sharma, and Meesaala, 2021; Ucoglu, 2020)
B13	introducing new types of services continuous audit, audit 4.0	(Tiron-Tudor and Deliu, 2021; Zhang, 2019)
B14	models being continuously updated with less effort due to constant changes in fraud patterns	(Ucoglu, 2020)
B15	offers digital assistance	(Tiron-Tudor and Deliu, 2021)
B16	provides accuracy and precision	(Tiron-Tudor and Deliu, 2021; Munoko et al., 2020; Deloitte, 2018)
B17	provides auditors more time to focus on more complex and value-added tasks	(Zemankova, 2019; EY, 2019)
B18	rational and accurate decision-maker, better judgments with the assistance of cognitive computing	(Tiron-Tudor & Deliu, 2021; Zhang, 2019; Deloitte, 2018; EY, 2019; Bhalerao et al., 2022)
B19	reduction of audit risk	(Tiron-Tudor and Deliu, 2021; Zemankova, 2019)
B20	testing all operations in a financial period	(PWC, 2017; Tiron-Tudor and Deliu, 2021; Zhang, 2019; Aksoy and Gurol, 2021; Puthukulam et al., 2021)
B21	tireless, selfless, no breaks, availability 24 hours per day and 7 days per week	(Christ et al., 2021; Tiron-Tudor and Deliu, 2021)

Source: own work based on literature review.

4. Research hypotheses, methodology, and results

This study contributes to the science by exploring the benefits of adopting artificial intelligence in the audit. The research question addressed in the study was: what are the benefits of AI adoption for organizations in the field of audit?

Based on the above research question, the following hypotheses were posed:

H1: AI has a significant effect on audit efficiency.

H2: AI has a positive impact on communication with clients.

H3: AI has a significant effect on the automation of routine, time-consuming audit processes.

The research was conducted in May and June 2022 and employed a questionnaire addressed to respondents who were accounting and auditing professionals as well as students.

Data were collected through the use of a non-interventional, anonymised, self-administered, web-based survey, which was distributed using social media and groups devoted to survey exchanges. The questionnaire items consisted of demographics, such as gender, age, education and status, and place of employment. The detailed characteristics of the respondents' demographics are presented in Table 2.

Table 2. Distribution of the sample members

Age	Frequency	Percentage	Place of employment	Frequency	Percentage
Up to 20 years	1	0.5	Unemployed	52	25.2
21-30 years	170	82.5	Microenterprise (1-9 employees)	31	15.0
31-45 years	27	13.1	Small enterprise (10-49 employees)	34	16.5
46-60 years	8	3.9	Medium-sized enterprise (50-249 employees)	31	15.0
Gender			Large enterprise (250 employees and more)	58	28.2
Female	166	80.6	Work experience		
Male	35	17.0	unemployed student	53	25.8
Not specified	5	2.4	employed	152	73.8
Education level			other	1	0.5
middle	71	34.5	Place of residence		
high	129	62.5	Rural	46	22.3
other	5	2.4	Urban	158	76.7
Not specified	1	0.5	Not specified	2	1.0

Source: own elaboration based on the analysed data.

The study employed quantitative research methodology with the support of SPSS software. First, the Cronbach's alpha coefficient for the entire scale, which included 21 items, was calculated. This coefficient, which provides an overall assessment of

the reliability of the measure and internal consistency, was high (0.946). Next, the frequencies and volatility measures were calculated. The statistics are presented in Table 3.

Table 3. The benefits of AI in audit

Benefit	Frequency					Mode	Sum
	strongly disagree (1)	disagree (2)	neither agree nor disagree (3)	agree (4)	strongly agree (5)		
b1	7	26	45	87	41	4	747
B2	6	6	31	96	67	4	830
B3	7	7	14	65	113	5	888
B4	6	11	41	91	57	4	800
B5	8	12	39	79	68	4	805
B6	4	11	45	88	58	4	803
B7	5	8	25	110	58	4	826
B8	12	28	43	76	47	4	736
B9	8	26	56	75	41	4	733
B10	6	9	51	92	48	4	785
B11	5	10	48	89	54	4	795
B12	8	3	35	103	57	4	816
B13	6	8	66	86	40	4	764
B14	8	8	44	91	55	4	795
B15	7	9	24	103	63	4	824
B16	10	13	21	101	61	4	808
B17	5	12	28	88	73	4	830
B18	6	12	57	84	47	4	772
B19	6	23	57	79	41	4	744
B20	6	14	34	88	64	4	808
B21	13	11	27	73	82	5	818

Numbering frequencies as in Table 1.

Source: own elaboration based on the analysed data.

The top benefits of AI in audit, as perceived by the respondents, were the possibility to automate repetitive redundant tasks and availability 24 hours per day and 7 days per week (mode = 5).

