HAKEMLİ Denetişim
Ortak Aklın Harmanı
Kamu İç Denetçileri Derneği Meşrutiyet Caddesi Konur Sokak No: 36/6 Kızılay - ANKARA
www.kidder.org.tr/denetisim/ • denetisim@kidder.org.tr
ISSN 1308-8335
Yıl: 15, Sayı: 2024 Ek Sayı, 117-128, 2024

Konferans Bildirisi

ARTIFICIAL INTELLIGENCE INVESTMENT, REALISTIC REPORTS AND FINANCIAL LOSS

(YAPAY ZEKA YATIRIMLARI, GERÇEKÇİ RAPORLAR VE FİNANSAL KAYIPLAR)

Korhan ARUN[1]

ABSTRACT

During audit planning, auditors examine the business of their firms. Still, the target is to minimize the discrepancy in the real planned financial statement of inspection and summary reports of internal audits. On the other hand, expenditures on artificial intelligence have been increasing in Turkish firms; according to the National Artificial Strategy document, AI will be part of every organizational process, including internal audits. Moreover, the literature supports a positive relationship between internal audits and firms' decreasing capital loss. So, this research aims to analyze the relationship between AI expenditures, internal audit reports, and the firms' historical loss. To reach this aim, suitable data was analyzed from 732 incorporated companies that are members of the Chamber of Trade and Industry/Tekirdag/Turkey. Structural equation modeling results show that AI investments decrease the discrepancy between financial statements and internal audit reports (β=-0.045). On the other hand, discrepancies found in the internal audit reports compared to real financial statements are increasing firms' financial losses by almost 10% (β=.118). In other words, investing in AI contributes to more realistic financial reports, resulting in fewer financial losses. From this perspective, this study is one of the leading studies that connects AI investment to internal audits and the financial performance of Turkish firms.

Keywords: Internal Audit, Artificial Intelligence, Audit Reports, Firm Loss, Discrepancy in Reports.
JEL Classification: M40, M42, C31, A10

ÖZ

Denetim planlaması sırasında denetçiler görev aldıkları firmaların işlerini incelerler ve denetler. Yine de hedef, denetimin gerçek planlanan mali tabloları ile iç denetimlerin özet raporları arasındaki tutarsızlığı en aza indirmektir. Öte yandan Türk firmalarında yapay zekâ harcamaları Ulusal Yapay Strateji belgesine göre arttığından, yapay zekâ, iç denetim faaliyetleri de dahil her organizasyonel sürecin bir parçası haline gelmesi beklenmektedir. Ayrıca bilim yazın, iç denetim ile firmaların sermaye kayıplarının azalması arasında pozitif bir ilişki olduğunu desteklemektedir. Bu nedenle bu araştırma, yapay zekâ harcamaları, iç denetim raporları ve firmaların finansal kayıpları arasındaki ilişkiyi analiz etmeyi amaçlamaktadır. Bu amaca ulaşmak için Ticaret ve Sanayi Odası/Tekirdağ/Türkiye'ye üye 732 anonim şirketten elde edilen veriler incelenmiş ve uygun olanları analiz edilmiştir. Yapısal eşitlik modellemesi sonuçları, yapay zekâ yatırımlarının mali tablolar ile iç denetim raporları arasındaki farkı azalttığını göstermektedir (β=-0,045). Öte yandan iç denetim raporlarında gerçek mali tablolarla karşılaştırıldığında ortaya çıkan farklılıklar, daha açık bir ifadeyle mali tablolar ile iç denetim raporları arasındaki artan farklılıklar, firmaların mali kayıplarını neredeyse %10 (β=0,118) oranında artırmaktadır. Başka bir deyişle, yapay zekaya yatırım yapmak daha gerçekçi finansal raporlara katkıda bulunarak daha az finansal kayıpla sonuçlanır. Bu açıdan bakıldığında bu çalışma, yapay zekâ yatırımını iç denetimlere ve Türk firmalarının finansal performansına bağlayan önde gelen çalışmalardan biridir.

Anahtar Kelimeler: *İç Denetim, Yapay Zekâ, Denetim Raporları, Firma Zararı, Raporlarda Farklılık.*

JEL Kodlamaları: *M40,M42, C31, A10*

[1] Assoc.Prof. Dr., Tekirdağ Namik Kemal University, OrcID: 0000-0001-7494-9591, karun@nku.edu.tr

1. INTRODUCTION

Strengthening the authority of internal auditors can help reduce state financial losses, though they lack the legal power to definitively determine such losses (Amiq et al., 2024). Artificial Intelligence (AI) is transforming internal auditing, offering enhanced efficiency and effectiveness opportunities. The adoption of AI in internal auditing is expected to reduce manual procedures, enable more comprehensive data analysis, and support value-added auditing services (Wassie & Lakatos, 2024). However, it is unclear whether investment in AI will increase the quality of internal audit reports. So, this research analyzes the relationship between AI, the quality of internal audit reports, and the financial loss of the organizations.

The impact of information technology on audit quality has been demonstrated in studies such as the work by Deribe and Regasa (2014). Furthermore, recent research by Collins Kindzeka (2023) highlighted the positive influence of AI applications on accounting, auditing, and financial reporting. These findings emphasize the significant and far-reaching effects of AI in these crucial areas. Additionally, the adoption of AI in internal auditing is expected to streamline manual processes, facilitate more extensive data analysis, and enhance the delivery of value-added auditing services, as discussed by recent research (Wassie & Lakatos, 2024). It's important to recognize that the integration of AI into internal audit functions may also pose challenges, such as the demand for new skills and competencies among auditors, as studied by Kahyaoglu and Aksoy (2021) and Meira (2019). While AI has the potential to automate certain routine tasks, it's unlikely to entirely replace human auditors, who will instead need to adapt to new roles and responsibilities (Almufadda & Almezeini, 2022). The financial consequences of implementing AI within organizations are significant and require careful consideration to ensure successful deployment and realization of benefits. Companies that choose to adopt AI technologies must allocate substantial financial resources to support the implementation and seamless integration of these technologies (Jöhnk et al., 2021). Therefore, organizations must consider investing in AI to elevate the quality of their internal audit reports.

