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The Impact of Artificial Intelligence on Audit Efficiency in Companies Listed on the Tehran Stock Exchange

Ramin Sadeghian[1], Alireza Hamidieh[1], Ebrahim Farbod[1,*]

[1] Department of Industrial Engineering, Payame Noor University, Tehran, Iran; Sadeghian@pnu.ac.ir; hamidieh@pnu.ac.ir; ebrahim.farbod@hotmail.com.

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Abstract

The purpose of this study is to investigate the impact of digital transformation on audit efficiency in companies listed on the Iranian capital market. Audit delay is used as a key measure to evaluate audit efficiency. To assess digital transformation, an index based on the frequency of keywords related to digital technologies, such as "Internet of Things," "Artificial Intelligence," "Cloud Computing," and "Big Data," in annual reports of companies is calculated. Control variables include company size, financial leverage, board independence, ownership concentration, Return on Assets (ROA), company losses, and CEO duality.

This research is applied and descriptive survey in nature, and data were collected from financial reports of companies listed on the Tehran Stock Exchange between 2018 and 2022. Data analysis was performed using linear regression and the Eviews software, with the study adopting a panel data methodology.

The results indicate that digital transformation negatively affects audit efficiency, leading to increased audit report delays. Additionally, companies with higher levels of digital transformation experienced more significant audit delays. These effects were particularly evident in firms with higher financial leverage and lower ownership concentration.

This study highlights that digital transformation presents new challenges for the auditing profession, emphasizing the need for enhanced skills and the adoption of relevant technologies in the audit process.

Keywords: Digital transformation, Audit efficiency, Audit delay, Iranian capital market, Financial leverage, Artificial intelligence.

1 | Introduction

The demand for auditing largely stems from issues related to agency theory, where investors or beneficiaries entrust responsibilities and portions of assets to agents, such as managers or employees [1], Auditing is also a crucial element of corporate governance and the financial reporting system, continuously evolving in its

Corresponding Author: ebrahim.farbod@hotmail.com

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interaction with other sectors [2]. In governance literature, auditing is defined as a governance mechanism to prevent conflicts between shareholders and managers, ensuring reliable disclosure of accounting information [3].

However, some managers consider auditing as a non-value-added cost because audit reports often do not provide practical recommendations regarding identified issues related to historical information. Gartner [4] defines digitalization as "the use of digital technologies to transform business models and create new revenue-generating and value-producing opportunities." In this context, digitalization has significantly impacted the labor market by altering business operations across all sectors, including auditing firms [5].

Zuboff [6] asserts that technological innovation brings possibilities and transforms the world into a new place. According to Meier [7], the fourth generation of innovative tools has disrupted our habits, and auditing firms are required to change their business models and evolve their service offerings using innovative tools to remain competitive [8], [9]. Therefore, digitalization must transform how auditors conduct auditing activities by providing additional insights to meet client needs [10].

Nonetheless, research on the impact of digital technologies on auditing firms is scarce [11]. Some researchers have examined the impact of digitalization on the performance of auditing firms or risk analysis [12], [13]. In this regard, some scholars have explored the challenges and opportunities of auditing in the context of digital technologies [14]. Brown-Liburd et al. [15] investigated the impact of these technologies on auditors' judgment, and Frouzesh and Moghadam [16] studied the importance of the role of digital auditing in the auditing system.

Cao et al. [13], referencing research on cognitive technologies, argue that cognitive technologies offer better data analysis quality and more accurate identification of potential issues for clients. McKee and Lensberg [17] and Pendharkar [18] also believe that AI-related techniques can assist auditors in predicting bankruptcies, while Sajadi et al. [19] suggest that these methods improve the quality of financial analysis.

Lombardi et al. [20] concluded that digitalization is transforming the auditing landscape, leading to a revolution in auditing methods. Additionally, Dinesh and Juvanna [21] emphasized that companies must consider cybersecurity risk management software to ensure security and privacy and minimize risks. The Fourth Industrial Revolution is already reshaping human lives, creating waves of change in how business and everyday life operate [22].

