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ARTIFICIAL INTELLIGENCE IN AUDITING: EVALUATING THE IMPACT OF GENERATIVE AND PREDICTIVE MODELS ON AUDIT QUALITY AND EFFICIENCY

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SUMMARY

Artificial intelligence (AI) is significantly contributing to beneficial transformations in auditing by enhancing analytical capabilities, automating monotonous tasks, and refining decision-making processes. This piece of research looks into the effects of predictive and generative AI on the quality of auditing as well as its efficiency. Moreover, the research examines how professional skepticism can influence the auditing process in environments where AI is actively used. The research was conducted on the basis of an applied explanatory design with the use of a quantitative cross-sectional method. Data for the study were gathered from a sample of 214 general auditors who work for either the Big Four or other leading international firms, together with information regarding the performance of 38 audit engagements. The application of hierarchical regression and Structural Equation Modeling (SEM) allowed researchers to prove their hypotheses. The current research indicates that predictive AI is able to positively influence the quality of auditing (fraud detection, anomaly detection, risk assessment, and so on) ($\beta=0.53$, $p<0.001$). Generative AI could improve the efficiency of auditing due to its key functions that include automation of documents, reports, and financial data ($\beta=0.47$, $p<0.001$). Additionally, professional skepticism could improve the quality of auditing as well ($\beta=0.29$, $p<0.01$). The results of the multiple regression model accounted for 52% of the overall audit performance, while the results of SEM ($\chi^2/df=2.11$, CFI=0.94, RMSEA=0.061, SRMR=0.054) showed satisfactory goodness of fit of the model. The findings of the study make a significant contribution to academia, providing the empirical basis for highlighting the critical roles of predictive and generative AI technologies. Moreover, the research findings are of great practical value for audit companies that are planning to implement AI into auditing processes. Finally,

the results show that there is a necessity to create frameworks for AI-led auditing processes that should strike a balance between technical advancement and human skills.

Key words: *artificial intelligence, generative AI, predictive analytics, audit quality, audit efficiency, machine learning, professional skepticism.*

INTRODUCTION

Background of the Study

AI has changed corporate practices by improving operational efficiency, decision-making, and analytics across industries. When used in the field of auditing, AI dramatically changes its approach due to automated data processing, continuous monitoring, and the use of sophisticated analytics. Traditional auditing methods that rely on manual verification and sampling are being supplemented by Machine Learning (ML) methods able to cover full data sets.

With ML algorithms, Predictive AIs support fraud detection, risk analysis, anomaly detection, and financial risk evaluation, thus helping improve the quality of audit processes and speed up routine processes. Lately, generative AI has helped enhance the audit function by assisting in documentation, summarization of financial information, generating reports, and aiding with the preparation of working papers, which helps improve efficiency and gives more opportunities for auditors to practice their professional judgment.

This paper examines issues related to algorithm transparency, reliability, bias, responsibility, and the importance of professional skepticism. Even though the effects of AI-based prediction and generative techniques have been assessed separately, very few studies have been conducted to examine how these two processes affect audit quality and efficiency. Thus, this paper aims to provide a detailed description of how predictive and generative AI technologies work and influence the process of auditing, based on the evidence collected from various auditors working in reputable auditing companies.

Research Problem

The application of AI in auditing markedly contrasts with the utilization of conventional auditing tools and methodologies. The integration of predictive AI and generative AI can enhance the quality of audits. Nonetheless, most studies assess the application of AI in auditing in isolation from each other, and not enough empirical evidence is available on how these two types of AI can influence audit quality and efficiency together and improve the auditor's ability to be skeptical. In addition, problems related to the algorithms used and the algorithms' transparency, reliability, and level of human intervention have not been solved yet. Therefore, this research study identifies this gap in the literature.

Research Questions

In light of the specified research challenge, the study examines the following research questions:

RQ1: How do predictive AI models impact audit quality outcomes in professional audit engagements?

RQ2: In what ways does generative AI tool usage influence audit documentation productivity and auditors' professional judgment?

Research Hypotheses

The subsequent hypotheses are presented to address the research questions:

H1: The deployment of predictive AI substantially enhances audit quality.

H2: The deployment of generative AI substantially enhances audit efficiency.

H3: The deployment of predictive AI enhances overall audit performance.

H4: The deployment of generative AI substantially enhances audit quality.

H5: Professional skepticism exerts a substantial positive influence on audit quality.

Key Contributions

This study makes the following key contributions:

- Analyses the distinct functions of predictive AI and generative AI regarding their influence on audit quality and efficiency within professional practices.
- Builds and approves a fully integrated AI-based model and framework for evaluating audit performance while using hierarchical regressions and SEM, which allows one to evaluate the effects of AI in auditing.
- Proves that professional skepticism is still relevant as human judgment contributes significantly to audit quality even in cases of conducting audits with the use of AI.
- Presents the practical implications for audit companies and regulatory bodies by providing data-supported recommendations for implementing AI technology and increasing auditor competence.

This paper is organized as follows. Section 2 presents a literature review and formulates hypotheses. Section 3 elucidates the research technique. Section 4 presents the empirical results. The discussion of the findings, interpretations, limitations, and recommendations for further studies is presented in Section 5. Section 6 ends with the conclusions of the study.