There are some negative aspects of using AI in internal auditing even if current academic research underscores both the potential benefits and challenges associated with the integration of artificial intelligence (AI) in the field of auditing. AI holds promise in enhancing audit efficiency, effectiveness, and quality through automating routine tasks, analyzing extensive datasets, and detecting irregularities (Hoffman et al., 2007; Seethamraju & Hecimovic, 2020; Wassie & Lakatos, 2024). However, the implementation of AI faces barriers such as regulatory constraints, data quality issues, and the demand for new skills (Ganapathy, 2023). Although the adoption of AI in internal auditing is deemed inevitable (Meira, 2019), it gives rise to concerns about job displacement and the evolving roles of auditors (Almufadda & Almezeini, 2022). Interestingly, conflicting findings exist, with one study suggesting a positive correlation between AI integration and a reduction in audit quality (Ramzan, 2023). Furthermore, auditors may exhibit "algorithm aversion" potentially limiting the effectiveness of AI in complex estimate evaluations (Commerford et al., 2020). These findings underscore the necessity of carefully assessing the impact of AI on the auditing profession.

There are three main contributions of this paper to the literature. Firstly, this paper addresses the potential argument that investing in AI might not necessarily increase the quality of internal audit reports, despite the enhanced efficiency and comprehensive data analysis capabilities it offers. Secondly, integrating AI into internal audit functions could lead to biases and errors in the analysis of financial data, thereby impacting the quality of internal audit reports by increasing the real financial losses of the organizations. Lastly, there may be a possibility that the demand for new skills and competencies among auditors due to the integration of AI may also hinder the quality of internal audit reports in the short term. So, AI investment can be unfit for the Turkish organizations for the internal audition.

2. HYPOTHESIS DEVELOPMENT

The incorporation of AI into audit processes and departments has revolutionized investment strategies, risk assessment, fraud detection, customer service, and regulatory compliance (Khan, 2024). Nevertheless, this integration necessitates considerable financial investments for development and implementation within financial services. Despite the substantial benefits offered by AI, organizations must adeptly handle the financial implications of its adoption to ensure enduring performance. In industries like healthcare, the integration of AI-driven Accounting Information Systems (AIS) has proven to greatly enhance the precision of financial reporting by reducing errors (Kimani, 2024). Although the initial investment in AIS automation may present a financial challenge, the long-term benefits more than outweigh the costs linked to embracing AI technology.

As artificial intelligence (AI) continues to advance, it's crucial for internal auditors to grasp its underlying principles, anticipate potential risks and opportunities, and adapt to the changing landscape of the profession (Alina et al., 2018). Research suggests that integrating AI into auditing processes can improve the reliability and quality of reporting, ultimately fostering greater trust among stakeholders in audit results (Vuković et al., 2024). Furthermore, the utilization of AI in audit procedures has the potential to enhance audit evidence, narrow the audit expectation gap, and potentially redefine the objective of audits, highlighting the positive impact of AI on audit quality (Mpofu, 2023). Additionally, the combination of AI with data analyses for financial statement items and fraud detection can significantly bolster audit quality by reducing costs and elevating the caliber of audit work (Mirzaei et al., 2022).

The integration of AI not only enhances the efficiency and effectiveness of audits but also streamlines fraud detection, contributing to increased accuracy and improved audit quality (Ikhsan et al., 2022). The incorporation of AI technologies in internal audit functions leads to optimized internal quality audits, yielding improved processes and outcomes (Buaton et al., 2022). Additionally, AI applications have a positive impact on accounting, auditing, and financial reporting, highlighting the significant influence of AI in these critical areas (Collins Kindzeka, 2023) (Kindzeka, 2023).

Understanding the impact of AI on the disparity between internal audit findings and actual financial reports requires acknowledging the crucial role of internal audit in upholding the accuracy and reliability of financial statements. Previous studies have highlighted the positive relationship between internal audits and the quality of financial statements, emphasizing the importance of internal audit functions in maintaining the credibility of financial reporting (Yusup & Juhara, 2020). Internal audits play a significant role in detecting errors, preventing fraud, and providing reliable accounting information for decision-making (Alwadie, 2024). The integration of AI technologies in auditing processes has the potential to enhance the quality and reliability of financial reports by automating tasks, improving efficiency, and offering advanced data analytics capabilities (Rodrigues et al., 2023). Through cognitive auditing processes, AI can assist auditors in identifying errors and issues in financial reports, thus reducing discrepancies and improving the accuracy of financial information (Dagunduro, et al., 2023).

Although AI adoption presents opportunities for enhancing financial performance, organizations should thoroughly assess the financial implications. It is crucial to engage in strategic planning, allocate resources wisely, and consider long-term benefits to navigate AI adoption effectively and secure sustainable financial results. However, the role of internal audit in upholding the precision and dependability of financial statements are positively correlated as discussed above.

H1: AI will decrease the gap between internal audits and real financial reports. The role of Internal Audit is of significant importance in shaping financial reporting processes and ensuring timely audits (Pizzini et al., 2015). The quality of the internal audit function is vital for upholding the reliability of financial reporting and preventing financial losses (Oladejo et al., 2021). Internal audit acts as a strong internal control mechanism that elevates the overall quality of financial reporting (Oladejo et al., 2021). Moreover, the impartiality of internal audit activities can cultivate collaboration between internal and external audits, leading to an improvement in the quality of financial reporting (Azzam et al., 2020).

Research findings reveal a direct correlation between internal audits and the accuracy of financial statements (Yusup & Juhara, 2020). The quality of internal audits positively influences the reliability of financial reports, demonstrating that a higher standard of internal audit improves financial statements (Sari et al., 2024). Furthermore, the internal audit function notably affects external audit fees, underscoring its importance in the financial reporting process (Felix, Jr. et al., 2001).

The relationship between internal audit and real financial reports is crucial for ensuring accurate and reliable financial information. A high-quality internal audit function can improve financial reporting, minimize risks, and support decision-making. However, some studies revealed complexities in these relationships, such as the mediating effect of internal audit committees on real earnings management (Ibrahim et al., 2020) and the potential substitution relationship between board quality and internal audit quality (Johl et al., 2013). So, it is important to analyze the effects of the gaps between internal audit quality and real financial reports quality on financial losses.

