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An examination of the effects of artificial intelligence-powered automation on the effectiveness of audit quality: An analytical study in U.S. organizations

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The increasing adoption of artificial intelligence (AI) has transformed organizational processes across industries, including the auditing profession. AI-powered audit automation enables organizations to enhance audit efficiency, improve analytical accuracy, and reduce operational costs, thereby improving audit quality. Despite the growing adoption of AI technologies in auditing practices, empirical evidence of their impact on audit quality in the United States remains limited. This study examines the effects of AI-powered automation on audit quality by focusing on three key dimensions: efficiency, accuracy, and cost-effectiveness. A quantitative research design was employed using a structured questionnaire distributed to auditors working in organizations across the United States. A total of 207 valid responses were collected and analyzed using correlation and multiple regression analyses to test the proposed hypotheses. The findings reveal that efficiency, accuracy, and cost-effectiveness all have significant positive effects on audit quality. Among these factors, efficiency emerged as the strongest predictor, followed by accuracy and cost-effectiveness. The results indicate that AI-enabled audit automation enhances the reliability, effectiveness, and overall quality of auditing processes by facilitating faster data processing, reducing human error, and optimizing resource utilization. This study contributes to the literature by providing empirical evidence on the role of AI-powered automation in improving audit quality within a highly regulated auditing environment. The findings offer valuable insights for audit practitioners, organizational leaders, and policymakers seeking to leverage AI technologies to strengthen audit performance and improve assurance outcomes. The study also provides a foundation for future research examining AI adoption and audit effectiveness across different industries and institutional contexts.

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1. Introduction

The use of artificial intelligence (AI) and automation has greatly improved business operations across various industries, reducing repetitive tasks, enhancing decision-making, and improving operational efficiency (EFF) (Fügener *et al.*, 2025; Helleckes *et al.*, 2026; Kokina & Davenport, 2017). In today's digital era, businesses have become increasingly dependent on modern technologies such as robotic process automation (RPA), data analytics, and AI systems to simplify complex operations in a faster and more precise manner (AlSuwaidi *et al.*, 2021; Gupta *et al.*, 2024; Jeresa, 2025; Malchyk *et al.*, 2022; Noor Othman Qatanani *et al.*, 2026; Vasarhelyi *et al.*, 2015). For example, the use of AI in industries such as finance, healthcare, manufacturing, and accounting has transformed operational processes within these sectors. In the auditing profession, AI has emerged as a significant innovation, fundamentally changing data collection, processing, and interpretation, thereby improving audit assurance and reliability (Appelbaum *et al.*, 2017; De Fano *et al.*, 2025; Uriarte *et al.*, 2025).

The concept of audit automation specifically refers to the convergence of information and communication technologies and AI systems, whereby audit functions traditionally performed by humans are automated. In the United States (U.S.), the adoption of audit automation has increased significantly, as major accounting firms such as Deloitte, KPMG, PwC, and EY utilize these technologies to improve audit quality (AUQ) and streamline auditing processes (Zeynalli *et al.*, 2026; Zhang *et al.*, 2021). The technology enables accountants to analyze vast amounts of data quickly while accurately identifying discrepancies in financial reporting systems (Hossain, 2026; Manson *et al.*, 1998). Machine learning and data analytics integrated into these technologies facilitate the continuous monitoring of financial transactions, thereby reducing human effort and minimizing errors (Laxman Chaudhary, 2021; Jin *et al.*, 2025). The benefits of audit automation are extensive. It enhances EFF, accuracy (ACC), and cost savings while improving the quality of audit judgments. It also facilitates timely data extraction, immediate assessment, and continuous monitoring, ultimately contributing to higher AUQ (Appelbaum *et al.*, 2017). Furthermore, these systems provide auditors with valuable insights into irregularities and risk assessment, which may be difficult to obtain through conventional auditing approaches (Hoti *et al.*, 2026; Schmitz & Leoni, 2019).