REVIEW OF LITERATURE

The emergence of AI has significantly influenced auditing by enhancing analytical capacities, automating paperwork, and promoting data-driven decision-making. AI has shifted auditing from traditional sampling techniques to continuous monitoring and advanced analytical tools. Predictive AI supports analytical processes better than conventional methods [16]. Subsequently, big data analytics plays a crucial role in establishing conditions conducive to the implementation of AI in auditing, as auditors can now handle extensive data sets, improve the quality of audit evidence collection, and augment decision-making processes [2]. Moreover, the application of ML and natural language processing has enhanced anomaly identification, fraud detection, risk assessment, and audit quality across various auditing types [4] [11]. More recently, generative AI has shown further progression by not only fulfilling automation functions but also obtaining cognitive functions [20]. For example, large language models (LLMs) help auditors with report generation, reviewing documents, summarizing evidence, and making working papers, making auditing processes more efficient. However, ethical questions, algorithmic bias, transparency, and reliability of AI outputs remain to be researched [1].

Recent investigations indicate the necessity of understanding both the advantages and the disadvantages of generative AI that transforms how evidence is synthesized and documented [17]. Many firms have embraced the technology without a system to analyze its influence on quality audit performance [5] [10]. On the one hand, the existing studies acknowledge the advantages of predictive AI, but few empirical studies have proved its effectiveness by means of objective indices, such as fraud detection accuracy and professionalism [4]. Conversely, there is insufficient information regarding the impact of generative AI on the efficiency of audit documentation [10]. The research on ChatGPT and other related applications has suggested that AI increases documentation efficiency but does not cancel the significance of professional skepticism and human judgment since the outputs produced by AI may not be accurate [9].

The application of AI in internal auditing has demonstrated its benefits in automation, ongoing evaluation, and advanced analysis, enhancing the audit process and markedly improving operational efficiency [19]. Research also shows that GPT-4 is able to carry out some of the reasoning functions that

experienced auditors complete, although human supervision should always be present [12]. Previous reviews concluded that predictive analytics provide the necessary support to a professional auditor's experience in the areas of fraud detection, audit process planning, anomaly detection, and risk assessment [6]. Previous studies identified AI-related technologies as tools that enhance high-quality audit performance while fulfilling the role of human decision-making [13] [18]. Experimental studies showed that the introduction of AI techniques improves audit work efficiency without negatively influencing the quality of the audit [14]. In terms of methodology, the use of SEM is suggested to study complex relationships following the verification of reliability and validity indicators, while the best practice represents a two-step SEM procedure in empirical research [8] [3].

Research Gap

Previous studies have mainly focused on the different types of AI and their applications within processes like fraud detection, risk assessment, audit integrity, document efficiency, and decision-making. However, there is a great deal of absence of data regarding the impact that the two types of AI together may have on the quality of an audit, audit efficiency, and the evaluation of professionals in audit dealings. The research focuses on the influence of predictive and generative AI on auditing performance.

Research Objectives

1. To examine how predictive AI models influence audit quality outcomes, particularly error detection accuracy and risk assessment.
2. To evaluate the impact of generative AI technologies on the productivity of audit documentation and the professional judgment of auditors during audit engagements.

METHODOLOGY

Research Design

This study employed an explanatory methodology and a quantitative approach to investigate the effects of predictive AI and generative AI on audit quality and efficiency. The primary survey data were amalgamated with the objective performance measure of audit quality for establishing relationships among relevant variables. The explanatory approach utilized allowed for hypothesis testing by means of statistical modeling and enhanced overall validity through mixing perceptual and objective measures. The study was based on a positivist approach of research philosophy, in which the hypotheses were tested using a deductive approach, whereby hypotheses were formulated according to a literature review. The framework of the study incorporated AI adoption, professional skepticism, audit quality, and audit efficiency concepts for achieving improved construct validity.

Study Area

The research encompassed a survey of professional external auditors working in well-known audit companies that have implemented the AI technology in their auditing processes. The study was focused on auditors from leading global accounting firms, including other important mid-tier firms such as BDO Global, Grant Thornton International, RSM International, and Mazars Group, along with the Big Four firms, namely Deloitte, PwC, Ernst & Young (EY), and KPMG. The reason for selecting the companies mentioned above is due to a considerable amount of funds invested by them in auditing technologies supported by artificial intelligence, which include predictive analysis, ML algorithms, anomaly detection automation, and AI-based generation of audit reports. Because this technology is widely used by these companies, it is appropriate to explore the influence of AI in auditing.

Sampling

The target group of the study included external auditors working actively within the audit engagements of the selected international accounting firms. Participants included audit associates, senior auditors, audit managers, and audit partners who have regularly applied AI-based audit tools. The process of

sampling was stratified random based on the type of firm and position in the company to ensure that all organizational strata would be fully represented. In total, 214 auditors filled in a questionnaire and 38 completed audit engagements. The sample covered the needs of SEM, which requires 10-15 cases per estimated parameter. In addition, the results of the power analysis show 0.87 power at a 5% significance level, which means that the sample is adequate for hypothesis testing.

Conceptual Framework

Figure 1 delineates the theoretical framework established for this study, depicting the anticipated correlations among audit performance, audit quality, audit efficiency, professional skepticism, and the integration of both predictive and generative AI technologies. Predictive AI is helpful for analytical audit tasks, which include fraud detection, anomaly detection, continuous auditing, and risk assessment, while generative AI is applicable for auditing procedures such as documentation, reporting, and summarization of evidence. Professional skepticism is regarded as an important behavioral concept relevant to AI-based auditing, which is responsible for a critical attitude toward the output derived from AI. In general, these concepts establish how these technologies contribute to audit quality, operational efficiency, and overall audit performance.