For further analysis, to determine distinct constructs and group similar variables into dimensions, the explanatory factor analysis with the extraction method, principal axis factoring, and rotation method: Promax with Kaiser was performed. The results of two tests, the Kaiser–Meyer–Olkin measure of sampling adequacy 0.936, and Bartlett’s test of sphericity, confirmed the suitability of the data for factor detection ($p < 0.001$). The Pattern Matrix (Table 4) displays the items and factor loadings for the rotated factors, with loadings less than 0.5 omitted to improve clarity.

Table 4. The Pattern Matrix

	Factor 1	Factor 2	Factor 3
B1		.613	
B2			.701
B3			.668
B6			.574
B7			.511
B8		.778	
B9		.797	
B12	.704		
B14	.736		
B15	.660		
B16	.726		
B17	.761		
B18	.667		
B19	.643		
B20	.690		
B21	.673		
Variance explained	10.368	1.528	1.170
Percent of variance explained	49.373	7.278	5.572
Cumulative variance explained, %	49.373	56.651	62.223

Numbering frequencies as in Table 1.

Source: own elaboration based on the analysed data.

Three factors with eigenvalues greater than 1 accounted for most of the variation (62.223%) in the data. The first factor accounted for 51.283% of the variance. Increased audit effectiveness and efficiency (0.714), accuracy and precision (0.726), and rational and accurate decision-making (0.667) have large positive loadings on factor 1, so this factor describes **audit efficiency**. The second factor, which is explained for 7.278% variance, has strong loadings on the benefits related to better client service (0.778), a better understanding of the client’s operations and the associated risks (0.797), and communications techniques with those charged with governance (0.613). The second factor describes **client communication and service**. The last factor explained 5.572% of the variance and had strong loadings on the benefits related to analysis and extraction data from semi and unstructured data (0.701), and automation of repetitive tasks (0.668). The factor represents **audit automation**. The research outcomes confirm the hypotheses H1, H2, and H3.

5. Conclusion

This paper focused on how AI can benefit the audit profession. According to the respondents, who were accounting and audit professionals and students adopting AI

can increase audit effectiveness and efficiency thanks to accuracy, precision, and rational decision making. AI is also beneficial in the automation of repetitive processes, especially in phases that require the performance of rules-based and time-consuming tasks and extract information from unstructured data such as contacts, emails, and social media. Moreover, AI can enhance communication and provide better service for clients.

However, the use of AI does not eliminate the need to exercise professional judgment and skepticism. AI is unlikely to replace professional skepticism and judgment because they require a great extent of the human element (Puthukulam et al., 2021). Furthermore, due to the adoption of AI and access to more information from a wide array of data and varying sources, the auditor's ability to critically assess audit evidence can be improved. On the other hand, IAASB underlines that auditors should avoid being overconfident in the use of automated tools and techniques, or relying on the outputs of such tools and techniques (IAASB, 2020).

New technologies, such as Artificial Intelligence, are being adopted into the audit sector but their implementation is still currently deemed to be at the teething stage (Mansoori and Khan, 2018). The AI solution requires considerable expenditure for software acquisition, training, consulting, and software management and maintenance (Zhang, 2019). For these reasons, small audit companies face serious challenges in AI adoption. However, in today's world of rivalry, if SMEs do not embrace available technologies, they may lose their competitive advantage (Bhalerao et al., 2022) and will no longer perform audit services. Therefore, small audit firms ought to understand the importance of AI and overcome the barriers and benefit from using customised AI solutions that meet the requirements of the SME sector (Bhalerao et al., 2022).

The research contributes to the literature in several ways. First, it presents the benefits of AI in the audit field. Second, it can be useful for practitioners to understand the meaning of AI to improve audit efficiency. The identification of benefits provides an important basis for further surveys aimed at removing the barriers to implementing AI in audit firms, especially in the SME sector. However, the findings have to be interpreted in light of certain limitations, the main one being the small sample size. The other limitation concerns the fact that this study focused only on respondents from Poland.

References

- Aksoy, T., and Gurol, B. (2021). *Artificial Intelligence in Computer-Aided Auditing Techniques and Technologies (CAATTs) and an application proposal for auditors* (pp. 361-384). https://doi.org/10.1007/978-3-030-72628-7_17
- Albawwat, I., and Frijat, Y. Al. (2021). An analysis of auditors' perceptions towards artificial intelligence and its contribution to audit quality. *Accounting*, 7(4), 755-762. <https://doi.org/10.5267/j.ac.2021.2.009>