This study is important because it addresses a research gap concerning the effect of automation on audit outcomes, particularly within the U.S. Although research on the effects of audit automation has been conducted internationally,

relatively few studies have focused on the U.S. auditing environment, which is governed by stringent regulatory frameworks, including the Public Company Accounting Oversight Board and the Generally Accepted Accounting Principles (Manson *et al.*, 1998). Within this context, understanding the impact of automation on AUQ is important from both practical and academic perspectives. Overall, this study addresses the limited research on AI's impact on AUQ from an information-processing perspective. The integration of AI and automated decision-making systems can significantly enhance organizations' information-processing capabilities. Drawing on the theoretical foundations of the Unifying Theory for Information, Efficiency Theory (ET), Organizational Information Processing Theory (OIPT), and the Dynamic Capabilities View (DCV), this study proposes that the EFF, ACC, and cost-effectiveness (CEF) of AI systems can substantially improve AUQ.

In particular, this study's findings contribute to understanding perceptions of AI's role in enhancing AUQ, thereby assisting practitioners and researchers in integrating this innovative technology into auditing practices. This study is distinctive because it provides a comprehensive assessment of how AI integration influences AUQ among both internal and external auditors in the U.S., an area that remains underexplored in the existing literature. Consequently, the study contributes to the growing body of knowledge on artificial intelligence and AUQ. Building on prior research, this study investigates the relationship between AI and AUQ in the U.S. service sector from the perspectives of both internal and external auditors. Additionally, it examines AI-related factors and AUQ indicators in service industries across developed economies, while considering the viewpoints of both auditor groups. AI research has generally been more prevalent in the manufacturing sector than in the service sector, particularly in both developed and developing countries. Therefore, this study validates the proposed AI model within U.S. service industries.

Furthermore, this study offers a valuable perspective on knowledge processes and operational engagement variables, in addition to the widely recognized view that AI can enhance organizational performance. AI infrastructure, EFF, ACC, and CEF are expected to have a significant impact on AUQ within the U.S. service sector. Consequently, the findings provide future researchers with a deeper understanding of these factors, which may support the development of more effective and empirically validated knowledge-process models. Moreover, the study framework provides a foundation for future research in this area. Additional investigations may be conducted

in sectors such as finance, hospitality, and education. Therefore, the purpose of this study is to examine the relationship between audit automation and AUQ within the U.S.

2. Literature review

Audit automation is the systematic use of technology, particularly AI, data analytics, and robotic tools, to perform audit procedures that would otherwise be performed manually. According to Adewale (2026) and Vasarhelyi *et al.* (2015), automation enables continuous auditing, whereby data are collected, analyzed, and reported in real time, thereby increasing both timeliness and reliability. Unlike traditional audits that rely on sampling, automated systems analyze complete datasets, reducing uncertainty and improving assurance quality (Appelbaum *et al.*, 2017). Kokina and Davenport (2017) stress that, while automation supports EFF, its most profound impact may be the transformation of the auditor's role, shifting auditors from data collection to data interpretation, risk analysis, professional judgment, and insight generation. This conceptual shift reflects a broader technological evolution within accounting—a transition from procedural execution to cognitive interpretation.

There are several forms of audit automation that collectively improve the audit lifecycle. The most basic form is RPA, which performs rule-based, repetitive activities such as data extraction, validation, and reconciliation without human intervention (Zhang *et al.*, 2021). Attended process automation extends this capability by enabling human auditors and automated systems to collaborate on tasks, ensuring oversight and adaptability during complex activities (Zhang *et al.*, 2021). More advanced forms include Cognitive Automation and AI-based auditing, which utilize machine learning algorithms for anomaly detection, risk prediction, and sentiment or pattern analysis across large financial datasets (Kokina & Davenport, 2017). Collectively, these forms of automation not only improve operational EFF but also enhance decision ACC and audit comprehensiveness, thereby providing a foundation for continuous assurance models aligned with modern business complexity.

