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Detecting the effect of artificial intelligence on internal audit performance: Empirical study in Saudia Arabia

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A B S T R A C T

This research attempts to investigate the effect of types of AI systems (assisted, augmented, and autonomous) on internal auditing in Saudi Arabia. A questionnaire was used to collect data from 150 internal auditors in Riyadh City. To confirm that the study's goals were met, the descriptive analytical method was used. The questionnaire data is analyzed, and hypotheses are tested, using the Smart pls application. The study's results show that there is a clear positive effect of AI systems, but different impacts vary according to the kind of AI systems, which is high in augmented systems, moderate in autonomous systems, and weak in assistive intelligence systems. Further studies on this subject can be conducted with larger sample sizes, especially if they are conducted globally. Based on these findings, future research can concentrate on national and cultural conditions. Additionally, companies should adopt more comprehensive involvement methods in internal auditing issues and the development of AI adoption in all company activities.

1. Introduction

In the contemporary era of swift technological progress, several businesses and sectors have acknowledged the significance of data analytics for artificial intelligence (AI) as crucial instruments for making decisions in their daily operations and enhancing their business models. AI helps businesses use technology to operate more efficiently and productively (Arinola & Olalekan, 2023). The auditor receives real-time data through data collection employing robots or machine learning technology (Ajayi et al., 2023). With the advent of personal computers in the 1980s, processing power became affordable and accessible. Like this, AI lowers the cost of prediction, enabling the instantaneous automation of routine and repeatable tasks by machines (Ergen, 2019). Therefore, AI and people collaborate to find answers to the complex issues of the day, enhance our capacity for self-education and decision-making, and more (Psarras et al., 2022). Internal audits evaluate how well a company operates to maintain adherence to established regulations. The function of internal auditing has grown in importance within organizations. After the United States' Institute of Internal Auditors was founded in 1941, the situation underwent a significant shift. Internal auditing has become a function of a value-added job that helps management achieve its strategic goals (Čular et al., 2020). By systematically evaluating, internal auditing can assist businesses in reaching their objectives. It also analyzes an organization's complete performance and guarantees adherence to laws, regulations, rules, processes, and organizational codes of behavior (Singh et al., 2021). AI technology assists in identifying issues with accounting processes. It also helps businesses identify issues with their records and financial statements. Implementing AI improves a company's accounting processes' accuracy even more. Furthermore, the use of AI has made it feasible to carry out audits in a timely, precise, and comprehensive manner. It has also been shown to be a successful method for reducing the likelihood of human error (Musa & Lefkir, 2024). Most researchers argue about the benefits and drawbacks of AI in this field. (The Institute of Internal Auditors, 2017) concluded that AI is ideally equipped to play a crucial role in internal

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auditing to better understand the strategic goals of the company and the procedures employed to achieve them. However, (Puthukulam et al., 2021) posed AI as a serious obstacle for businesses with constrained funding. Additionally, auditors can apply AI to increase audit operations' efficacy in pricey ways. Automation will not be able to replace auditors, but the role of the auditor will shift in perspective. Rehman and Hashim (2022) further stated that AI may give internal auditors of fraud quick risk assessments and observance to cut down on fraud. Furthermore, Wassie and Lakatos (2024) saw a lot of people have lost their employment because of AI, which has replaced all repetitive duties and activities with computers and robots. All businesses want to use AI products because of their high degree of accuracy**.**

Established in 1992, the Saudi Organization for Certified Public Accountants (SOCPA) is responsible for the advancement of accounting and external auditing standards in Saudi Arabia through its technical committees (Al-Twaijry et al., 2003)**.** To increase IIA membership and manage CIA examinations so that local internal auditors may get CIA certification, the first IIA Chapter was founded in 1982 at ARAMCO in Saudi Arabia (Alzeban & Sawan, 2013)**.** Most prior research conducted in Saudi Arabia concentrated on the purpose and role of internal audits. The study by Woodworth and Said (1996) aimed to find out what internal auditors in the country thought about whether auditees' responses to internal audit scenarios differed based on their nationality. Analyze the degree of coordination and cooperation between managers and partners in external audit firms and directors of internal audit sections in Saudi corporations**.** Al-Twaijry et al. (2004) focused on institutional theory to interpret the internal audit in the Saudi company's sector. Al-Shetwi et al.,(2011) studied how the internal audit function affects the caliber of financial reporting**.** (Sawan, N.2013). study the role of the internal audit function in the public sector context. Alzeban and Gwilliam (2014) examined the variables influencing the Saudi public sector's internal audit effectiveness. Alzeban (2019) studied the effects of internal audit standard compliance on Saudi financial reporting quality.