- Albitar, K., Gerged, A. M., Kikhia, H., and Hussainey, K. (2021). Auditing in times of social distancing: The effect of COVID-19 on auditing quality. *International Journal of Accounting and Information Management*, 29(1), 169-178. <https://doi.org/10.1108/IJAIM-08-2020-0128>
- Bertomeu, J., Cheynel, E., Floyd, E., and Pan, W. (2021). Using machine learning to detect misstatements. *Review of Accounting Studies*, 26(2), 468-519. <https://doi.org/10.1007/s11142-020-09563-8>
- Bérubé, M., Giannelia, T., and Vial, G. (2021). *Barriers to the implementation of AI in organizations: Findings from a Delphi study* (Proceedings of the Annual Hawaii International Conference on System Sciences, 2020-Janua, pp. 6702-6711). <https://doi.org/10.24251/hicss.2021.805>
- Bhalerao, K., Kumar, A., Kumar, A., and Pujari, P. (2022). A study of the barriers and benefits of artificial intelligence adoption in small and medium enterprise. *Academy of Marketing Studies Journal*, 26(1), 1-6.
- Christ, M. H., Emett, S. A., Summers, S. L., and Wood, D. A. (2021). Prepare for takeoff: improving asset measurement and audit quality with drone-enabled inventory audit procedures. *Review of Accounting Studies*, 26(4), 1323-1343. <https://doi.org/10.1007/s11142-020-09574-5>
- Commerford, B. P., Dennis, S. A., Joe, J. R., and Ulla, J. (2022). Man versus machine: Complex estimates and auditor reliance on Artificial Intelligence. *Journal of Accounting Research*, 60(1). <https://doi.org/10.1111/1475-679X.12407>
- Davis, F. D. (1985). A technology acceptance model for empirically testing new end-user information systems: Theory and results. *Management, Ph.D.*, (291). <https://doi.org/oclc/56932490>
- Deloitte. (2018). *Cognitive technology to comply with new accounting standards*. Retrieved from <https://www2.deloitte.com/za/en/pages/audit/articles/cognitive-technology-expedites-new-accounting-standards-compliance.html>
- EY. (2019). *Audit innovation*. Retrieved from https://www.ey.com/en_gl/audit/innovation
- Hasan, A. R. (2022). Artificial Intelligence (AI) in accounting and auditing: A literature review. *Open Journal of Business and Management*, 10(01), 440-465. <https://doi.org/10.4236/ojbm.2022.101026>
- Hołda, A. (2010). Istota badań próbkowych w rewizji finansowej i dobór prób badawczych. *Zeszyty Naukowe Uniwersytetu Ekonomicznego w Krakowie*, (829). <https://r.uek.krakow.pl/bitstream/123456789/27111/1/170626644.pdf>
- Hoogduin, L. A. (2019). Using machine learning in a financial statement audit. *Compact*, (4), 4-8.
- IAASB. (2020). *Non-authoritative support material related to technology: frequently asked questions (faq) _ the use of automated tools and techniques when identifying and assessing risks of material misstatement in accordance with ISA 315* (revised 2019). Retrieved from <https://www.ifac.org/system/files/publications/files/IAASB-Technology-FAQ-Automated-Tools-Techniques.pdf>
- International Federation of Accountants [IFAC]. (2009). *ISA 200, overall objectives of the independent auditor and the conduct of an audit in accordance with international standards on auditing* (Issue January 2009, pp. 72-100). Retrieved from [http://www.ifac.org/sites/default/files/publications/files/2012 IAASB Handbook Part I_Web.pdf](http://www.ifac.org/sites/default/files/publications/files/2012%20IAASB%20Handbook%20Part%20I_Web.pdf)
- International Federation of Accountants [IFAC]. (2019). *ISA 315 (Revised), identifying and assessing the risks of material misstatement*. Retrieved from <https://www.ifac.org/system/files/publications/files/ISA-315-Full-Standard-and-Conforming-Amendments-2019-.pdf>
- International Federation of Accountants [IFAC]. (2009). *ISA 500, audit evidence*. Retrieved from <https://www.ifac.org/system/files/downloads/a022-2010-iaasb-handbook-isa-500.pdf>
- International Federation of Accountants [IFAC]. (2009). *ISA 530, audit sampling*. Retrieved from <https://www.ifac.org/system/files/downloads/a027-2010-iaasb-handbook-isa-530.pdf>
- Karmańska, A. (2020). *The determinants of key audit matters in listed companies in Poland, in accounting, reporting and auditing*. Meeting the needs of the information providers and users.
- Kokina, J., and Davenport, T. H. (2017). The emergence of artificial intelligence: How automation is changing auditing. *Journal of Emerging Technologies in Accounting*, 14(1), 115-122. <https://doi.org/10.2308/jeta-51730>