The benefits of audit automation extend beyond process optimization. Automation improves EFF by accelerating the completion of audit procedures while maintaining or enhancing AUQ (Ahmad *et al.*, 2021; Almaiah *et al.*, 2022; Al Kurdi *et al.*, 2021; Appelbaum *et al.*, 2017). It enhances ACC by minimizing human error and ensuring consistent application of audit procedures across engagements. Cost benefits arise from reduced labor hours and operational overhead, enabling audit firms to allocate resources to

innovation and value-added services for clients (Johri *et al.*, 2026). Furthermore, automation strengthens risk management through the real-time detection of suspicious transactions and by alerting auditors to potential issues well before they affect financial statements (Zhang *et al.*, 2021). Overall, these advantages enhance AUQ, which is defined as the credibility, reliability, and ACC of financial assurance provided by auditors (Vasarhelyi *et al.*, 2015).

However, the adoption and integration of audit automation within firms are influenced by the interplay of several factors, including technological infrastructure, organizational readiness, staff competencies, regulatory compliance, and financial investment capacity (Appelbaum *et al.*, 2017). Firms with more advanced digital ecosystems and supportive leadership are more likely to achieve successful implementation. Conversely, inadequate training and overly rigid regulatory environments may hinder implementation efforts (Zhang *et al.*, 2021). These interrelated factors influence not only the extent of automation adoption but also its long-term impact on AUQ.

This study focuses on four critical factors: three independent variables—EFF, ACC, and cost savings—and one dependent variable, AUQ. EFF represents the extent to which automation optimizes audit processes and reduces time expenditure. ACC refers to the precision and consistency of audit outcomes, while cost savings capture the financial benefits of implementing automation. AUQ, the dependent variable, reflects the overall reliability and assurance value of audit outcomes within an automated auditing environment (Vasarhelyi *et al.*, 2015).

This study proposes that the EFF, ACC, and CEF of AI systems can significantly enhance AUQ by utilizing the theoretical frameworks of ET, OIPT, and the DCV. In particular, this study's findings help quantify perceptions of AI's contributions, which may assist researchers and practitioners in integrating this disruptive technology into their auditing processes.

The DCV has attracted considerable scholarly attention as a means of better understanding the significance of an organization's strategic capabilities and their impact on organizational performance. According to scholars in this field, dynamic capabilities may help explain variations in firm performance within a particular industry while enabling organizations to expand and maximize the use of their resources (Liu *et al.*, 2013; Schilke *et al.*, 2018). Maintaining and developing the operational competencies required to carry out and coordinate organizational activities is a central concern of the DCV. The theory is based on the premise that dynamic capabilities can transform a firm's existing resources, positions, and operational capabilities,

thereby creating new opportunities for optimizing its strategic assets (Schilke *et al.*, 2018). Additionally, the DCV emphasizes integrating and reconfiguring internal and external capabilities to generate innovations that can adapt to changing business environments. Therefore, it is not surprising that previous studies have employed the DCV to understand IT-related competencies and outcomes at the organizational level (Akter *et al.*, 2023; Li *et al.*, 2020; Mandal, 2019). Research has shown that dynamic capabilities improve organizational performance both before and during the COVID-19 pandemic. Although the concept has been more extensively studied in developed countries, developing markets possess unique sociocultural and economic characteristics that warrant further investigation.

According to OIPT, because complexity and uncertainty are inherent in today's business environment, organizations with strong capabilities in information collection, analysis, and utilization are better positioned to anticipate change and make proactive adjustments that enhance organizational resilience. OIPT suggests that organizations should adopt two performance-enhancing strategies to respond to changes in the business environment: (i) acquire higher-quality information and (ii) improve their information-processing capabilities (Fan *et al.*, 2017; Srinivasan & Swink, 2015). Therefore, OIPT provides a comprehensive theoretical foundation for understanding organizational resilience by emphasizing an organization's ability to acquire resources and process information effectively. Organizations are encouraged to make full use of information, expertise, employee experience, preparedness, and other resources transferred through business networks in order to improve internal processes and obtain higher-quality information (König *et al.*, 2018). According to the OIPT literature, these capabilities are strategically important for enabling organizations to recover quickly from disruptive events. Following March's (1991) seminal work on ambidextrous learning, an increasing body of research has recognized its importance in acquiring information to overcome challenges, enhance resource utilization, and expand resource pools. Therefore, we believe that the theoretical foundations of DCV and OIPT, together with organizational agility, data quality, readiness, top management commitment, and AI capabilities, are appropriate for this study.