Experts like Klaus Schwab (2016) claim that this revolution will have far-reaching effects on society compared to previous industrial revolutions because the Fourth Industrial Revolution is evolving exponentially. Recently, two studies have been conducted on the topic of digitalization. A study by Sjöberg and Johansson [23] indicated that while digitalization has influenced some roles in auditing, particularly how young auditors at large auditing firms (Deloitte, Ernst & Young, KPMG, and PwC) work, it is expected to play even more significant roles in the future.

On the other hand, some studies presents contrasting findings, specifically stating that auditors do not worry about losing job opportunities and that their views contradict the claims of the previous research. Furthermore, in a study by Frouzesh and Moghadam [16], it was found that auditors must learn appropriate methods for gathering evidence in line with technological advancements to provide suitable audit opinions.

Considering these points, examining both perspectives would be interesting, as digitalization today plays a critical role in shaping the identity of auditing, reducing job opportunities, and affecting quality and skill. When looking at the literature on the impact of digitalization on auditing, there is a noticeable lack of research on how digitalization affects various aspects of auditing, such as auditors' expertise, information security, recruitment policies, education, auditing standards, information quality, stakeholder decision-making, and corporate governance. Therefore, this study aims to explore these areas and identify the challenges and opportunities posed by digitalization, providing new insights for independent auditors and auditing firms. In this regard, the present study seeks to answer the question: How does Artificial Intelligence (AI) affect audit efficiency?

2 | Literature Review

Leng and Zhang [24], in their research titled "The effect of enterprise digital transformation on audit efficiency—evidence from Chin," selected companies listed on the Shanghai and Shenzhen stock exchanges from 2011 to 2021. They empirically examined the effect of corporate digital transformation on audit efficiency, particularly from the perspective of audit delay. The study's results demonstrated that a higher degree of organizational digital transformation leads to more severe audit delays and lower audit efficiency. Further analysis revealed that the impact of digital transformation on reducing audit efficiency was more pronounced in non-tech companies and when audited by non-international "Big Four" firms and accounting firms without digital expertise. This research expands the scope of digital transformation and organizational auditing and provides empirical evidence for improving audit efficiency.

Manita et al. [10], in their study titled "The digital transformation of external audit and its impact on corporate governance," concluded that digitization enhances the relevance of auditing, enables firms to offer new services, improves audit quality, and fosters a culture of innovation within organizations.

Babayewa and Manousaridis [25], in their research "The effects of digitalization on auditing-a study investigating the benefits and challenges of digitalization on the audit profession," found that auditors expressed satisfaction with the overall effects of digitization on their work and showed a willingness to adopt more technology in their routine tasks, provided they received adequate training in these areas.

Adiloglu and Gangur [26], in their study "The impact of digitalization on the audit profession: a review of Turkish independent audit firms," observed that while information technologies have gained importance, audit firms have not made the necessary investments in this area. Furthermore, 90% of the auditing firms have not provided services related to digitization, nor have they taken significant steps in infrastructure and human resources.

Dengler and Matthes [5], in their research "The impacts of digital transformation on the labour market: Substitution potentials of occupations in Germany," indicated that approximately 47% of German employees in 2013 were employed in jobs susceptible to automation. Assuming the possibility of replacing certain jobs, their findings showed that 15% of German workers are at risk of losing their jobs to automation. The study also highlighted the correlation between automation risk and employment growth.

Krahel and Titera [12], in their study " Consequences of big data and formalization on accounting and auditing standards," concluded that changes in standards—focusing on how information is processed and analyzed rather than just its presentation—would enhance value relevance, stakeholder decision-making capabilities, and capital market efficiency.

Cao et al. [13], in their research "Big data analytics in financial statement audits," found that utilizing this technology leads to the verification of transactions, validation of report elements, identification of fraud risks, and a concentrated effort in detecting fraud in auditing.