Nevertheless, the Kingdom of Saudi Arabia's experience with AI systems' influence on internal audits has not been explored in the literature currently available on internal auditing. Additionally, research in this area is still weak, with few studies on AI and internal audits conducted in Middle Eastern nations like the Kingdom of Saudi Arabia. The goal of this paper is to fill this research gap.

2. Literature Review

The ability of a computer or robot to mimic human intellect through software and algorithms is known as AI. AI is capable of intellectual activities such as knowledge-based learning and logical reasoning (Manickam et al., 2022)**.** It is a combination of hardware and software that works like the brain of a human being and is capable of complex decisions based on available data (Yoon, 2020). Robots with AI can understand, think, and learn just like people. This implies that it would be feasible to program machines to mimic human intelligence (Liew, 2018)**.** Research indicates that the economic impact of AI has grown dramatically in the last few years and will accumulate to $15 billion by 2030 (Palomares et al., 2021)**.** Semantic analysis, image and speech recognition, data mining, machine learning, and other related technologies are all included together under the general term AI. AI, machine learning, and statistics are combined in data mining to identify patterns in copious amounts of data. AI is also used for auditing program documentation and logs, as well as the user interface (Gotthardt et al., 2020)**.** The types of artificial intelligence systems include:

1-Assisted AI systems: are systems that perform tasks for humans with little to no human-machine interaction. Helping people with analysis, planning, and decision-making is the main goal of assistive intelligence systems (Alsamhi et al., 2022)**.** This kind of system is designed to help someone do a task with the least amount of time, effort, and errors possible (Coşar et al., 2020)**.** Which aid in human decision-making and action. Because of their mechanical intelligence, assisted AI systems can perform routine, everyday tasks (Munoko et al., 2020)**.**

2 -Augmented AI systems: The purpose of assistive technology applications is to create intelligent technologies that enable people to accomplish things that they might find challenging or impossible to perform alone (Yau et al., 2021). when AI supports or companions a human. AI can enhance human decision-making abilities with this method. AI has proven useful in adaptive process automation, improving resource efficiency and process flexibility while freeing up human labour for more creative tasks (Madni, 2020)**.** The objective of assistive intelligence is to increase human capacities, enabling an individual to be knowledgeable and capable of making strategic decisions based on the system's insights (Hassani et al., 2020)**.**

3- Autonomous AI systems, which can adapt to varied environments and hence behave independently without human intervention. In this scenario, humans delegate decision-making to AI. AI could be required to deal with new scenarios, as well as more efficiently connect with humans (Abràmoff et al., 2020)**.** Autonomous intelligence systems can operate independently of human intervention and produce a sequence of activities within the constraints of a decision. These systems function in human environments that are not limited, such as cyber defense, intelligence analysis, autonomous vehicles, and distributed robots (Laitinen & Sahlgren, 2021).