According to Yampolskiy (2013), the "brute force" (BF) approach is a universal algorithm from which the proposed EFF framework is derived. BF is a method of solving complex computational problems by considering every possible solution. BF is generally regarded as an inefficient problem-solving approach and is often

considered impractical for solving complex, real-world problems of substantial size. However, a noteworthy and often overlooked characteristic of this approach is that it can produce the most accurate, rather than approximate, solutions to difficult computational problems (e.g., Nondeterministic polynomial time [NP]-Hard and NP-Complete problems). In this study, BF is examined within a broader context. Specifically, BF may be inefficient in several ways, such as representing every symbol in text strings that could otherwise be compressed. More generally, EFF refers to the extent to which resources—such as time, space, and energy—are utilized effectively to achieve a desired objective. In complexity theory, EFF is a characteristic of algorithms that solve problems using a number of computational steps bounded by a polynomial function of the problem size. The boundary function depends on the size of the problem instance. Although algorithmic EFF can often be improved at the expense of solution quality, this is typically acceptable when approximations are permissible. Additionally, EFF may be understood as the ability to represent redundant data in shorter, more effective forms (Yampolskiy, 2013).

In summary, OIPT explains how AI reduces information-processing uncertainty in auditing activities, DCV explains how AI adoption enhances organizational agility within audit firms, and ET describes how AI reduces costs and improves productivity. This study integrates ET, OIPT, and DCV into a unified framework that conceptualizes AI-enabled audit systems as capability-enhancing information-processing mechanisms that simultaneously improve EFF, decision quality, and organizational flexibility.

Previous studies on AI in auditing have primarily focused on performance outcomes, such as EFF and ACC, while paying limited attention to how AI transforms information-processing practices and dynamic capability development within audit firms. In particular, limited evidence exists regarding how AI enhances adaptive auditing capabilities (DCV), reduces information asymmetry (OIPT), and improves cost EFF (ET) in highly regulated environments such as the U.S. audit market. Within the U.S. context, it can be argued that the high level of regulatory enforcement, the extensive audit litigation environment, the advanced digital maturity of audit firms, and the early adoption of AI technologies by large firms increase information-processing demands. Consequently, ET, OIPT, and DCV become particularly relevant, further underscoring the importance of AI-enabled dynamic capabilities. Additionally, each construct in this study was operationalized in accordance with its underlying theoretical framework to ensure construct validity across

ET, OIPT, and DCV perspectives. AI capability (DCV-based) reflects indicators of integration, learning, and adaptability; information-processing EFF (OIPT-based) reflects speed, uncertainty reduction, and decision clarity; and cost EFF (ET-based) reflects reduced audit hours and lower costs per engagement.

We have significantly strengthened the theoretical contribution of this study by explicitly integrating ET, OIPT, and the DCV into a coherent framework that explains how AI-enabled auditing systems simultaneously improve EFF, increase information-processing capacity, and develop dynamic audit capabilities. We also provide a stronger justification for the U.S. context, grounded in the sophistication of digital auditing and the intensity of regulatory requirements. Furthermore, we clarify the theoretical gap associated with the limited use of integrated multi-theoretical explanations in previous AI-auditing research. By explicitly linking all measurements to their underlying theoretical constructs, we further enhance construct operationalization.