H2: Discrepancies (gaps) between internal audits and real financial reporting will increase financial losses. In other words, more gaps between internal audits and real financial reporting will increase financial losses.

3. METHODOLOGY

3.1 Sample and Data

The Tekirdağ region in Turkey is home to a diverse range of industries that make significant contributions to the local economy. Agriculture is a key sector, focusing on producing essential crops such as wheat and sunflower for human and animal consumption *(Badem, 2024)*. The agricultural industry plays a crucial role in the region's economy, emphasizing the importance of farming activities in Tekirdağ. Furthermore, tourism is an important economic driver in Tekirdağ, attracting visitors to explore the region's cultural and natural attractions. Businesses in this sector manage long-term bank credit, accounts receivable, and balancing liabilities to ensure sustainable growth and financial stability. The telecommunications sector in Tekirdağ also plays a vital role in providing communication services to residents and businesses in the region. Moreover, the manufacturing sector in the region, particularly industries like steel truss construction, contributes to the production and employment landscape of Tekirdağ *(Tüfekci et al., 2020)*. In summary, the industries in the Tekirdağ region of Turkey encompass agriculture, construction, tourism, forestry products, telecommunications, manufacturing, and more, playing a crucial role in driving economic growth, creating employment opportunities, and contributing to the overall development of Tekirdağ, showcasing the diverse industrial landscape of the region.

In the province of Tekirdağ, a total of 11,579 commercial enterprises are currently in operation. Among these, there are 1,384 stock joint companies, 4,895 limited companies, 69 collective companies, 4 economic enterprises, and 5,227 private enterprises. A survey was conducted specifically targeting the owners or top managers of stock joint companies whose contact information is listed in the database of the Tekirdağ Chamber of Commerce and Industries (1232). Although 732 surveys were distributed, only 187 were deemed suitable for analysis. This was primarily due to the lack of AI investment in many companies, while others were excluded because they did not undergo official internal audits.

Table 1. Sample Characteristics (N=187)

Firm Size	<100 employees	38
	100–249 employees	42
	250–499 employees	61
	500–999 employees	27
	1000–4999 employees	17
	≥5000 employees	2
Tenure of the respondent in the organization (years)		
	<1	17
	2–5	62
	6–10	91
	≥10	17

The comprehensive data presented in Table 1 provides invaluable insights into the diverse characteristics of the participating firms and the extensive experience levels of the survey respondents. An analysis of the distribution of firm sizes reveals a prevalent presence of medium-sized firms, which may serve as fertile ground for fostering intrapreneurial endeavors. Furthermore, the tenure data uncovers a noteworthy representation of employees with varying degrees of substantial experience, indicating that the gathered insights likely offer a nuanced and well-rounded comprehension of the organizational landscape.

The questionnaire consisted of four questions about financial statements, AI investments, and financial losses. The first question is «Does your company have AI investments or a budget for AI? The second question is «Has your company ever had an internal audit in the last three years? » The third question is «Has your company faced financial losses for at least three years? The fourth question is «Have the discrepancies between internal audit reports and real financial statements been increasing? ». Ordinally measuring attitudes or opinions using Likert scales, which range from "strongly disagree" to "strongly agree," yields data that can be analyzed through SEM (structural equation modeling) as long as specific conditions are satisfied (Brown & Maydeu-Olivares, 2011). So, in this research, the answers were collected on five-point Likert scale (1: strongly disagree, 3: neither agree nor disagree, 5: strongly agree).

Table 2. Mean, STDEV, T values, p values

Variables	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Adjusted corporate investment_to Artificial Intelligence -> Discrepancy found in the _internal audit report	-0.045	-0.048	0.020	2.274	0.023
Discrepancy found in the _internal audit report -> Historical Loss	0.118	0.133	0.058	2.037	0.042

According to Table 2, for the adjusted corporate investment to Artificial Intelligence reflecting a discrepancy found in the internal audit report, the original sample was -0.045, and the sample mean stood at -0.048, with a standard deviation of 0.020. The T statistics calculated was 2.274, leading to a p-value of 0.023. In the case of the discrepancy found in the internal audit report leading to historical loss, the original sample was 0.118, with a sample mean of 0.133, and a standard deviation of 0.058. This resulted in T statistics of 2.037 and a p-value of 0.042.

Table 3. Correlations

	(1)	**(2)**	**(3)**
(1) Adjusted corporate investment_to Artificial Intelligence	1	-0.045	-0.004
(2) Discrepancy found in the _internal audit report		1	0.118
(3) Historical Loss			1

The correlation analysis in Table 3 reveals the relationships among three variables: adjusted corporate investment in artificial intelligence, discrepancies in internal audit reports, and historical loss. The first variable, adjusted corporate investment in artificial intelligence, shows a correlation of 1 with itself, indicating a perfect correlation. When examining its correlation with discrepancies found in internal audit reports, a slight negative correlation of -0.045 is observed, suggesting that as corporate investment in artificial intelligence increases, discrepancies in internal audits may slightly decrease, although this relationship is weak. Furthermore, the correlation between adjusted corporate investment in artificial intelligence and historical loss is negligible, with a value of -0.004, indicating no significant relationship between these two variables.

The discrepancies revealed in internal audit reports show a perfect correlation of 1 with themselves, indicating a consistent pattern. Furthermore, there is a weak positive correlation of 0.118 between discrepancies in internal audit reports and historical loss, suggesting a tendency for higher discrepancies in audit reports to be linked to greater historical losses. Overall, the correlations suggest that while there are some connections among the variables, especially between discrepancies in internal audits and historical loss, the relationships involving adjusted corporate investment in artificial intelligence are minimal. This analysis provides insights into how these variables interact, although the weak correlations suggest that further investigation may be necessary to understand the underlying dynamics fully.