3. Internal Auditing and AI

The Institute of Internal Auditors, which was founded in 1941 to train and develop internal auditors, is credited with establishing internal auditing. According to its definition, internal auditing is an impartial, independent procedure that offers the company assurances and guarantees about how it controls its operations and offers suggestions for development and additional value creation(Rylska, 2018). Large-scale projects, complicated production and administrative systems, corporate growth and branch expansion, and the ensuing issues with financial and accounting systems have all contributed to the increased importance of internal auditing in business (Paul, 2019). It became vital to confirm that the company's programs were sufficient for accomplishing its goals and that its activities adhered to the set plans. This necessitated continual evaluation and participation in the problem's solution through an in-depth and informed briefing on the performance and operations of the company (Ghalib et al., 2020). Internal auditing is a method to assess and improve corporate governance, control, and risk management effectiveness, by offering strategies to uphold and enhance it, it helps the company accomplish its goals(Soh & Martinov-Bennie, 2018). Internal auditing is an essential part of the financial reporting process and has been proven to help firms maintain effective governance. Because of this, the success of internal auditing contributes to the practice of integrated financial reporting and influences the disclosure of financial information in a more thorough manner (Muhtar et al., 2020). Internal auditing departments need to adapt to the way AI is developing and take advantage of its potential to meet the demands of a more complex company environment. Internal auditors need to be well-versed in the technology to effectively handle the advantages and difficulties presented by integrating AI into audit operations(Fedyk et al., 2022). AI affects the environment for auditing, like evidence, and audit findings. After gathering and assessing the information, auditors must draw auditing conclusions, and formulate auditing views based on their expertise, experience, and judgment (Gao & Han, 2021). Robotic Process Automation helps auditors by automating manual and repetitive rule-based tasks. The status of auditors may be improved by highlighting higher-order thinking skills and supporting them with the planning, execution, and execution of audits (Nonnenmacher et al., 2021). Internal audits can get involved in AI initiatives right away and offer guidance that helps them be implemented successfully. The management of risks regarding the dependability of the underlying algorithms and the data they are based on should be ensured by an internal audit (The Institute of Internal Auditors, 2017). Instead of concentrating on repetitive tasks, AI assists auditors in concentrating more on essential areas like forecasting and the evaluation of risk potentials, which reveal irregularities (Puthukulam et al., 2021). It is becoming more evident that the goal of IA needs to change from sample-dependent and compliance audits to audits that are more advanced, thorough, useful, systematized, capable of fixing problems, predictive, and capable of uncovering fraud (Khan et al., 2020). AI can significantly improve audit efficiency by lowering costs and facilitating the efficient handling and processing of copious amounts of data (Eulerich & Wood, 2023).

Identifying the factors that required examination makes the auditor's job of classifying trends and patterns in datasets faster than if they did it by hand. Understanding technology risks and spotting cyberattacks that could jeopardize business goals require the use of security. Implementing information security policies aids in a corporate organization's ability to promote morality and optimistic outlooks among its employees(Khalaf et al., 2023).

Because internal audit planning is flexible, it is expected that technical risks—especially cybersecurity concerns—will increase. Internal auditors are becoming more required to offer advisory services, which is changing the way they do their daily work. Therefore, as internal audit teams gradually integrate current technologies, such as data analysis tools, digital skills become increasingly valuable (Korol et al., 2022). As AI technology advances, low-level audit activities will eventually be performed by AI systems. AI will undertake many of the current tasks carried out by staff-level auditors. (Wassie & Lakatos, 2024). On the other hand, capital-oriented improved technologies have led to a decline in people-oriented activity in certain industries. There is a chance that AI-powered robots will take the place of internal auditors in the IA if they do not continue to improve their skills (Parker & Grote, 2020).

4. Hypotheses Development

Many studies have addressed the effects of using artificial intelligence on auditing, including:

Abdolmohammadi (1991) examined audit duties in AI by providing managers and audit partners with a set of tasks to perform, after obtaining instructions and definitions pertinent to each audit task. The results demonstrate varied effects of audit techniques on decision-making. The degree of difficulty of the audit tasks depends on the auditor level and specialisation, which both significantly impact. Additionally, Huang et al. (2008) examined variables from the viewpoint of internal auditors that affect the acceptance of audit procedures aided by computers. The results show that external factors, such as system quality and organisational support, have enhanced understanding of the factors impacting perceived utility and usability. Gonzalez et al. (2012) examined the motivations behind internal auditors' desire to use contemporary auditing technologies. The study discovered that expectations among internal auditors about their degree of accountability and social influence are crucial factors. Internal auditors in North America are more likely to employ modern technology when conducting their audits. The goal of Huang and Rust (2018) was to investigate how AI can take over all job functions and replace human labor entirely. where AI first replaces some of the tasks of the job. The results showed that rather than replacing at the job level, AI replacement typically occurs at the task level. The auditor would be aware of the type of AI object being used, as well as its benefits and hazards. The aim of Puthukulam et al. (2021) was to ascertain the perceptions of auditors regarding the impact of internal auditors' recommendations about AI in Oman on audit efficiency. The results found a significant positive correlation between professional judgment, professional skepticism, and AI-assisted auditing methods. It also helps to enhance the detection of errors and substantial misstatements. Albawwat and Frijat (2021) concentrated on how various AI types are seen to be beneficial, easy to use, and contribute to audit quality. The findings show that while auditors view Autonomous AI systems as difficult to use, they view Assisted and Augmented AI systems as simple to use in auditing. The study by Fedyk et al. (2022) investigated how AI affects the caliber and efficacy of audits in eight leading US public accounting firms. The findings showed that technical degrees, relative youth, and male gender predominate among AI employees, though not all of them. Within the organization, AI is a centralized function, with staff members spread across multiple teams and regions. The primary goal of using AI in audits is to improve quality, followed by enhanced efficiency. Rehman and Hashim (2022) aimed to know the impact of AI on internal audit functions in publicly traded Omani firms. The results showed that although there are still obstacles to AI adoption and use, AI can accomplish necessary tasks and act as a business's governance management system with the help of IA.