In particular, this study describes AI-enabled auditing as a step-by-step process for capability development. First, AI automation increases operational EFF by reducing audit time, manual effort, and resource consumption (ET). Second, these EFF gains enhance OIPT by enabling audit firms to process larger volumes of financial data more rapidly, accurately, and with less uncertainty. Third, improved information-processing capability allows audit firms to develop dynamic audit capabilities (DCV) by continuously learning, adapting audit procedures, identifying emerging risks, and reconfiguring audit practices in response to changing regulatory and organizational environments. Consequently, improvements in AUQ result from the interaction of EFF gains, enhanced information-processing capability, and adaptive organizational capabilities rather than from any single theoretical mechanism. This integrative explanation constitutes the study's primary theoretical contribution. Therefore, this study highlights that ET explains how AI creates resource EFF, OIPT explains how those efficiencies are transformed into superior information-processing capabilities, and DCV explains how enhanced information processing develops adaptive audit capabilities that ultimately improve AUQ. This integrated mechanism extends previous AI-auditing studies, which have generally focused on isolated performance outcomes, such as EFF or ACC, rather than on explaining the full capability-development process. The theoretical framework section has been updated accordingly.

Furthermore, in terms of construct operationalization, training and monitoring items may be viewed as

antecedents rather than indicators of the focal constructs. Upon further consideration, we acknowledge that these factors are more indicative of enabling conditions than of EFF or CEF. Consequently, we have reassessed the conceptual alignment of these indicators and clarified whether they should be retained or removed based on their consistency with the underlying theoretical constructs. Specifically, CEF indicators are explicitly linked to resource optimization and cost-reduction outcomes rather than capability antecedents, whereas EFF indicators are more clearly associated with reduced effort, faster task completion, and enhanced productivity.

In conclusion, this paper contributes to the literature by demonstrating that ET, OIPT, and DCV interact sequentially rather than independently. The initial benefit of AI-enabled auditing is improved operational EFF (ET), which enhances the firm's ability to process audit information and reduce uncertainty (OIPT). Enhanced information-processing capability subsequently facilitates the development of adaptive auditing routines and the continuous reconfiguration of audit methods in response to emerging risks and regulatory changes (DCV). Therefore, AUQ is explained not merely as a direct outcome of EFF gains but as the result of an integrated capability-development process.

The EFF of audit functions can be greatly improved by reducing the time spent on those functions. The traditional audit function is considered time-consuming because it involves numerous manual tasks, such as data gathering, sampling, and testing. The use of automated audit systems enables auditors to analyze all available data, thereby greatly reducing the repetitive nature of manual procedures and completing the audit process at a much faster rate (Vasarhelyi *et al.*, 2015). Kokina and Davenport (2017) stressed that automated audit systems enable auditors to focus primarily on higher-level analysis and interpretation rather than on data processing, thereby achieving substantial time savings. In addition, the convergence of AI and data analytics enables auditors to conduct continuous audits rather than periodic ones, thereby improving overall responsiveness and productivity. Moreover, a study by Appelbaum *et al.* (2017) showed that audit automation systems can process a continuous flow of data in real time, enabling auditors to identify irregularities immediately. Similarly, a study by Zhang *et al.* (2021) showed that attended process automation systems facilitate instant data validation, thereby reducing turnaround times. Thus, it can be ascertained that the adoption of automation results in improved flexibility and responsiveness on the part of audit firms, thereby optimizing resource utilization; therefore, this study formulates the first hypothesis:

H1: EFF has a positive impact on AUQ.

Accuracy is one of the most essential elements of AUQ, as it establishes the credibility of financial data. The use of audit automation eliminates the risk of human error contaminating the results, as it involves programmed operations based on fixed logic. Khaled and Oweis (2022) demonstrated in their study on AI-driven tools for audit automation that data validation achieved high ACC with no discrepancies. By reducing the burden of recurring human errors, such as those in data entry, reconciliation, and sampling, professionals can devote themselves to high-risk and highly complex areas, thereby improving the overall ACC of audit outcomes. In addition, research indicates that automation enhances auditors' ability to detect hidden irregularities. For example, a study by Schmitz and Leoni (2019) found that technologies such as blockchain, AI, and traceability systems improve audit verification processes by increasing traceability and ACC. In a related study, Manson *et al.* (1998) indicated that, in both the U.S. and the United Kingdom, the ACC of risk assessment and reporting is positively affected by the use of audit automation. It can therefore be concluded that a more precise audit process can result from the use of audit automation. Hence, this study formulates the second hypothesis:

H2: ACC has a positive impact on AUQ.