3.2 Model Fit

The comparison between the saturated and estimated models is summarized using several statistical metrics, including the Standardized Root Mean Square Residual (SRMR), d_ULS, d_G, Chi-square, and Normed Fit Index (NFI). The d_ULS (Squared Euclidean Distance) measures the difference between the empirical and model covariance matrices. A lower d_ULS value indicates a better fit, compared to a confidence interval. Similarly, d_G (Geodesic Distance) serves the same purpose using a different calculation method. Both are evaluated against a confidence interval to determine model fit (Vojvodic & Hitz, 2022; Wu et al., 2023).

Both the saturated and estimated models exhibit an SRMR of 0.000, indicating a perfect fit in terms of residuals. The d_ULS statistic is also 0.000 for both models, suggesting no discrepancies in the unweighted least squares distance. Similarly, the d_G statistic, which measures the goodness of fit, is 0.000 for both models, reinforcing the notion of an ideal fit. Regarding the Chi-square statistic, the saturated model shows a value of 0.000, while the estimated model has a Chi-square value of 0.001. Although the Chi-square for the estimated model is slightly above zero, it remains very close to a perfect fit, indicating that the model does not significantly deviate from the observed data. Lastly, the Normed Fit Index (NFI) is reported as 1.000 for both models, indicating a perfect fit relative to the null model.

This analysis suggests that both the saturated and estimated models fit the data exceptionally well. In summary, the metrics indicate that both models demonstrate excellent fit characteristics, with all relevant statistics suggesting minimal discrepancies and a high level of alignment with the observed data (Byrne, 2010; Hu & Bentler, 1999; Kline, 2016).

3.3 Hypotheses Testing

Structural Equation Modeling (SEM) is a statistical technique widely used in social science research for developing and testing complex theoretical models (Al-Baity, 2023). SEM allows researchers to explore relationships between latent and observed variables effectively (Hair, 2017). In social research, SEM has been instrumental in investigating various phenomena such as predictors of entrepreneurial intentions, impact of social activities, and determinants of pro-environmental behavior intentions (Jambol et al., 2024). By utilizing SEM, researchers can develop comprehensive models integrating theoretical constructs, empirical data, and practical implications, leading to a deeper understanding of social dynamics and behaviors (Olabanji et al., 2024). Consequently, SEM is used to analyze the data in this research.

Structural Equation Modeling (SEM) is a strong statistical method used for hypothesis testing in various research situations. It helps researchers understand complex relationships among observed and hidden variables, providing a comprehensive framework for testing theoretical models. SEM combines factor analysis and multiple regression analysis, allowing for the simultaneous examination of multiple dependent relationships.

R-Square and R-Square Adjusted are also analyzed. In the given data context, we can examine the R-square and adjusted R-square values for two variables: discrepancies found in internal audit reports and historical loss.

Discrepancy Found in Internal Audit Reports:

- The R-square value is 0.002, indicating that only 0.2% of the variance in discrepancies found in internal audit reports can be explained by the independent variables in the model, suggesting a very weak explanatory power.

- The adjusted R-square is 0.001, accounting for the number of predictors in the model. The adjusted value is slightly lower than the R-square suggesting that the inclusion of additional predictors does not substantially improve the model's explanatory power.

Historical Loss:

- The R-square value for historical loss is 0.014, meaning that 1.4% of the variance in historical loss can be explained by the independent variables in the model, indicating a low level of explanatory power.

- The adjusted R-square is 0.013, again showing a minimal increase in explanatory power when accounting for the number of predictors.

The low R-square values suggest that the models may not effectively capture the relationships of interest. However, SEM remains valuable for hypothesis testing, allowing researchers to test specific hypotheses about variable relationships and assess the significance of individual paths within the model. Researchers can enhance their models by incorporating or removing variables based on theoretical considerations or empirical evidence.

In this study, Structural Equation Modeling (SEM) was conducted using the free version of SmartPLS.. SmartPLS is a valuable tool for social science research for multiple reasons. To start, it is particularly advantageous for simultaneously analyzing multiple regression equations, which makes it perfect for examining intricate relationships between variables in social science studies (Mukhsin & Suryanto, 2022). This capability enables researchers to effectively explore complex relationships and dependencies within their models. Additionally, SmartPLS is well-suited for conducting Structural Equation Modeling (SEM), a statistical method frequently utilized in social science research to analyze complex relationships between latent and observed variables (Siddiqi et al., 2020). Through the use of SmartPLS for SEM analysis, researchers can evaluate the direct and indirect effects of variables, test theoretical models, and assess the overall fit of their models.

Table 4. Path Coefficients

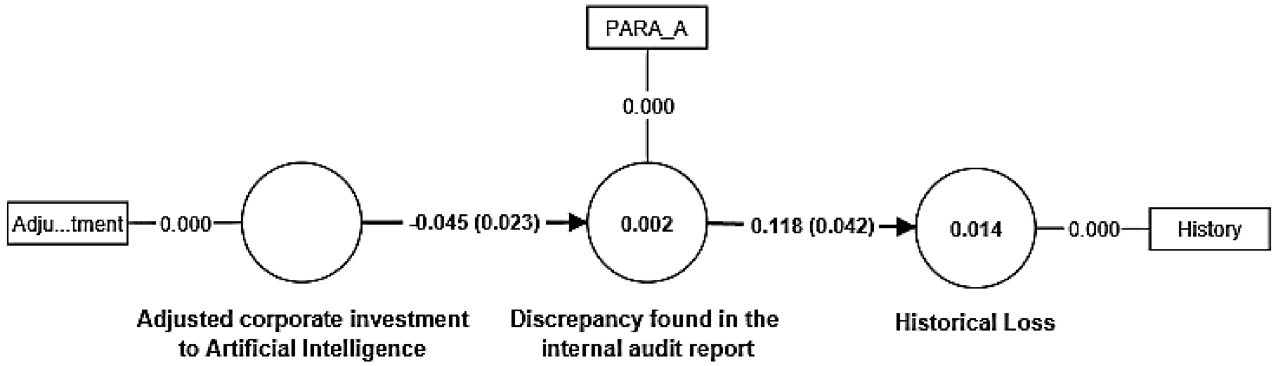
Variables (Nomenclature)	Discrepancy found in the internal audit report	Historical financial Loss
Adjusted corporate investment in Artificial Intelligence	-0.045	-0.005
Discrepancy found in the _internal audit report		0.118

The results from Table 4 reveal that the path coefficients show a statistically significant relationship between discrepancies in internal audit reports and an increase in the financial historical loss of the organizations (β=.0.118). The data also indicates that for every one-unit investment in Artificial Intelligence (AI), there was a 0.045-point decrease in discrepancies within the internal audit reports. Therefore, we have strong support for both Hypotheses 1 and 2.