The study by Ajayi et al. (2023) investigated how Nigerian commercial banks could enhance the caliber of their internal audits with the aid of AI. According to the study's findings, commercial banks' internal audits have benefited from their usage, which has led to improvements in efficiency, accuracy, and real-time detection. Eulerich and Wood (2023) demonstrated how AI may enhance each auditing step. Internal auditors can examine the audit process and start adopting AI use cases once they have set objectives and understood the advantages and disadvantages of the IA's structure and organization. The study by Wassie and Lakatos (2024) intended to expedite internal audit operations, this article aims to display recent advancements in AI technology research. According to the report, AI can support the internal audit function of the business by enabling more value-added auditing services, eliminating manual procedures, and offering considerable strategic oversight.

Therefore, the following hypotheses are stated:

H1: *Assisted AI systems affect internal auditing in Saudi companies.*

H2: *Augmented AI systems affect internal auditing in Saudi companies.*

H3: *Autonomous AI systems affect internal auditing in Saudi companies.*

5. Methods

The study explores the impact of AI on internal auditing in Saudi companies. Data was collected by questionnaire from the study sample (internal auditors and accountants In the Emirate of Riyadh). To confirm that the study's goals were met, the descriptive analytical method was used. The questionnaire data is analyzed, and hypotheses are tested, using the Smart PLS application.

6. Results

6.1 Applying PLS-SEM

To evaluate the structural model, we employed partial least squares structural equation modelling or PLS-SEM. PLS-SEM is the suggested statistical method when the model has higher-order components (Hair et al., 2022), which adds credence to PLS-SEM's appropriateness for the current study.

Measurement model assessment

- *Construct reliability, indicator reliability, and convergent validity*

The Partial Least Squares Structural Equation Modeling (PLS-SEM) results began with an assessment of model fitness by examining factor loadings (FL). According to Hair et al. (2022), FL values above 0.7 are considered favourable. In Fig.1 and Table 1, most FL values exceeded 0.7, confirming the reliability of the study's measures.

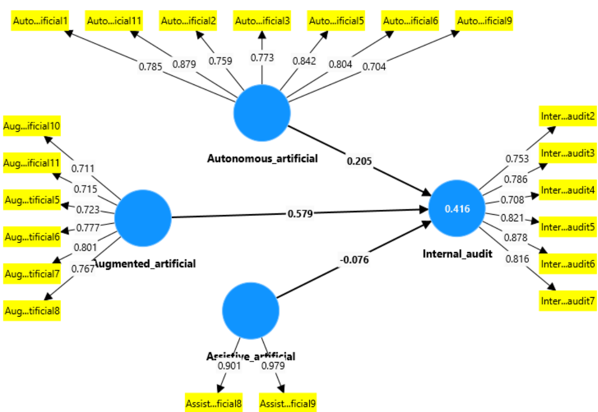

Fig. 1. The results of testing the hypotheses

The evaluated Cronbach's alpha (CA) values to guarantee internal consistency, aiming for values above 0.7. Table 1 demonstrates that every construct was higher than this cutoff. However, it is advised to assess composite reliability (CR) and rho_Alpha in addition to CA because of worries about Cronbach's alpha's underestimation. According to Hair et al. (2022), both composite reliability (CR) and rho should be greater than 0.7 for confirmatory purposes. Table 1 demonstrates acceptable values for all constructs meeting this requirement. Convergent validity also evaluates the relationship between a measure and related conceptual measures. When a construct's average variance extracted (AVE) is more than 0.5, it is said to have convergent validity.