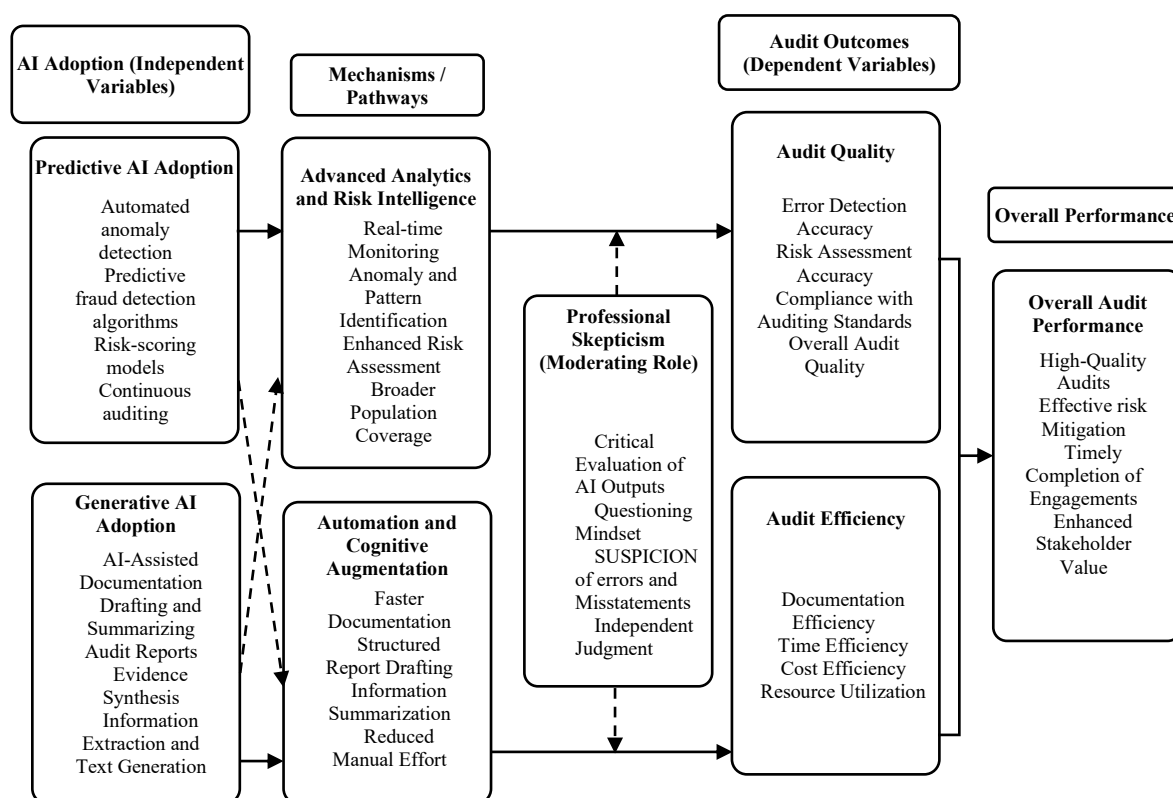


Figure 1. Proposed conceptual framework for AI-enabled audit performance

Data Collection

This study involved a six-month data-gathering period utilizing both primary and secondary data sources. Primary data was obtained via structured online surveys distributed to professional auditors. Whenever clarification of the responses was required, follow-up interviews were held. Secondary data was used in the form of anonymized audit performance information related to each audit engagement, such as audit hours, budgeted versus actual audit costs, misstatement detection information, and financial restatement information whenever available. In order to maintain adherence to professional and ethical standards, confidentiality agreements were signed with all firms that participated in the research. In order not to disclose any identifying information, the study was based entirely on anonymized organizational data. Out of a total of 310 questionnaires distributed, 227 were received back, including 214 completed

questionnaires after screening. Therefore, the total response rate used in the study was 69%, which is adequate for professional survey research.

Measurement of Variables

All factors were assessed with established instruments derived from prior research in auditing and information systems, with minor modifications to align with AI auditing. The perceptual constructs were evaluated based on the five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The use of predictive AI was assessed by analyzing the application of ML in auditing tasks, including anomaly detection, fraud detection, risk rating, and continuous auditing. The use of Generative AI was measured through AI-focused preparation of documentation, reports, summaries, and working papers. The skepticism of the auditors was measured using standardized behavior measures reflecting the degree of the auditors' skepticism in evaluating the audit evidence and the proposals generated by AI. The audit quality was measured through using perceptual and objective measures, which included error detection, audit accuracy, and audit results, while audit efficiency was considered based on the fact that the duration of audit completion, usage of resources during the audit, productivity of documentation, and budget execution were used.

Model for Data Analysis

Empirically assessing the proposed theoretical framework utilizing SEM was carried out. The assessment regarding this theoretical framework consisted of two principal phases: during the first phase, the measurement model was evaluated in terms of its reliability and validity, while in the second phase, the relationships among the constructs being studied were explored in order to verify the hypotheses developed.

The calculation process of descriptive statistics was started to obtain information regarding the respondents and the distribution of the constructs being used. Reliability and validity were assessed using Composite Reliability (CR), Average Variance Extracted (AVE), and Variance Inflation Factor (VIF). Finally, the analysis of the structural relationships was conducted based on the usage of path coefficients, coefficients of determination (R^2), adjusted R^2 , and commonly used model-fit indices of SEM.