Cost-effectiveness is a primary reason for promoting the use of audit automation. By using audit automation, reliance on human execution is reduced, leading to lower labor costs and higher EFF (Manson *et al.*, 1998). According to Vasarhelyi *et al.* (2015), the use of continuous auditing enabled by technology implies reduced reliance on comprehensive manual auditing, thereby reducing costs. Cost savings were also noted in a study by Appelbaum *et al.* (2017), which found that, as a result of audit automation, data processing can be performed without additional human labor, thereby making firms more cost-efficient. In addition, audit automation enhances CEF by reducing rework associated with human errors and omissions. Kokina and Davenport (2017) observed that, by ensuring a higher level of ACC in data collection and processing, automation eliminates the need for corrections, which can be very costly. Furthermore, as identified by Zhang *et al.* (2021), automation enables flexibility in coping with fluctuating workloads and maximizes human resource utilization without necessarily requiring additional personnel. Therefore, it not only reduces the operational costs associated with auditing but also enhances a firm's financial viability. Therefore, this study formulates the third hypothesis (Figure 1):

H3: CEF has a positive impact on AUQ.

3. Methodology

A structured research instrument was developed to determine demographic attributes and primary variables. The study employed a causal research design and the positivist research approach to examine how three important aspects of audit automation—EFF, ACC, and CEF—affect AUQ. Participants' perceptions of the three independent variables—EFF, ACC, and CEF—as well as the dependent variable, audit quality, were assessed using a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Venkatesh *et al.* (2003), Kijasanayotin *et al.* (2009), and Valenzuela *et al.* (2011) provided the six-item EFF construct employed in this investigation. Some items reflect audit-related EFF, even though they originate from a broader AI context (e.g., training enhances the effective use of AI systems in audit workflows). The EFF construct captures the extent to which AI solutions reduce the time and cognitive effort involved in audit processes. Because they directly represent audit workflow effectiveness, items evaluating task completion time and reduced manual effort were retained. Training- and competency-related items were included because, according to ET and DCV theories, they constitute enabling capabilities and EFF outcomes in their own right.

Five items adopted from He *et al.* (2023) were used to measure the ACC construct. In fact, OIPT, which asserts that sophisticated information-processing mechanisms enhance decision ACC in complex and uncertain situations, serves as the primary theoretical foundation for the ACC construct. By improving analytical precision and reducing the limitations of human processing, AI systems enhance the quality and reliability of audit judgments within the auditing context. The CEF construct, derived from Tadi (2024), was measured using five items. CEF is operationalized through optimizing audit engagement resources, such as reducing audit hours and allocating audit personnel more efficiently. Items related to general operational monitoring and threat detection were included in this analysis because they address AI risk management functions and audit cost structures.

To develop hypotheses deductively and improve data variability and generalizability, the study employed a cross-sectional design with an explanatory survey (Saunders *et al.*, 2015). Quantitative research methods were used to assess models and hypotheses for generating findings and generalizations (Collis & Hussey, 2021). Self-administered Google Form questionnaires were the primary means of data collection from organizations in the U.S. A total of 207 of 437 registered companies that employed AI in their auditing operations participated in this study, yielding a response rate of 47.3%. According to Easterby-Smith *et*