Table 1
Construct reliability, indicator reliability, and convergent validity

	Items	Factors (FL)	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Assistive artificial	Assistive_artificial8	0.901	0.885	1.285	0.939	0.885
	Assistive_artificial9	0.979				
Augmented artificial	Augmented_artificial10	0.711	0.846	0.863	0.885	0.562
	Augmented_artificial11	0.715				
	Augmented_artificial5	0.723				
	Augmented_artificial6	0.777				
	Augmented_artificial7	0.801				
	Augmented_artificial8	0.767				
Autonomous artificial	Autonomous_artificial1	0.785	0.906	0.964	0.922	0.631
	Autonomous_artificial11	0.879				
	Autonomous_artificial2	0.759				
	Autonomous_artificial3	0.773				
	Autonomous_artificial5	0.842				
	Autonomous_artificial6	0.804				
	Autonomous_artificial9	0.704				
Internal audit	Internal_audit2	0.753	0.883	0.895	0.911	0.633
	Internal_audit3	0.786				
	Internal_audit4	0.708				
	Internal_audit5	0.821				
	Internal_audit6	0.878				
	Internal_audit7	0.816				

- ***Discriminant validity***

At the end of the measuring model, several tests were run to assess discriminant validity(DV). DV is the measure of how one latent construct varies from other latent variables. Diverse methods might be employed to verify the prerequisites of DV. The Heterotrait-Monotrait ratio (HTMT) is one such method.

Table 2
DV using the Heterotrait-monotrait ratio (HTMT)

	Assistive_artificial	Augmented_artificial	Autonomous_artificial	Internal_audit
Assistive_artificial				
Augmented_artificial	0.304			
Autonomous_artificial	0.123	0.185		
Internal_audit	0.26	0.663	0.236	

- ***Structural model assessment***

Using previously published research, the structural model's evaluation entailed a study of the connections between the various constructs (Hair et al., 2022). We specifically modelled direct impacts in the model used in our investigation. I used 5000 subsamples with bias-corrected bootstrapping to evaluate these direct effect hypotheses, yielding 95% confidence intervals. Please refer to Table 3 and Fig. 2 for more information.

- ***Hypotheses testing***

In the context of hypotheses testing, we found the following results. First, Hypothesis 1 (H1) was not supported. Specifically, Assistive Artificial did not have a positive influence on Internal audit, but this effect was not statistically significant (β = -0.076, t = 0.756, p > 0.450). The associated effect size was small (F2 = 0.009). Second, Hypothesis 2 (H2) was supported. Augmented artificial had a positive and significant influence on Internal audit (β = 0.579, t = 6.167, p < 0.000), with a large effect size (F2 = 0.525). Finally, Hypothesis 3 (H3) was also not supported. Autonomous artificial did not have a positive influence on Internal audit, but the effect was not statistically significant (β = 0.205, t = 1.261, p > 0.207), with a large effect size (F2 = 0.072).

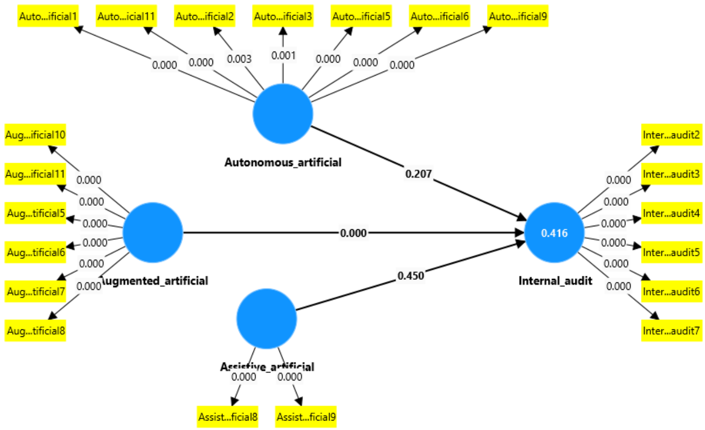

Fig. 2. The results of the process assessment

Table 3
Hypotheses testing results.