Furthermore, the analysis shows that the adjusted corporate investment in AI is linked to a reduction of 0.045 in the discrepancies found in the internal audit report and real financial reports, along with a further decrease of 0.005 in historical financial loss. In essence, the path analysis results demonstrate that investment in AI has the potential to reduce discrepancies in internal audit reports by 0.045% (supporting H1), but may also lead to a 0.005% increase in financial loss. These findings support the notion that while investment in AI requires organizational capital, the benefits outweigh the negative effects.

These results support the research that found the critical role of the internal audit function in ensuring the quality of financial reporting by monitoring risks, evaluating internal controls, and detecting potential manipulations in financial procedures (Gebrayel et al., 2018). This emphasizes the significance of aligning internal audit discoveries with real financial reports to minimize financial risks and losses. Setyahuni et al. (2022) have highlighted internal audit quality as a key factor in determining financial reporting quality. Effective internal audit practices, combined with strong corporate governance frameworks, are essential for upholding the credibility of financial reporting. Discrepancies between internal audit assessments and financial reports may erode trust in the organization's financial disclosures, potentially causing financial losses due to reduced investor confidence and heightened regulatory oversight is crucial to ensure alignment between internal audit reports and actual financial reports to mitigate financial risks and prevent potential losses in organizations. Consistency and accuracy between internal audit findings and financial disclosures are vital for maintaining transparency, reliability, and compliance with regulatory standards. Any discrepancies between internal audit assessments and actual financial outcomes could lead to financial losses, reputational damage, and legal implications, highlighting the importance of robust internal audit practices in safeguarding organizational finances.

Figure 1. Model and Path Analysis Results



In Figure 1, the paths of the research model and coefficients between the variables are visually depicted. The numbers enclosed within the circles serve to indicate the adjusted R-squared values, which provide a measure of how well the independent variables explain the variability of the dependent variable. The R2 adjusted value of 0.002 pertaining to the discrepancies identified in the internal audit report variable suggests that a mere 0.002 percent of the discrepancies can be attributed to the utilization of AI. This indicates a very low level of association between the use of AI and the discrepancies identified in the internal audit report.

Artificial intelligence (AI) has been increasingly integrated into auditing processes, offering various benefits. These include improved sampling procedures, reduced labor and time in audits, and increased efficiency, and effectiveness leading to enhanced audit quality (Mpofu, 2023). It has been noted that AI can be valuable in evaluating data quality within internal audit functions (Wassie & Lakatos, 2024). The results of this study support the article that found the use of cognitive auditing, which involves AI technology, can help auditors detect errors and discrepancies in financial reports (Noordin et al., 2022). Additionally, AI systems support continuous auditing, offering tools to effectively evaluate AI systems for internal audit functions (Lidiana, 2024).

AI techniques like machine learning and natural language processing have proven effective in detecting accounting fraud (Iman Supriadi, 2024). However, in the literature, it has not been stated that the gap between the internal audit reports and real financial documents is rooted in fraud. So, the fraud practices can be separated from the errors of the internal audit or financial reports. Studies have shown that the application of AI in auditing processes enhances effectiveness, efficiency, and cost benefits (Al- Dahabi et al., 2024). The integration of AI, machine learning, and data analytics reshapes the audit landscape, empowering auditors with tools to improve efficiency and accuracy (Ebirim et al., 2024).

Investments in AI tools have been found to reduce costs for customers, increase productivity, and decrease the workforce in external public audit settings (Lazăr Pleşa et al., 2023). Internal audit and risk assessment are crucial for early risk detection in complex business processes, especially with increasing digitalization (Kahyaoglu & Aksoy, 2021). The adoption of data analytics, blockchain, and AI in various industries promises a paradigm shift in the internal auditing profession (Nwachukwu et al., 2021). AI collaborates with internal control systems to enhance the reliability of accounting information by reducing information risk (Askary et al., 2018).

4. CONCLUSIONS AND RECOMMENDATIONS

The integration of artificial intelligence (AI) into auditing processes can significantly enhance the effectiveness, efficiency, and quality of audits. AI technologies, including machine learning and natural language processing, have been instrumental in improving sampling procedures, detecting accounting fraud, and enabling continuous and cognitive auditing. Additionally, these advancements assist in internal audit functions and risk assessment, and ensure the reliability of accounting information, marking a transformative shift in the auditing and accounting landscape. The Tekirdağ region in Turkey has a diverse industrial landscape that significantly contributes to the area's economy. Major sectors include agriculture, construction, tourism, forestry products, telecommunications, and manufacturing. These industries drive economic growth, create employment opportunities, and contribute to the overall development of Tekirdağ. As a result, data was collected from the Tekirdag region.

This paper discusses the impact of Artificial Intelligence (AI) on the field of internal auditing, positing that AI has the potential to enhance the efficiency and effectiveness of auditing processes. It is suggested that by incorporating AI, internal auditors can reduce manual tasks, conduct more thorough data analyses, and provide more valuable audit services, which could potentially lead to a decrease in the financial losses organizations face. However, there's also an acknowledgment of the ambiguity regarding whether investing in AI technology directly improves the quality of internal audit reports. Results show the transformative role of AI in accounting and auditing and its contribution to improved audit quality by reducing discrepancies between internal audits and real financial reports. Nonetheless, the integration of AI in this field is not without challenges, including the need for investment. Thus, the financial implications of AI implementations for organizations are highlighted, underlining the slight burden on organizational capital and finance.

The analysis suggests that investing in AI can slightly reduce internal audit report discrepancies by 0.045% but might also result in a marginal increase in financial loss by 0.005%. Furthermore, there's a noted positive correlation of 0.118 between another type of discrepancy in internal audit reports and historical financial losses.