Mathematical Description

The R^2 quantifies the fraction of variance in the dependent variable elucidated by the independent variables, as articulated in equation (1):

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad (1)$$

where SS_{res} denotes the residual sum of squares and SS_{tot} denotes the total sum of squares.

The adjusted coefficient of determination accounts for the number of explanatory variables in the model and is computed using equation (2):

$$Adjusted R^2 = 1 - \frac{(1 - R^2)(n - 1)}{n - k - 1} \quad (2)$$

where n is the sample size and k denotes the number of predictor variables.

VIF was utilized to evaluate multicollinearity among predictor variables, as delineated in equation (3):

$$VIF = \frac{1}{1 - R_j^2} \quad (3)$$

where R_j^2 represents the coefficient of determination obtained by regressing one independent variable against the remaining predictor variables.

CR was utilized to assess the internal consistency of latent constructs and was computed using equation (4):

$$CR = \frac{(\sum \lambda)^2}{(\sum \lambda)^2 + \sum (1 - \lambda^2)} \quad (4)$$

where λ denotes the standardized factor loading for each indicator.

Convergent validity was evaluated by the AVE, calculated using equation (5):

$$AVE = \frac{\sum \lambda^2}{n} \quad (5)$$

where λ represents the standardized factor loading and n denotes the number of indicators associated with the construct.

The overall goodness-of-fit of the SEM was evaluated using the Chi-square/degrees of freedom ratio (χ^2/df), Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). These indices were used to determine the adequacy of the proposed model in explaining the observed relationships among the study constructs.

RESULTS

Sample Details

The final sample included 214 professionals working in the audit profession, selected from within the four largest audit corporations and important medium-sized accounting firms. 61.7% of the respondents represented the Big Four, while 38.3% were part of medium-sized audit firms. The sample included audit associates (31.8%), senior auditors (36.9%), managers (22.0%), and partners (9.3%). A majority of respondents (41.6%) possessed five to ten years of expertise in audit practice, hence validating the sample's suitability for evaluating artificial intelligence usage in the auditing sector.

Measurement Model Evaluation

Reliability Analysis

The assessment of internal consistency reliability was conducted via Cronbach's alpha analysis. The results demonstrate that the constructions exhibited strong reliability, with a minimum reliability value of 0.70, surpassing the acceptable threshold of 0.70. Despite all constructs having the alpha values of predictive AI ($\alpha = 0.86$), generative AI ($\alpha = 0.88$), professional skepticism ($\alpha = 0.84$), and audit quality (perceptual) ($\alpha = 0.82$).

Validity Assessment

This research demonstrates that construct validity has been achieved through the application of convergent and discriminant validity tests. Convergent validity is demonstrated when factor loadings exceed 0.70 and AVE values are above 0.50. This means that the items are able to effectively capture the essence of their constructs. Discriminant validity was also confirmed to be achieved through the assessment of constructs, as required by the Fornell–Larcker criterion and Heterotrait–Monotrait (HTMT) ratios being below the advisable cut-off of 0.85.

Generative AI Adoption

Adoption of Generative AI was assessed by considering the responses from the participants with respect to how much utilized the Generative AI tools in their audit activities. For this purpose, various tasks such as preparing working documents of the audit, writing management letters, summarizing financial statements, preparing audit reports, and providing automated explanations regarding audit results were included in this study. It is important to note that responses were captured using the five-point Likert scale since high values mean that the Generative AI technologies were employed in audit practices to a larger extent.

Table 1. Demographic characteristics of the respondents (N = 214)

Variable	Category	Frequency	Percentage (%)
Firm Type	Big Four	132	61.7
	Mid-tier	82	38.3
Position	Associate	68	31.8
	Senior	79	36.9
	Manager	47	22.0
Experience	Partner	20	9.3
	< 5 years	74	34.6
	5–10 years	89	41.6
	> 10 years	51	23.8

Table 1 shows the demographic characteristics of the respondents. The sample comprises both the Big Four (61.7%) and the leading mid-tier auditing firms (38.3%) and includes auditors with different positions and experience. The composition indicates that the surveyed respondents have substantial professional experience in AI-enabled audit environments.