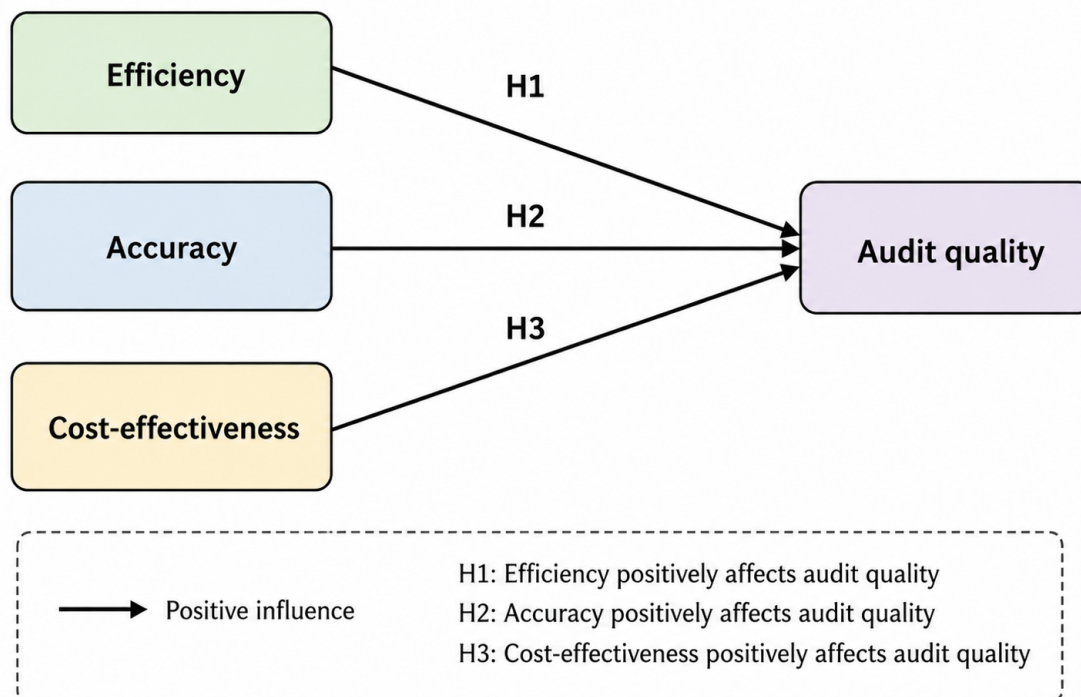


Figure 1. The study's theoretical model. Image created by the authors.

al. (2012) and Saunders *et al.* (2015), at a 95% confidence level and a margin of error of $\pm 5\%$, at least 205 completed surveys were required. Consequently, the 207 responses obtained from auditors with varying levels of experience were considered sufficient for regression analysis (Easterby-Smith *et al.*, 2012). Participants were informed that participation in the study was entirely voluntary, and ethical approval was granted by Alfa Plus USA (Reference No. 18-643-2025). Furthermore, all data collected was kept confidential and used solely for academic purposes. Finally, participants were informed that there were no known risks or harms associated with the study for either the organization or its participants.

Collis and Hussey (2021) state that if a study uses employees as the unit of analysis, the organization's human resources department may provide a list of employees. However, due to regulations protecting employee information, which render such information private, secure, and inaccessible, organizations were unable to provide sampling lists for this study. Therefore, convenience sampling was considered the least costly and most time-efficient sampling technique, providing easy access to a sufficiently large sample (Easterby-Smith *et al.*, 2012; Malhotra *et al.*, 2006). Additionally, because of its practicality and convenience, convenience sampling is frequently used in research (Malhotra *et al.*, 2006).

Accordingly, convenience sampling was employed in this investigation. Respondents were selected using a convenience sampling method. This method is widely recognized in organizational and auditing research for its practicality and EFF (AlNajdawi *et al.*, 2025a, 2025b). The survey was made available to all managers, directors, and senior management personnel who were officially involved in auditing operations and possessed comprehensive knowledge of the AI application aspects within their respective organizations.

The Statistical Package for the Social Sciences (SPSS 25.0, IBM, United States) was used to analyze the data. Descriptive statistics were employed to provide an overview of the respondents and their general responses. Inferential statistical analyses included multiple regression analysis (MRA) to determine the effect of AI-powered factors on AUQ, factor analysis for construct validation, and Cronbach's alpha for reliability testing. The hypotheses were tested at significance levels of 0.05 and 0.01.

The regression coefficient is used to evaluate the cause-and-effect relationship between variables when testing the theoretical models proposed in the study. MRA is a statistical technique useful for examining the relationship between a single criterion variable and multiple predictor variables (Hair *et al.*, 2019). In multiple regression, variables must be classified as dependent or independent.