This paper does not focus on the direct capital investment required for organizations to invest in AI. Instead, it identifies the organizational readiness factors essential for successful AI implementation.

Investing in artificial intelligence (AI) for organizations requires a substantial financial commitment, involving expenses for infrastructure, hardware, and software (Al-Baity, 2023). This financial commitment may present challenges, especially for smaller institutions that might find such investments to be prohibitively expensive. The incorporation of AI technologies in various sectors, such as finance, calls for significant financial resources to facilitate the implementation and maintenance of AI systems (Lu et al., 2024). Furthermore, the development and maintenance of AI models necessitate specialized skills in data science, machine learning, and AI, thereby underscoring the financial investment required (Jambol, 2024).

In the realm of small and medium-sized enterprises (SMEs), the adoption of artificial intelligence (AI) to enhance competitiveness and drive growth requires overcoming financial barriers (Kabakci & Ince, 2023; Peretz-Andersson et al., 2024). SMEs seeking to unleash the transformative potential of AI must navigate financial constraints alongside other obstacles. The financial considerations associated with establishing and operating AI labs underscore the significant influence of financial factors on AI implementation (Hergan, 2022). Organizations must allocate resources efficiently to support the infrastructure, attract talent, and sustain AI initiatives. However, in Turkish business organizations, AI is primarily used as an auxiliary tool, with businesses still hesitant to fully rely on it (Karaboga & Vardarlier, 2020).

In a nutshell, this text emphasizes the significant impact of artificial intelligence (AI) on auditing and accounting practices, particularly in enhancing their efficiency and quality. AI technologies like machine learning and natural language processing improve sampling, detect fraud, and support continuous and cognitive auditing, thus revolutionizing the field. In the context of Tekirdağ, Turkey, the diverse industrial landscape including agriculture, construction, tourism, and manufacturing, serves as a backdrop for discussing AI's role in internal audits, risk assessment, and ensuring reliable accounting information. The paper argues that AI can reduce manual tasks and enhance data analysis in audits, potentially mitigating financial losses but also notes the financial challenges of adopting AI. Investment in AI technologies require considerable financial resources, particularly for infrastructure and talent, which might be challenging for smaller enterprises. Despite these hurdles, AI's transformative potential for improving audit quality and reducing discrepancies in financial reporting is acknowledged, alongside the necessity for organizational readiness and financial commitment for successful AI implementation.

5. REFERENCES

Al-Baity, H. H. (2023). The Artificial Intelligence Revolution in Digital Finance in Saudi Arabia: A Comprehensive Review and Proposed Framework. *Sustainability*, *15*(18), 13725. https://doi.org/10.3390/su151813725

Alina, C. M., Cerasela, S. E., & Gabriela, G. (2018). Internal Audit Role in Artificial Intelligence. *Ovidius University Annals: Economic Sciences Series*, *XVIII*(1), 441–445.

Almufadda, G., & Almezeini, N. A. (2022). Artificial Intelligence Applications in the Auditing Profession: A Literature Review. *Journal of Emerging Technologies in Accounting*, *19*(2), 29–42. https://doi.org/10.2308/JETA-2020-083

Alwadie, A. (2024). Impact of Technology on Auditing: Evidence in Developing Countries. *International Journal for Scientific Research*, *3*(2), 29–48. https://doi.org/10.59992/IJSR.2024.v3n2p2

Amiq, B., Prawesthi, W., Taufik, M., Widodo, H., Seti, S., & Aranggraeni, R. (2024). Increasing Internal Auditor Accountability in Law of State Financial Management. *Journal of Law and Sustainable Development*, *12*(1), e2877. https://doi.org/10.55908/sdgs.v12i1.2877

Askary, S., Abu-Ghazaleh, N., & Tahat, Y. A. (2018). Artificial Intelligence and Reliability of Accounting Information. In S. A. Al-Sharhan, A. C. Simintiras, Y. K. Dwivedi, M. Janssen, M. Mäntymäki, L. Tahat, I. Moughrabi, T. M. Ali, & N. P. Rana (Eds.), *Challenges and Opportunities in the Digital Era* (Vol. 11195, pp. 315–324). Springer International Publishing. https://doi.org/10.1007/978-3-030-02131-3_28

Azzam, M. J., Alrabba, H. M., AlQudah, A. M., & Mansur, H. M. A. (2020). A study on the relationship between internal and external audits on financial reporting quality ,. *Management Science Letters*, 937–942. https://doi.org/10.5267/j.msl.2019.10.001

Badem, M. (2024). Agricultural Structure of Tekirdağ Province and Evaluation of Agricultural Supports. *International Journal of Innovative Approaches in Agricultural Research*, *8*(1), 45–61. https://doi.org/10.29329/ijiaar.2024.656.5

Brown, A., & Maydeu-Olivares, A. (2011). Item Response Modeling of Forced-Choice Questionnaires. *Educational and Psychological Measurement*, *71*(3), 460–502. https://doi.org/10.1177/0013164410375112

Buaton, R., Muhammad, Z., Elviwani, & Dilham, A. (2022). Optimization of Higher Education Internal Quality Audits Based on Artificial Intelligence. *Journal of Artificial Intelligence and Engineering Applications (JAIEA)*, *1*(2), 158–161. https://doi.org/10.59934/jaiea.v1i2.83

Byrne, B. M. (2010). *Structural Equation Modeling with AMOS Basic Concepts, Applications, and Programming*. Routledge.

Collins Kindzeka, K. (2023). Impact of Artificial Intelligence on Accounting, Auditing and Financial Reporting. *American Journal of Computing and Engineering*, *6*(1), 29–34. https://doi.org/10.47672/ajce.1433

Commerford, B. P., Dennis, S. A., Joe, J. R., & Wang, J. (2020). Man Versus Machine: Complex Estimates and Auditor Reliance on Artificial Intelligence. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3422591

Dagunduro, M. E., Falana, G. A., Adewara, Y. M., & Busayo, T. O. (2023). Application of Artificial Intelligence and Audit Quality in Nigeria. *Advances in Multidisciplinary and Scientific Research Journal Publication*, *11*(1), 39–56. https://doi.org/10.22624/AIMS/HUMANITIES/V11N1P4

Dazok Donald Jambol, Oludayo Olatoye Sofoluwe, Ayemere Ukato, & Obinna Joshua Ochulor. (2024). Transforming equipment management in oil and gas with AI-Driven predictive maintenance. *Computer Science & IT Research Journal*, *5*(5), 1090–1112. https://doi.org/10.51594/csitrj.v5i5.1117

Deribe, W. J., & Regasa, D. G. (2014). Factors Determining Internal Audit Quality: Empirical Evidence from Ethiopian Commercial Banks. *Research Journal of Finance and Accounting*, *5*, 86–94.