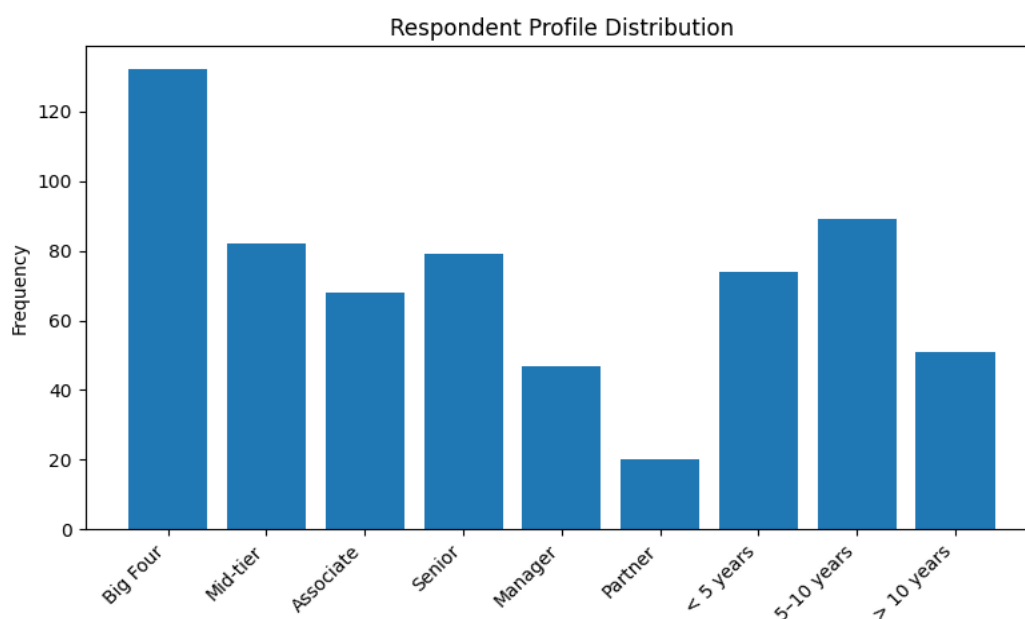


Figure 2. Respondent profile distribution

In figure 2, the respondents are explained in terms of their company type, job title, and number of years of experience. The majority of the respondents are from the Big Four audit companies, and people from all ranks of the organization are included in the sample. Using the experience of people (five to ten years) in the audit profession shows that the study is based on the people whose interactions with AI-related audits are of a material nature.

All of the quantitative features of the variables examined in the study are displayed in table 2. With an average value of ($M = 3.87$), the variable of Predictive AI Adoption has been shown to be used extensively in audit work, whereas Audit Quality has shown the highest overall mean value ($M = 4.01$). A standard deviation of less than one for every variable implies that there is not much variation among the responses.

Table 2. Descriptive statistics of the study variables ($N = 214$)

Variable	Mean	Std. deviation	Minimum	Maximum
Predictive AI Adoption	3.87	0.74	2.10	5.00
Generative AI Adoption	3.42	0.81	1.90	5.00
Audit Quality	4.01	0.69	2.45	5.00
Audit Efficiency	3.76	0.72	2.30	5.00
Professional Skepticism	3.95	0.66	2.50	5.00

Correlation Analysis

To examine bivariate relationships of important factors between major constructs, Pearson correlation coefficients were computed.

Table 3. Pearson correlation matrix of the study variables

Variable	1	2	3	4	5
1. Predictive AI	1				
2. Generative AI	0.48**	1			
3. Audit Quality	0.62**	0.41**	1		
4. Audit Efficiency	0.57**	0.53**	0.60**	1	
5. Professional Skepticism	0.29**	0.18*	0.46**	0.33**	1

- $P < 0.05$
- ** $p < 0.01$

Predictive AI utilization has a substantial positive link with both audit efficiency ($r = 0.57$, $p < 0.01$) and audit accuracy ($r = 0.62$, $p < 0.01$), as shown in table 3, implying that ML-based analytics results in a higher level of efficiency and accuracy. The moderate connection between audit efficiency ($r = 0.53$, $p < 0.01$) and audit quality ($r = 0.41$, $p < 0.01$) suggests that generative AI technology is playing an increasing role in both audit process speed and audit quality. Professional skeptics have a moderate positive correlation with audit quality ($r = 0.46$, $p < 0.01$), meaning that applying critical thinking towards AI outcomes results in audits that obtain better results. The correlation between these two factors has not exceeded 0.80, which means that there is no occurrence of serious multicollinearity.

Multicollinearity Diagnostics

The value of the Variance Inflation Factor (VIF) was calculated to check multicollinearity.

Table 4. Multicollinearity diagnostics of the predictor variables

Predictor Variable	VIF	Tolerance
Predictive AI	1.78	0.56
Generative AI	1.64	0.61
Professional Skepticism	1.32	0.76

Table 4 reports the analysis of multicollinearity based on the VIF and tolerance measures. The VIF values obtained are far less than the suggested cut-off of 5.0, while the tolerance scores surpassed 0.20, thus verifying the lack of multicollinearity amongst the independent variables used in the analysis. As a result, the independent variables are found suitable for regression and SEM analysis.

Hypothesis-Based Analysis

Multiple Regression Analysis

The hypotheses were tested using hierarchical multiple regression analysis. Control variables (auditor experience, firm size, and industry expertise) were collected in Step 1, while independent variables were collected in Step 2. The statistical significance was tested at $p < 0.05$.

Model 1: Predictive AI → Audit Quality

Table 5. Hierarchical regression results for predictive AI adoption and audit quality

Variables	Model 1 (Controls) β	Model 2 (Predictive AI) β
Auditor Experience	0.18*	0.11
Firm Size	0.22**	0.14*
Industry Specialization	0.16*	0.09
Predictive AI Adoption	—	0.49***
R^2	0.21	0.46
ΔR^2	—	0.25***
F-statistic	18.72***	42.91***

- $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

The hierarchical regression study evaluating the effect of Predictive AI Adoption on Audit Quality is displayed in table 5. The addition of Predictive AI greatly improved the explained variance from 21% to 46%, signifying noteworthy degrees of incremental explanatory power. Furthermore, the standardized regression coefficient ($\beta = 0.49$, $p < 0.001$) indicates that the use of predictive AI is a significant predictor of audit quality.