- Law, K., and Shen, M. (2021). *How does artificial intelligence shape audit firms?* (Nanyang Business School Research Paper, 20-31). <https://doi.org/http://dx.doi.org/10.2139/ssrn.3718343>
- Maurer, M. (2021). PwC to Spend \$12 Billion on Hiring, Expanding Expertise in AI, Cybersecurity. *The Wall Street Journal*. Retrieved from <https://www.wsj.com/articles/pwc-to-spend-12-billion-on-hiring-expanding-expertise-in-ai-cybersecurity-11623758400>
- Munoko, I., Brown-Liburd, H. L., and Vasarhelyi, M. (2020). The ethical implications of using artificial intelligence in auditing. *J Bus Ethics*, (167), 209-234. <https://doi.org/https://doi.org/10.1007/s10551-019-04407-1>
- Panetta, K. (2019). *The CIO's guide to Artificial Intelligence*. Retrieved from <https://www.gartner.com/smarterwithgartner/the-cios-guide-to-artificial-intelligence>
- Pedrosa, I., Costa, C. J., and Aparicio, M. (2020). Determinants adoption of computer-assisted auditing tools (CAATs). *Cognition, Technology and Work*, 22(3), 565-583. <https://doi.org/10.1007/s10111-019-00581-4>
- Polska Agencja Nadzoru Audytowego. (2021). *Badanie sprawozdań finansowych przez firmy audytorskie na podstawie sprawozdań rocznych za rok 2020 oraz wyników kontroli*. Retrieved from <https://pana.gov.pl/wp-content/uploads/2021/10/badanie-sprawozdan-finansowych-przez-firmy-audytorskie-na-podstawie-sprawozdan-rocznych-za-rok-2020-oraz-wynikow-kontroli.pdf>
- Puthukulam, G., Ravikumar, A., Sharma, R. V. K., and Meesaala, K. M. (2021). Auditors' perception on the impact of artificial intelligence on professional skepticism and judgment in Oman. *Universal Journal of Accounting and Finance*, 9(5), 1184-1190. <https://doi.org/10.13189/ujaf.2021.090527>
- PwC. (2017). *Harnessing the power of AI to transform the detection of fraud and error*. Retrieved from <https://www.pwc.com/gx/en/about/stories-from-across-the-world/harnessing-the-power-of-ai-to-transform-the-detection-of-fraud-and-error.html>
- Serpeninova, Y., Makarenko, S., and Litvinova, M. (2020). Computer-assisted audit techniques: classification and implementation by auditor. *Public Policy and Accounting*, 1(1), 44-49. <https://doi.org/10.26642/ppa-2020-1-44-49>
- Tiron-Tudor, A., and Deliu, D. (2021). Reflections on the human-algorithm complex duality perspectives in the auditing process. *Qualitative Research in Accounting and Management*. <https://doi.org/10.1108/QRAM-04-2021-0059>
- Ucoglu, D. (2020). Current machine learning applications in accounting and auditing. *Pressacademia*, 12(1), 1-7. <https://doi.org/10.17261/pressacademia.2020.1337>
- Vein, C., and Sidhu, H. (2018). Using drones to enhance audits. *School of Accountancy*. Retrieved from <https://www.journalofaccountancy.com/podcast/using-drones-to-enhance-audits.html>
- Zemankova, A. (2019). (Proceedings – 2019 3rd International Conference on Control, Artificial Intelligence, Robotics and Optimization, ICCAIRO 2019, pp. 148-154). <https://doi.org/10.1109/ICCAIRO47923.2019.00031>
- Zhang, A. (Chanyuan). (2019). Intelligent process automation in audit. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3448091>
- Zhang, Y., Xiong, F., Xie, Y., Fan, X., and Gu, H. (2020). The impact of Artificial Intelligence and blockchain on the accounting profession. *IEEE Access*, (8), 110461-110477. <https://doi.org/10.1109/ACCESS.2020.3000505>

SZTUCZNA INTELIGENCJA W AUDYCIE

Streszczenie: Celem artykułu jest wskazanie korzyści płynących z zastosowania sztucznej inteligencji (AI) w badaniu sprawozdań finansowych. Posłużono się kwestionariuszem ankiety. Próbą badawczą objęto 206 praktyków i studentów audytu i rachunkowości. Zastosowano analizę czynnikową metodą głównych składowych z rotacją Promax. Wyniki wskazują, że w opinii respondentów zastosowanie sztucznej inteligencji zwiększa efektywność audytu. Sztuczna inteligencja usprawnia komunikację i obsługę klienta. Ponadto AI może zautomatyzować czasochłonne i rutynowe zadania. Powyższe trzy czynniki odpowiadają za 62,223% wariancji. Wyniki badania wskazują na korzyści płynące z implementacji sztucznej inteligencji w audycie i mogą wspierać menedżerów we wdrażaniu nowych technologii w ich organizacjach. Ograniczeniem badawczym jest fakt, że badanie koncentruje się na respondentach jedynie z Polski.

Słowa kluczowe: audyt, sztuczna inteligencja, uczenie maszynowe.