Felix, Jr., W. L., Gramling, A. A., & Maletta, M. J. (2001). The Contribution of Internal Audit as a Determinant of External Audit Fees and Factors Influencing This Contribution. *Journal of Accounting Research*, *39*(3), 513–534. https://doi.org/10.1111/1475-679X.00026

Ganapathy, V. (2023). AI in Auditing: A Comprehensive Review of Applications, Benefits and Challenges. *Shodh Sari-An International Multidisciplinary Journal*, *02*(04), 328–343. https://doi.org/10.59231/SARI7643

Gebrayel, E., Jarrar, H., Salloum, C., & Lefebvre, Q. (2018). Effective association between audit committees and the internal audit function and its impact on financial reporting quality: Empirical evidence from Omani listed firms. *International Journal of Auditing*, *22*(2), 197–213. https://doi.org/10.1111/ijau.12113

Glory Ugochi Ebirim, Beryl Odonkor, Ese Eigbadon Oshioste, Kehinde Feranmi Awonuga, Nduniuisi Leonard Ndubuisi, & Odunayo Adewunmi Adelekan. (2024). Evolving trends in corporate auditing: A systematic review of practices and regulations in the United States. *World Journal of Advanced Research and Reviews*, *21*(1), 2250–2262. https://doi.org/10.30574/wjarr.2024.21.1.0312

Hair, J. F. (Ed.). (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (Second edition). Sage.

Hergan, K. (2022). Challenges implementing and running an AI-Lab: Experience and Literature Review. *Biomedical Journal of Scientific & Technical Research*, *45*(4). https://doi.org/10.26717/BJSTR.2022.45.007222

Hoffman, B. J., Blair, C. A., Meriac, J. P., & Woehr, D. J. (2007). Expanding the criterion domain? A quantitative review of the OCB literature. *Journal of Applied Psychology*, *92*(2), 555–566. https://doi.org/10/cvdk6n

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10/dbt

Ibrahim, G., Mansor, N., & Ahmad, A. U. (2020). The Mediating Effect Of Internal Audit Committee On The Relationship Between Firms Financial Audits And Real Earnings Management. *International Journal of Scientific & Technology Research*, *9*, 816–822.

Ikhsan, W. M., Ednoer, E. H., Kridantika, W. S., & Firmansyah, A. (2022). FRAUD DETECTION AUTOMATION THROUGH DATA ANALYTICS AND ARTIFICIAL INTELLIGENCE. *Riset*, *4*(2), 103–119. https://doi.org/10.37641/riset.v4i2.166

Iman Supriadi. (2024). The audit revolution: Integrating artificial intelligence in detecting accounting fraud. *Akuntansi Dan Teknologi Informasi*, *17*(1), 48–61. https://doi.org/10.24123/jati.v17i1.6279

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or Not, AI Comes—An Interview Study of Organizational AI Readiness Factors. *Business & Information Systems Engineering*, *63*(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7

K. Johl, S., Kaur Johl, S., Subramaniam, N., & Cooper, B. (2013). Internal audit function, board quality and financial reporting quality: Evidence from Malaysia. *Managerial Auditing Journal*, *28*(9), 780–814. https://doi.org/10.1108/MAJ-06-2013-0886

Kabakci, G. E., & Ince, Y. (2023). Artificial Intelligence's Impact on SMEs: AI in Practice Restructuring Small and Medium-Sized Businesses. *Proceeding Book of 2nd International Conference on Frontiers in Academic Research ICFAR 2023*, 153–160. https://doi.org/10.59287/as-proceedings.456

Kahyaoglu, S. B., & Aksoy, T. (2021). Artificial Intelligence in Internal Audit and Risk Assessment. In U. Hacioglu & T. Aksoy (Eds.), *Financial Ecosystem and Strategy in the Digital Era* (pp. 179–192). Springer International Publishing. https://doi.org/10.1007/978-3-030-72624-9_8

Karaboga, U., & Vardarlier, P. (2020). Examining the use of artificial intelligence in recruitment processes. *Bussecon Review of Social Sciences (2687-2285)*, *2*(4), 1–17. https://doi.org/10.36096/brss.v2i4.234

Khan, A. K. M. K. (2024). AI in Finance Disruptive Technologies and Emerging Opportunities. *Journal of Artificial Intelligence General Science (JAIGS) ISSN:3006-4023*, *3*(1), 155–170. https://doi.org/10.60087/jaigs.v3i1.76

Kimani, B. (2024). Influence of Accounting Information Systems (AIS) on Financial Reporting Accuracy. *American Journal of Accounting*, *6*(1), 37–47. https://doi.org/10.47672/ajacc.1787

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (Fourth edition). The Guilford Press.