Model 2: Generative

AI → Audit Efficiency

Table 6. Hierarchical regression results for generative AI adoption and audit efficiency

Variables	Model 1 (Controls) β	Model 2 (Generative AI) β
Auditor Experience	0.14*	0.08
Firm Size	0.25**	0.17*
Industry Specialization	0.12	0.06
Generative AI Adoption	—	0.44***
R^2	0.19	0.39
ΔR^2	—	0.20***
F-statistic	16.85***	34.67***

- $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

The findings regarding the impact of Generative AI Adoption on Audit Efficiency, according to the hierarchical regression, are shown in table 6. The introduction of Generative AI in the model increased its explanatory power by 20%, from 19% to 39%. The significant standardized coefficient ($\beta = 0.44$, $p < 0.001$) indicates that the greater the degree of Generative AI Adoption, the better the Audit Efficiency.

Model 3: Combined AI Variables → Overall Audit Performance

(Audit performance = composite of quality and efficiency)

Table 7 displays the combined regression model assessing the impact of both generative and predictive AI adoption on overall audit performance. The model accounts for 52% of the variation in audit performance and demonstrates that both AI techniques have a significant positive effect. Predictive AI also has a greater impact, which indicates the perceived relevance of predictive analysis towards ensuring total audit performance.

Table 7. Hierarchical regression results for overall audit performance

Variables	β	t-value	p-value
Auditor Experience	0.09	1.72	0.087
Firm Size	0.15*	2.54	0.012
Industry Specialization	0.07	1.29	0.198
Predictive AI Adoption	0.41***	7.84	0.000
Generative AI Adoption	0.33***	6.12	0.000
R ²	0.52		
Adjusted R ²	0.50		
F-statistic	45.83***		

*** p < 0.001

SEM

SEM was carried out using IBM SPSS AMOS Version 29. Using two separate steps [2], the measurement model's validity was verified by Confirmatory Factor Analysis (CFA). Following this, the structural model was estimated in order to verify the relationship between AI predictive adoption, AI Generative adoption, Professional Skepticism, Audit Quality, and Audit Efficiency.

Using Maximum Likelihood Estimation (MLE), the parameter estimates were obtained. The path coefficients were standardized, and significance was measured using critical ratios (t-values) and p-values. A reflective measurement model was adopted in the study. The model used only those factors whose factor loadings were greater than 0.70, while the model fit was assessed using Chi-square/df (<3.0), CFI (>0.90), RMSEA (<0.08), and SRMR (<0.08) parameters.

The constructs of the model were investigated using SEM using AMOS/SmartPLS, and both direct and indirect relationships among the constructs were assessed.

Model Fit Indices

Table 8. SEM fit indices

Fit Index	Recommended Threshold	Obtained Value	Interpretation
Chi-square/df	< 3.00	2.11	Acceptable
CFI	> 0.90	0.94	Good Fit
RMSEA	< 0.08	0.061	Good Fit
SRMR	< 0.08	0.054	Good Fit

In table 8, it can be observed that the satisfactory statistics of the goodness of fit of the suggested SEM model. Each of the model fitness indices meets the threshold criteria such as $\chi^2/df = 2.11$, CFI = 0.94, RMSEA = 0.061, and SRMR = 0.054, verifying that the model is sufficient to represent the observable data and is applicable for testing the hypotheses.

The SEM presentation in figure 3 shows the relations between different notions such as Predictive AI Adoption, Generative AI Adoption, Professional Skepticism, Audit Quality, Audit Efficiency, and Overall Audit Performance. The computed route coefficients indicate that Predictive AI Adoption exerts

the greatest favorable influence on Audit Quality, whilst Generative AI Adoption demonstrates the most significant effect on Audit Efficiency. Professional Skepticism also contributes significantly to Audit Quality. The model was estimated using Maximum Likelihood Estimation (MLE), and the fit indices ($\chi^2/df = 2.11$, CFI = 0.94, RMSEA = 0.061, and SRMR = 0.054) indicate a good overall model fit, supporting the proposed structural relationships among the study constructs.