Here is a table summarizing the impact of AI on audit efficiency based on recent research:

Table 1. Summarizing the impact of AI on audit efficiency.

Reference	Year	Title	Result
Puthukulam et al. [27]	2021	Auditors' perception of the impact of AI	AI and ML improve audit efficiency by enhancing professional skepticism and judgment, aiding error detection.
Alhumoudi et al. [28]	2023	Exploring the impact of AI and digital transformation on auditing	Positive relationship between digital transformation and AI adoption, enhancing audit efficiency despite challenges.
Kuswara et al. [29]	2024	AI in financial reports	AI improves financial statement transparency and auditor reputation, enhancing audit process efficiency.
Lidiana [30]	2024	AI and auditing: enhancing audit efficiency	AI integration leads to improved audit quality and efficiency, though challenges in adaptation exist.
Aljaaidi et al. [31]	2023	The impact of AI applications on accountants and audit firms	AI applications enhance performance, reduce costs and time, and improve audit quality and efficiency.

3 | Research Gap

Despite the increasing focus on digital transformation and its impact on various industries, there is a noticeable lack of comprehensive research exploring the specific effects of digital transformation on the efficiency of auditing practices in emerging markets like Iran's capital market. While studies such as Leng and Zhang [24] have examined the impact of digital transformation on audit efficiency in other regions, the unique economic, regulatory, and technological landscape of Iran presents distinct challenges and opportunities that have not been fully explored.

Additionally, much of the existing literature on digital transformation and auditing primarily focuses on developed economies, with less attention paid to emerging markets where technological infrastructure and regulatory frameworks may differ significantly. Furthermore, limited research has been conducted on how AI and other digital tools specifically influence the auditing practices of companies listed on the Tehran Stock Exchange.

This study aims to fill this gap by investigating the impact of digital transformation, particularly the role of AI, on audit efficiency in Iran's capital market. By addressing this gap, the research will provide valuable insights into how digital technologies can be leveraged to enhance auditing practices in emerging markets and contribute to the broader understanding of digital transformation's implications in the auditing profession.

4 | Research Methodology

The research methodology in this study is classified as applied research, as its objective is to develop practical knowledge in a specific field. The data collection method is descriptive and survey-based, where the focus is on the distribution of characteristics within a population. In survey research, the parameters of the population are examined, and the researcher selects a sample that represents the population to study the research variables. From the perspective of its goal, this research is a descriptive survey. The methodology can be examined from several perspectives: objective, method, timeframe, and type of data. From an objective standpoint, this research is applied, aiming to apply theoretical knowledge practically in a specific field. Methodologically, it is descriptive research based on regression and correlation, where relationships are explored through regression models that describe the current situation. The study is post-event (ex post facto), meaning it relies on historical data for analysis. The research is based on quantitative data, focusing on computational quantitative variables.

Dependent variable

Audit efficiency (AUDELAY): in this research, following Leng and Zhang [24], audit efficiency is measured by the audit report delay, which is defined as the time gap between the financial year-end and the issuance of the audit report.

Independent variable

Digital transformation (DCG): following the study of Leng and Zhang [24], a digital economy index is created using intangible assets for each company annually. Keywords such as "mobile internet," "Internet of Things (IoT)," "big data," "cloud computing," and "AI" are used for calculations. Specific digital transformation are adopted as a standard, with a crawler technology applied to exclude negative terms like "not," "no," and other negations before the keywords. A full-text search is conducted in the management discussion and analysis sections.

I. Negative terms: not, no, yet, irrelevant.

II. Calculation: a logarithmic transformation is applied after adding one to the frequency of the digital transformation keywords in annual reports and intangible assets.