	Estimate	t	p	Status
Assistive_artificial → Internal_audit	-0.076	0.756	0.45	Not Supported
Augmented_artificial → Internal_audit	0.579	6.167	0	Supported
Autonomous_artificial → Internal_audit	0.205	1.261	0.207	Not Supported

- *Coefficient of determination*

By measuring the percentage of variance in the outcome variables that the predictors account for, the coefficient of determination (R^2) is a statistic used to evaluate a model's predictive power. R2 values were divided into three categories by Cohen (1988): small (R2 = 0.20), medium (R2 = 0.50), and big (R2 = 0.80). According to the analysis, the factors' combined effects on the internal audit outcomes (Assistive artificial, Augmented artificial, and Autonomous artificial) accounted for 41.16% of the variation (R2 = 0.416). As a result, the model showed a moderate impact size based on the R2 values (see Table 4).

Table 4
R-square

	R-square
Internal_audit	0.416

Effect size

As shown by the F2 statistic, F2 levels are categorized into three groups according to Cohen's (1988) classification: high (F2 = 0.35), moderate (F2 = 0.15), and weak (F2 = 0.02). It is clear from looking at Table 5's data that a variety of effect sizes are included in this study. As a result, we deduce that each predictor has a varied and complex effect on the variation that the result factors explain.

Table 5
Effect sizes of the latent variables.

	Internal_audit	Effect size
Assistive_artificial	0.009	Weak
Augmented_artificial	0.525	Large
Autonomous_artificial	0.072	Moderate

Path collinearity

Also known as the Variance Inflation Factor (VIF) or Common Method Bias, this study looked at VIF values to make sure they stayed below 3.3. Elevated VIF values can indicate pathological collinearity (PC) and common method bias(CMB) (Kock, 2015). The observed VIF values, as shown in Table 13, were found to be within an acceptable range, demonstrating the absence of PC and CMB in the study model. This illustrates how well the measurement and structural models performed.

Table 6
Variance Inflation Factor (VIF)

	Internal_audit
Assistive_artificial	1.095
Augmented_artificial	1.093
Autonomous_artificial	1.002

7. Discussion

Based on the previous results, the study concluded that there is a noteworthy impact for augmented AI systems, while there is a moderate effect for autonomous AI, and this effect is less for assistive AI. The literature also supports the study's findings. AI is reviewed during audit responsibilities that are pertinent to each audit duty and activity, According to Abdolmohmmadi (1991) Internal auditors in North America are more likely to employ modern technology when conducting their audits, according to (Gonzalez et al., 2012). (Huang & Rust, 2018) showed that AI replacement typically occurs at the task level. The auditor would be aware of the type of AI object being used, as well as its benefits and hazards. Puthukulam et al. (2021) discovered that using AI in conjunction with human contact is necessary to improve the quality of audits.

Additionally, Fedyk et al. (2022) found that the goal of using AI in audits is to improve quality, and then boost efficiency**.** (Rehman & Hashim, 2022) showed that although there are still obstacles to AI adoption and use, AI can accomplish necessary tasks with the help of IA. (Ajayi et al., 2023) found that commercial banks' internal audits have benefited from AI usage, which has led to improvements in efficiency, accuracy, and real-time detection. (Eulerich & Wood, 2023) found that internal auditors can examine the audit process and start adopting AI use cases once they have set objectives. (Wassie & Lakatos, 2024) found that AI can support the internal audit function of the business.
Additionally, (Albawwat & Frijat, 2021) auditor prefers Augmented AI systems due to their ease of use and expected benefit, while the impact of Autonomous AI systems is less due to the difficulty of use they expect. The results of this study differ from the current study because assisted AI systems have an important effect, which is not consistent with the current study.

8. Conclusion

This study examined how AI systems contribute to internal audits in Saudi Arabia. The results found that there is a clear positive impact of AI systems, but different impacts according to the kind of AI systems, which is high in augmented systems, moderate in autonomous systems, and weak in assistive intelligence systems. The study's main limitation is reflected in the sample 150 responses from Al Riyadh. Furthermore, use only questionnaires to collect data. Further studies on this subject can be conducted with larger sample sizes, especially if they are conducted globally. The most advantageous AI applications that internal auditors think should be created and implemented are highlighted in this study. It shows that these auditors will accept several types of AI systems to varying degrees. Also, further studies are required to explore how AI systems contribute to internal auditing. The most recent advancements in AI would require auditing educators to modify their curricula. Future advancements in auditing education would need to adopt an interdisciplinary strategy to realize these improvements.

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