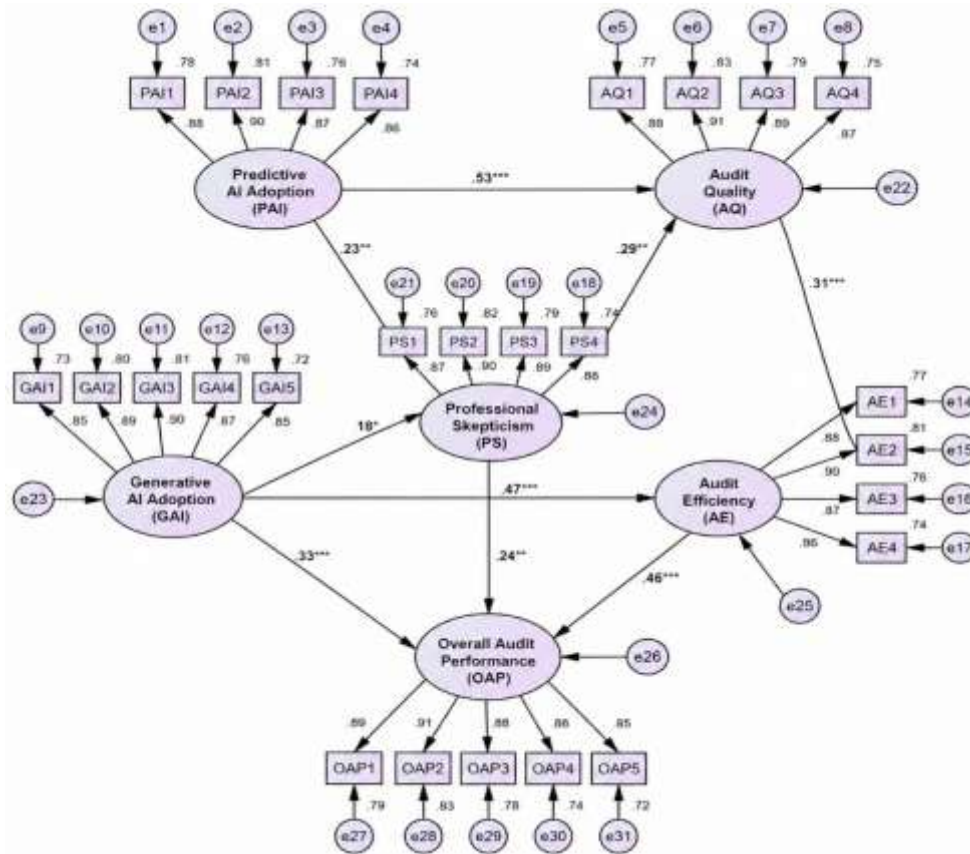


Figure 3. SEM results for AI-enabled audit performance

Structural Path Results

Table 9. Structural path coefficients of the proposed SEM

Path	Standardized β	t-value	p-value
Predictive AI $\rightarrow$ Audit Quality	0.53***	8.72	0.000
Generative AI $\rightarrow$ Audit Efficiency	0.47***	7.95	0.000
Professional Skepticism $\rightarrow$ Audit Quality	0.29**	4.12	0.000
Predictive AI $\rightarrow$ Audit Efficiency	0.31***	5.46	0.000
Generative AI $\rightarrow$ Audit Quality	0.26**	3.98	0.000

** $p < 0.01$

*** $p < 0.001$

The SEM findings demonstrate a substantial influence of predictive AI and generative AI on audit outcomes, as indicated by the results in table 9. The findings show that the most impactful of both types of AI on audit quality is the predictive AI ($\beta = 0.53$), while the generative AI is influential in terms of audit efficiency ($\beta = 0.47$). The professional skepticism contributes positively to the audit quality ($\beta = 0.29$). It appears that auditors applying AI outputs critically can improve audit quality. The results from SEM confirm the regression findings but produce a stronger evidence base since the process of estimation and measurement errors is done jointly.

Moderation Analysis

Hierarchical regression was utilized to create and assess the interaction terms to evaluate the moderating effect of professional skepticism on the link between generative AI and audit quality. As for interaction effects, simple slope analysis was conducted to reveal the association of high skepticism with AI performance.

Hypothesis Testing Results

The findings give empirical proof of the suggested relationships. Firstly, it indicates a significant positive link between the adoption of predictive AI and audit quality ($\beta = 0.49$, $p < 0.001$; SEM $\beta = 0.53$, $p < 0.001$). The robustness of the correlation demonstrates that ML-based anomaly detection, predictive risk scoring, and automated analytics substantially improve the accuracy of error identification and the precision of risk evaluation.

H1 suggested that predictive AI adoption influences audit quality. H1's regression analysis was in agreement with this conclusion ($\beta = 0.49$, $p < 0.001$), and SEM results also supported this finding ($\beta = 0.53$, $p < 0.001$).

H2 suggested that adoption of Generative AI increases audit efficiency. This hypothesis was supported by regression ($\beta = 0.44$, $p < 0.001$) and SEM ($\beta = 0.47$, $p < 0.001$).

H3 proposed that predictive AI adoption positively affects overall audit performance. The combined model showed a significant contribution of predictive AI ($\beta = 0.41$, $p < 0.001$), confirming the hypothesis.

H4 posits that the application of Generative AI enhances audit quality. The SEM analysis revealed a substantial beneficial effect ($\beta = 0.26$, $p < 0.01$), therefore corroborating H4.

H5 posited that Professional Skepticism had a beneficial impact on audit quality. SEM results validated a substantial positive correlation ($\beta = 0.29$, $p < 0.01$), corroborating H5.

The presence of predictive AI indicates that regression analysis had been conducted, resulting in an increase of explained variability in audit quality from 21% to 46%, which indicates the important additional value brought by predictive AI. Moreover, the implementation of generative AI considerably improves the efficiency of audits ($\beta = 0.44$, $p < 0.001$; SEM $\beta = 0.47$, $p < 0.001$). Based on operational metrics verification, audit hours and cost variance were lessened during the use of generative tools for documenting and summarizing purposes. The introduction of generative AI into the model brings the explained variance in audit efficiency from 19% to 39%. Finally, the interaction of predictive and generative AI improves the efficiency of audit variability by 52%.

The standardized regression coefficients along with the structural path coefficients for the five suggested hypotheses are shown in figure 4. The adoption of predictive AI significantly enhances audit quality ($\beta = 0.53$), whereas the adoption of generative AI closely improves audit efficiency ($\beta = 0.47$). The other hypotheses also have positive and statistically meaningful effects, thus showing that there is support for all the predicted relations in the structural model.

In comparison to generative AI, predictive AI had a greater impact on performance, indicating that analytics related to fraud detection and risk assessment lead to more reliable quality improvements. The degree of professional skepticism positively influences audit quality (SEM $\beta = 0.29$, $p < 0.01$), indicating that auditors who critically evaluate AI outputs get superior outcomes.