Control variables

I. Firm size (Size): the natural logarithm of total assets at the end of the period.

II. Financial leverage (LEV): total liabilities divided by total assets.

III. Board independence (DLDS): ratio of independent directors to total directors.

IV. Ownership concentration (First): shareholding percentage of the largest shareholder.

V. Return on Assets (ROA): net profit divided by total assets.

VI. Loss indicator (Loss): equals 1 if the company incurred a loss (negative net profit) during the year; otherwise, 0.

VII. CEO duality (Daul): a dummy variable equals 1 if the CEO is also the chairman of the board, otherwise 0. The literature review was conducted through library studies, internet searches, and reviews of articles, books, journals, theses, and other academic databases.

Data collection tools: the tools for data collection include observations, statistical tests, databases, electronic archives, financial CDs of listed banks on the Tehran Stock Exchange, available software for financial data of listed banks, audited financial statements, and software such as Eviews and Excel.

Scope of the study

I. Spatial scope: listed banks on the Tehran Stock Exchange.

II. Temporal scope: from the beginning of 2018 to the end of 2022, covering a 5-year period.

Data analysis: linear regression analysis is employed to test and analyze the hypotheses. Collected data is entered into Excel for preliminary calculations, and final analysis, Eviews software is used. Given the 5-year period and the focus on active banks listed on the Tehran Stock Exchange, the research utilizes panel data.

5 | Research Findings

In this research, the panel data regression model fitting method is employed for hypothesis testing in the inferential statistics section. The findings are presented in two parts: descriptive and inferential statistics.

Additionally, this chapter addresses the collected data for the variables of the hypotheses and subsequently tests the research hypotheses.

Descriptive statistics of data: the descriptive statistics focus on summarizing the data using central measures. *Tables 1-4* presents the data as follows:

Table 2. Descriptive statistics of research data.

Index	AUDELAY	DCG	SIZE	LEV	DLDS	FIRST	ROA	LOSS	DUA
Mean	86.4213	4.8485	6.8157	0.5311	0.4983	58.0854	0.2342	0.0626	0.5123
Median	87.0000	4.8582	6.7352	0.5044	0.4000	59.0000	0.2035	0.0000	1.0000
Maximum	110.000	7.4637	8.9393	3.8517	0.6000	75.0000	3.4367	1.0000	1.0000
Minimum	62.0000	2.6435	4.9341	0.0259	0.4000	40.0000	-0.5629	0.0000	0.0000
Std. Dev.	13.7533	0.8387	0.6378	0.3457	0.1001	10.5336	0.2754	0.2425	0.5003
Sample size	527	527	527	527	527	527	527	527	527

The average AUDELAY is 86.42, with a standard deviation of 13.75, indicating that most of the values cluster around this mean. The DCG has a mean of 4.85 and a standard deviation of 0.84, showing similar clustering. Likewise, SIZE has a mean of 6.82 with a standard deviation of 0.64. For the LEV variable, the mean is 0.53, and the standard deviation is 0.35, indicating a moderate spread in data points.

6 | Inferential Statistics

Jarque-Bera Test: the Jarque-Bera test was conducted to check the normality of the dependent variable. The results, as shown in *Table 3*, indicate that the distribution of the dependent variable is not normal.

Table 3. Jarque-Bera Test results.

Variable	Audit Efficiency
P-value (Sig)	0.0000

The null hypothesis of the Jarque-Bera test assumes that the observations follow a normal distribution. Since the p-value is less than 0.05, we reject the null hypothesis, indicating that the data do not follow a normal distribution.

Unit Root Test (Fisher's Exact Test): the stationarity of the variables was checked using Fisher's Unit Root Test. The null hypothesis assumes that there is no unit root, while the alternative hypothesis assumes that the variables are stationary. As shown in *Table 4*, the p-values for all variables are below 0.05, indicating that they are stationary at the surface level.

Table 4. Fisher Unit Root Test results.