Lazăr Pleşa, T., Popescu, C., & Pleşa, I. T. (2023). From Digitization to Artificial Intelligence in External Public Audit. *Valahian Journal of Economic Studies*, *14*(1), 47–59. https://doi.org/10.2478/vjes-2023-0006

Lidiana, L. (2024). AI and Auditing: Enhancing Audit Efficiency and Effectiveness with Artificial Intelligence. *Accounting Studies and Tax Journal (COUNT)*, *1*(3), 214–223. https://doi.org/10.62207/g0wpn394

Lu, H., Peng, Y., Ding, J., & Fu, Z. (2024). Integration and transformation: The impact and applications of artificial intelligence in the financial sector. *Applied and Computational Engineering*, *42*(1), 140–146. https://doi.org/10.54254/2755-2721/42/20230769

Meira, M. F. P. (2019). *O impacto da Inteligência Artificial na Auditoria*. https://api.semanticscholar.org/CorpusID:226809589

Mirzaei, A., Hajizade, M., & Hajizade, H. (2022). Studying the effect of artificial intelligence on improvement of various quality criteria in relation to audit work in Iran. *International Journal of Health Sciences*, 12623–12635. https://doi.org/10.53730/ijhs.v6nS1.8181

Mpofu, F. Y. (2023). The application of Artificial Intelligence in external auditing and its implications on audit quality? A review of the ongoing debates. *International Journal of Research in Business and Social Science (2147- 4478)*, *12*(9), 496–512. https://doi.org/10.20525/ijrbs.v12i9.2737

Noordin, N. A., Hussainey, K., & Hayek, A. F. (2022). The Use of Artificial Intelligence and Audit Quality: An Analysis from the Perspectives of External Auditors in the UAE. *Journal of Risk and Financial Management*, *15*(8), 339. https://doi.org/10.3390/jrfm15080339

Nwachukwu, C. E., Usman, T. O., Akhor, S. O., & Oladipupo, A. O. (2021). Auditing in the New Age of Industry 4.0: The Need for More Research. *International Journal of Business Strategy and Automation*, *2*(1), 17–28. https://doi.org/10.4018/IJBSA.20210101.oa2

Olabanji, S. O., Oladoyinbo, O. B., Asonze, C. U., Oladoyinbo, T. O., Ajayi, S. A., & Olaniyi, O. O. (2024). Effect of Adopting AI to Explore Big Data on Personally Identifiable Information (PII) for Financial and Economic Data Transformation. *Asian Journal of Economics, Business and Accounting*, *24*(4), 106–125. https://doi.org/10.9734/ajeba/2024/v24i41268

Oladejo, M., Yinus, S. O., Kampala International University, Shittu, S., ,Ladoke Akintola University of Technology, Nigeria, Rutaro, A., & Kampala International University. (2021). INTERNAL AUDIT PRACTICE AND FINANCIAL REPORTING QUALITY: PERSPECTIVE FROM NIGERIAN QUOTED FOODS AND BEVERAGES FIRMS. *Kampala International University Interdisciplinary Journal of Humanities and Social Sciences*, *2*(1), 410–428. https://doi.org/10.59568/KIJHUS-2021-2-1-24

Peretz-Andersson, E., Tabares, S., Mikalef, P., & Parida, V. (2024). Artificial intelligence implementation in manufacturing SMEs: A resource orchestration approach. *International Journal of Information Management*, *77*, 102781. https://doi.org/10.1016/j.ijinfomgt.2024.102781

Pizzini, M., Lin, S., & Ziegenfuss, D. E. (2015). The Impact of Internal Audit Function Quality and Contribution on Audit Delay. *AUDITING: A Journal of Practice & Theory*, *34*(1), 25–58. https://doi.org/10.2308/ajpt-50848

Ramzan, S. (2023). Perception of Artificial Intelligence in the Auditing Industry of British Columbia. *International Journal of Scientific and Research Publications*, *13*(5), 252–260. https://doi.org/10.29322/IJSRP.13.05.2023.p13733

Rodrigues, L., Pereira, J., Da Silva, A. F., & Ribeiro, H. (2023). The impact of artificial intelligence on audit profession. *Journal of Information Systems Engineering and Management*, *8*(1), 19002. https://doi.org/10.55267/iadt.07.12743

Sari, G. I., Suhaili, A., & Lesfandra, L. (2024). The Mediation Role of Audit Quality: Impact Internal Audit Strategy, Auditor Ethics, and Accounting Culture on Financial Report Quality. *Atestasi : Jurnal Ilmiah Akuntansi*, *7*(1), 300–316. https://doi.org/10.57178/atestasi.v7i1.779

Seethamraju, R. C., & Hecimovic, A. (2020). Impact of Artificial Intelligence on Auditing—An Exploratory Study. *Americas Conference on Information Systems*. https://api.semanticscholar.org/CorpusID:220795188

Setyahuni, S. W., Purusa, N. A., Prayogi, J., & Mujib, M. (2022). Internal Audit Quality, Corporate Governance, and Corporate Social Responsibility: Determinants of Financial Reporting Quality. *BALANCE: Economic, Business, Management and Accounting Journal*, *19*(2), 113. https://doi.org/10.30651/blc.v19i2.10683

Tüfekci, M., Tüfekci, E., & Dikicioğlu, A. (2020). Numerical Investigation of the Collapse of a Steel Truss Roof and a Probable Reason of Failure. *Applied Sciences*, *10*(21), 7769. https://doi.org/10.3390/app10217769

Vojvodic, M., & Hitz, C. (2022). Relation of Data Governance, Customer-Centricity and Data Processing Compliance. *Central European Business Review*, *11*(5), 109–148. https://doi.org/10.18267/j.cebr.310

Vuković, B., Tica, T., & Jakšić, D. (2024). Challenges of using digital technologies in audit. *Anali Ekonomskog Fakulteta u Subotici*, *51*, 15–30. https://doi.org/10.5937/AnEkSub2300014V

Wassie, F. A., & Lakatos, L. P. (2024). Artificial intelligence and the future of the internal audit function. *Humanities and Social Sciences Communications*, *11*(1), 386. https://doi.org/10.1057/s41599-024-02905-w

Wu, W., Widiatmo, G., & Riantama, D. (2023). What motivates customers to repurchase online under social distancing? *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1155302

Yusup, M., & Juhara, D. (2020). Influence of Internal Audit On the Quality of Financial Statements: (Survey on Private Sector Manufacturing Companies in Bandung). *Jurnal Ekonomi, Bisnis & Entrepreneurship*, *14*(2), 56–61. https://doi.org/10.55208/jebe.v14i2.205

Zain Mohammad Ali Al- Dahabi, Rula Yousef Hajjaj, & Fatima Ali Algazo. (2024). Attitudes of auditors about employing artificial intelligence in the auditing process: Jordanian auditing companies are an example. *International Journal of Science and Research Archive*, *11*(2), 1765–1776. https://doi.org/10.30574/ijsra.2024.11.2.0679