And this means that the quality of AI is not just about how advanced its technology is, but it is about how well humans are monitoring to ensure everything is. As you can see, the overall results show that AI adoption is improving audit performance in the future and that various types of AI are affecting it in a number of dimensions.

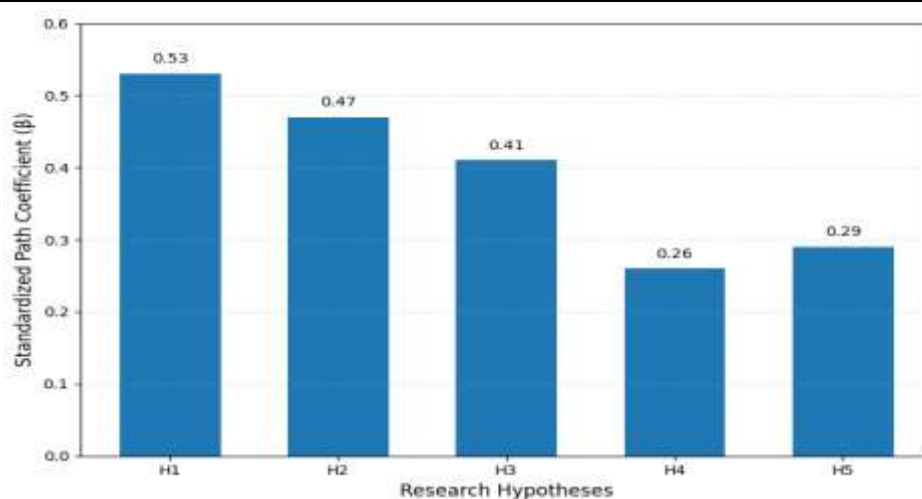


Figure 4. Standardized effects of the proposed hypotheses

DISCUSSION

It has been found that predictive and generative AI contribute to audit performance improvement by very different measures. While predictive AI has been found to influence audit quality the most due to its role in risk evaluation, fraud detection, and detection of anomalies, generative AI is good for improving the efficiency of auditing processes. Professional skepticism again proves that human judgment is important in verifying AI outputs and making trustworthy conclusions. The results of this investigation are in agreement with the results of earlier research indicating that predictive analytics assists in the evaluation of audit evidence [13]. Likewise, prior studies have proven its success in fraud detection [15]. Furthermore, generative AI has been discovered to decrease the time spent performing monotonous paperwork and improve audit efficiency [18]. More recent evidence has also confirmed the role of generative AI in the increase of productivity and effectiveness of businesses [7].

This study contributes to the growing literature on AI-assisted auditing by providing actual evidence of the beneficial effects of predictive and generative AI on audit quality and efficiency. From the perspective of application, the findings indicate that audit firms need to keep investing in AI technologies while enhancing the digital skills of auditors through continuous training. The findings also show the significance of combining the capabilities of AI with professional skepticism to achieve high-quality audit results.

Limitations

This study has several shortcomings. First, it is difficult to track the evolution of AI adoption over time due to the cross-sectional design. Secondly, despite using secondary data on the level of involvement, the variable AI adoption was determined based on self-reported data; therefore, the possibility of response bias may be a factor. Eventually, the research was based on professional auditors working at the Big Four and middle-tier firms, which constrained the applicability of results to small audit companies and other regulatory environments.

Suggestions

The use of predictive and generative AI technologies should not replace professional judgment when applied by auditing firms. Auditors need to undergo ongoing training to enhance their AI competency levels and develop skepticism when applying AI results to the auditing process. Therefore, it would be prudent for regulators to create guidelines for the moral and appropriate application of AI in auditing.

Future Research

The impact of applying AI on audit effectiveness over time can be investigated in subsequent studies using longitudinal research approaches. Comparison between studies done in different states, industries, and contexts can make results applicable in many more cases. Apart from that, the result of subsequent research may focus on aspects like explainable AI (XAI), AI governance, measures of transparency of algorithms, and collaboration with humans.

CONCLUSION

The research provides empirical evidence that artificial intelligence (AI) adoption alters the overall performance of audits, improving quality as well as efficiency. The study effectively surveys 214 expert auditors and assesses 38 audit cases to demonstrate how generative and predictive AI forms the foundation for the contemporary revolution of auditing procedures. The results show a significant correlation between the use of predictive AI and the quality of auditing ($r=0.62$, $p<0.01$). The findings of regression and SEM analysis show that predictive techniques greatly improve the prediction of audit quality (from 21% to 46%; $\beta=0.53$, $p<0.001$) facilitate anomaly detection processes. At the same time, generative AI significantly improves audit performance ($\beta=0.44$, $p<0.001$; SEM $\beta=0.47$, $p<0.001$), significantly decreasing the amount of time and funds spent on documentation due to automation of drafting and systematization of the data used. Together, both forms of effective technology account for 52% of the overall audit performance variance. The study also indicates that human control can hardly be excluded; professional skepticism contributes positively to audit quality ($\beta=0.29$, $p<0.01$), and auditors who generate objective conclusions from the AI data get better results. Hence, it can be said that AI is an important technology and requires an organization with a proper management system and training. Additionally, future investigations into the use of large language models in continuous audits, as well as the use of generative and predictive models in detecting fraud and evaluating complex risks, should be considered.

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