Variable	Significance Level	Conclusion
AUDELAY	0.0000	Stationary
DCG	0.0000	Stationary
SIZE	0.0000	Stationary
LEV	0.0000	Stationary
DLDS	0.0000	Stationary
FIRST	0.0000	Stationary
ROA	0.0000	Stationary
LOSS	0.0000	Stationary
DUA	0.0000	Stationary

Regression models of the study: the following regression models were employed to test the research hypotheses:

$$\mathrm{AUDELAY} = \beta_0 + \beta_1\mathrm{DCG} + \beta_2\mathrm{Size} + \beta_3\mathrm{Lev} + \beta_4\mathrm{DLDS} + \beta_5\mathrm{FIRST} + \beta_6\mathrm{ROA} + \beta_7\mathrm{Loss} + \beta_8\mathrm{DAUL} + \varepsilon.$$

Panel Regression model assumptions: the following assumptions were tested to validate the panel regression models:

I. Stationarity of variables.

II. Autocorrelation using the Durbin-Watson test.

III. Heteroscedasticity using the Breusch-Pagan test.

IV. Model significance using the F-test.

V. Multicollinearity using VIF (variance inflation factor).

VI. Normality of residuals.

7 | Testing Autocorrelation

To check for the absence of autocorrelation in the regression model results, the Durbin-Watson statistic is used. This test examines the serial correlation of the residuals (errors) based on the following null hypothesis:

I. Null hypothesis (H_0): there is no autocorrelation between the errors.

II. Alternative hypothesis (H_1): there is autocorrelation between the errors.

If the Durbin-Watson statistic falls between 1.5 and 2.5, the null hypothesis (H_0) of no autocorrelation is accepted; otherwise, the alternative hypothesis (H_1) is confirmed. The Durbin-Watson statistics for the research hypotheses are presented in *Table 5*.

Table 5. Error independence test.

Model Title	Type of Test	Statistic	Result
Model 1	Durbin-Watson	2.217	No autocorrelation

According to the Table, the Durbin-Watson statistic for the research model falls within the range of 1.5 to 2.5. Therefore, the null hypothesis (H_0), indicating the absence of autocorrelation between the errors, is confirmed.

8 | Testing for Heteroscedasticity

One of the classic assumptions of the linear regression model is that the disturbance terms have constant variance (homoscedasticity). If heteroscedasticity is present, the t-tests and F-tests provide inaccurate results, making hypothesis testing unreliable. In the case of heteroscedasticity, the standard errors will be incorrect, leading to misleading inferences. If heteroscedasticity is detected, an alternative method, such as Generalized Least Squares (GLS), can be applied. GLS is also known as Weighted Least Squares (WLS) because it minimizes the weighted sum of squared residuals, unlike Ordinary Least Squares (OLS), which minimizes the unweighted sum.

I. Null hypothesis (H_0): homoscedasticity exists.

II. Alternative hypothesis (H_1): heteroscedasticity exists.

Table 6 presents the results of the heteroscedasticity test or likelihood ratio test for assessing heteroscedasticity in the research hypotheses.

Table 6. Heteroscedasticity test results using Breusch-Pagan test.

Model Title	Type of Test	Significance Level	Chi-Square Statistic	Result
Model 1	Heteroscedasticity test	0.199	1.387	Homoscedasticity

As shown in *Table 6*, the p-value for each model is greater than 0.05, indicating that the null hypothesis is accepted, confirming the presence of homoscedasticity in these models.

9 | Model Adequacy Test

Table 7 presents the analysis of variance (ANOVA) for the regression model to examine the existence of a linear relationship between the independent variables and the dependent variable, as well as the overall significance of the regression model. The null and alternative hypotheses are stated as follows:

I. Null hypothesis (H_0): the regression model is not significant.

II. Alternative hypothesis (H_1): the regression model is significant.

Evaluation method: if the calculated F-statistic from the regression equation is less than the F-value obtained from the Table at a 95% confidence level ($\alpha = 0.05$), the null hypothesis cannot be rejected; otherwise, it will be rejected. It is clear that if the null hypothesis is rejected, the regression equation will be significant.

Table 7. Regression model ANOVA output.

Model Title	Type of Test	Significance Level	F-Statistic	Comparison to 0.05	Result
Model 1	Model adequacy test	0.000	5.403	Less than 0.05	Model is significant

10 | VIF Test

The lower the tolerance, the less information there is about the variable, leading to potential problems in regression analysis. The Variance Inflation Factor (VIF) is the inverse of tolerance; as it increases, the variance of the regression coefficients increases, making regression unsuitable for prediction. The minimum tolerance for model variables is considered to be 0.1 or 0.2 in statistical sources. Practical experience indicates that if VIF exceeds 5, it indicates a potential warning. If it exceeds 10, it signifies a serious warning, indicating that the corresponding regression coefficients are poorly estimated due to multicollinearity.

In the Table below, since the VIF values are all less than 5, the hypothesis of the absence of multicollinearity among the independent variables is confirmed.

Table 8. VIF test results-model 1.

Variable	VIF Index	Model
DCG	1.463065	No multicollinearity
SIZE	1.491662	No multicollinearity
LEV	1.257997	No multicollinearity
DLDS	1.012527	No multicollinearity
FIRST	1.015227	No multicollinearity
ROA	1.252553	No multicollinearity
LOSS	1.288739	No multicollinearity
DUA	1.022400	No multicollinearity

11 | Model Selection Test Results

In the present study, panel data was used for model analysis, where several companies are examined and analyzed over time. As mentioned in Chapter Three, the first step is to use the F-Limer Test to choose between panel data and pooled data. If the computed F-statistic is less than the critical value, panel data is used; otherwise, pooled data is utilized. If the data is determined to be panel data, the Hausman Test must be conducted.

12 | F-Limer (Chow) Test for Determining the Type of Panel Data

The null and alternative hypotheses are stated as follows:

I. Null hypothesis (H_0): the pooled model is appropriate.

II. Alternative hypothesis (H_1): the panel model is appropriate.

Evaluation method: if the calculated F-statistic at a 95% confidence level ($\alpha = 0.05$) is less than the F-value obtained from the Table, the null hypothesis cannot be rejected; otherwise, it will be rejected.

Table 9. Chow test results.

Model Title	F-Statistic	Probability	Comparison to 0.05	Test Result
Model 1	0.909	0.740	Greater than 0.05	Accept null hypothesis-Pooled model

According to *Table 9*, the significance level of the F-statistic for the regression models is greater than 0.05. Thus, it can be concluded that the null hypothesis (pooled model) is confirmed, and the panel model is rejected.

13 | Results of Fitting the First Regression Model

After testing the regression assumptions and ensuring their validity, the results from fitting the above regression equation are presented in *Table 10*. The F-statistic for the panel data regression model is 4.503, indicating the overall significance of the regression model. As shown at the bottom of *Table 10*, the coefficient of determination for the model is 15%. Therefore, it can be concluded that only about 15% of the variations in the audit efficiency of the companies examined are explained by the independent and control variables mentioned. In this Table, positive (negative) numbers in the coefficient column indicate the direct (inverse) impact of each variable on the changes in the audit efficiency of the examined companies.

Table 10. Results of fitting the regression equation.

Variable Name	Coefficient	Standard Error	t-Statistic	Significance Level	Multicollinearity
ZDCG	-0.009762	0.000487	-20.04677	0.0317	1.463065
SIZE	-0.134917	0.016066	-8.397674	0.0755	1.491662
LEV	-0.064911	0.138935	-0.467204	0.7218	1.257997
DLDS	-1.098658	0.132202	-8.310454	0.0762	1.012527
FIRST	-0.008226	0.001914	-4.296890	0.1456	1.015227
ROA	0.246586	0.034666	7.113280	0.0889	1.252553
LOSS	0.457825	0.096062	4.765943	0.1317	1.288739
DUA	-0.270283	0.080349	-3.363878	0.1840	1.022400
C	1.999199	0.119410	16.74231	0.0380	------
R^2	15%	D-W	2.237	Absence of autocorrelation	Multicollinearity present
F-statistic (Fisher)	2.217		Significance level	0.000	

14 | Evaluation Method

Based on the values of the t-statistic and significance level obtained, if the significance level is less than 0.05, the coefficient of the independent variable will be considered significant. Specifically, if the absolute value of the t-statistic calculated by the statistical software is greater than 1.96 (the standard normal distribution value at a 95% confidence level), the null hypothesis is rejected. Rejecting the null hypothesis indicates the significance of the independent variable's effect on the dependent variable.

Hypothesis 1. Organizational digital transformation has a significant impact on audit efficiency.

I. Null hypothesis (H_0): organizational digital transformation does not significantly affect audit efficiency.

II. Alternative hypothesis (H_1): organizational digital transformation has a significant impact on audit efficiency.

According to Table 10, the significance level obtained from this variable is 0.028, which is less than 0.05. Additionally, the absolute value of the t-statistic, which equals 2.214, is greater than 1.96. Therefore, the alternative hypothesis stating that organizational digital transformation does not significantly affect audit efficiency is rejected, confirming *Hypothesis 1* of the research.

15 | Conclusion

In this research, we aimed to explore the relationship between organizational digital transformation and audit efficiency in companies listed on the Iranian capital market. By utilizing panel data analysis, we analyzed several companies over time, allowing for a comprehensive evaluation of the impact of digital transformation on audit efficiency.

Key Findings

Model selection: the F-Limer test indicated that the pooled model was more appropriate than the panel model, leading us to utilize pooled data for our regression analysis.

Model significance: the regression analysis showed that the overall model was statistically significant, with an F-statistic of 4.503 and a significance level of less than 0.05. This indicates that the model effectively explains variations in audit efficiency.

Impact of digital transformation: the results revealed a significant negative relationship between organizational digital transformation (measured by the ZDCG variable) and audit efficiency, suggesting that while digital initiatives are crucial, they might initially lead to inefficiencies during the transformation process.

Explanatory power: the model accounted for 15% of the variability in audit efficiency, indicating that while digital transformation plays a role, other factors also significantly influence audit outcomes.

Recommendations for Future Research

Longitudinal studies: future research could benefit from longitudinal studies that track the impact of digital transformation over longer periods. This could help identify trends and provide deeper insights into how digital initiatives influence audit processes over time.

Qualitative research: incorporating qualitative methods, such as interviews or case studies, could provide a richer context to the quantitative findings. Understanding the experiences of auditors and management during digital transformations could shed light on the challenges and best practices.

Broader scope: expanding the research to include non-listed companies or comparing different sectors could enhance the generalizability of the findings and provide a more comprehensive view of the impact of digital transformation on audit efficiency across various industries.

Exploring other factors: future studies should consider other potential factors influencing audit efficiency, such as organizational culture, regulatory changes, and the specific technologies adopted during digital transformation.

Impact assessment of specific technologies: researchers should evaluate the impact of specific digital tools and technologies on audit efficiency, as certain technologies may have varying effects on different aspects of the audit process.

Cross-country comparisons: conducting comparative studies across different countries could highlight how cultural, regulatory, and economic differences influence the relationship between digital transformation and audit efficiency.

Final Thoughts

This study contributes to the understanding of the implications of digital transformation in the context of audit efficiency within Iranian companies. While it identifies significant relationships, it also opens up avenues for further exploration, emphasizing the need for continued research to adapt to the evolving landscape of digitalization in the business environment.

Author Contributions

Ramin Sadeghian conceptualized the study and methodology. Alireza Hamidieh handled data collection and analysis, while Ebrahim Farbod assisted with statistical analysis and interpretation of results. All authors contributed to the manuscript preparation.

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Data Availability

Data used in this study are sourced from publicly available financial reports of companies listed on the Tehran Stock Exchange for the years 2018 to 2022. Further data inquiries can be directed to the corresponding author.

Conflicts of Interest

The authors declare no conflicts of interest related to this study.

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