Similarly, regression analysis is appropriate when both the independent and dependent variables are measured on a metric scale. MRA seeks to predict the value of a dependent variable selected by the researcher using independent variables with known values. Furthermore, regression analysis assigns weights to each independent variable to maximize predictive ACC. These weights facilitate the interpretation of each variable's effect on prediction by representing the relative contribution of each independent variable to the overall forecast. However, correlations among independent variables can make interpretation more difficult. Regression coefficients, which are linear combinations of independent variables, often yield the best predictions of dependent variables. Regression analysis estimates the regression equation using a single independent variable, whereas MRA estimates multiple regression coefficients and regression equations involving two or more independent variables. In regression analysis, a very low significance value—typically less than 0.05—indicates that the coefficient is unlikely to have occurred by chance. Accordingly, if the significance value of a multiple regression coefficient exceeds 0.05, researchers may conclude that the relationship may have occurred by chance (Saunders *et al.*, 2015).

Before applying the MRA model, the following assumptions should be satisfied, according to Saunders *et al.* (2015). First, the variables should be measured at the interval level. Second, the data for both the dependent and independent variables should be normally distributed. Third, there should be a strong relationship between the independent and dependent variables and no excessive correlation among two or more predictors (multicollinearity), as multicollinearity makes it difficult to identify the unique contribution of each variable. According to Collis and Hussey (2021), normality is assessed using standard deviation, skewness, and kurtosis. Brown (2006) states that skewness values should fall between -3 and $+3$, while kurtosis values should range between -10 and $+10$. According to Easterby-Smith *et al.* (2012), in a normal distribution, approximately 68% of observations fall within one standard deviation of the mean, 95% fall within two standard deviations, and 99.9% fall within three standard deviations. Regarding the third assumption of the MRA model, Hair *et al.* (2019) recommend several techniques for assessing multicollinearity, including Tolerance and variance inflation factor (VIF) values. According to Hair *et al.* (2019), there is no indication of multicollinearity problems when tolerance values exceed 0.10 and VIF values are below 10.

Self-administered questionnaires are a common method of data collection in business and service research.

Questionnaire-based research operationalizes variables of interest through a series of questions derived from established or newly developed scales. Although surveys are among the most widely used methods in the social sciences, the validity and reliability of empirical results may be threatened by common method bias (CMB) and variance. To assess CMB, the collected data were examined using Harman's single-factor test. The results revealed that the largest factor accounted for 29.57% of the total variance. According to Podsakoff *et al.* (2003), this value is below the 50% threshold. Therefore, the results indicate that CMB was not a significant concern in the data.

4. Data analysis

4.1. Respondents' analysis

The demographic breakdown shows that 57% of respondents were women and 43% were men. A substantial proportion of respondents were in the 35–44 and 45–54 age groups, accounting for 41.5% and 36.2%, respectively. The vast majority held postgraduate degrees: 49.8% had master's degrees and 42.5% held doctoral degrees. Senior auditors accounted for 30.9% of respondents, while audit managers accounted for 22.2%. In terms of professional experience, substantial proportions of respondents had between 4 and 10 years (30.4%) and more than 10 years (27.5%), while 28% had a comparable level of experience. Overall, the demographic results indicate that most participants were highly educated and experienced auditors, providing assurance that the responses reflect informed professional perspectives.

4.2. Model and causal measurement analysis

The results of the Cronbach's alpha test demonstrated strong internal reliability for the constructs, as illustrated in Table 1. EFF had a Cronbach's alpha of 0.703, ACC had the highest coefficient of 0.894, and CEF had a coefficient of 0.726. These findings indicate reliability levels ranging from acceptable to excellent. Additional validity testing was conducted using factor loadings. The loading values for EFF ranged from 0.513 to 0.863, those for ACC ranged from 0.622 to 0.898, and the factor loadings for CEF ranged from 0.560 to 0.984. All values were substantially higher than the widely accepted minimum threshold of 0.50, indicating that the items strongly represented their respective constructs. Consequently, these results provide strong evidence of the measurement model's validity. Discriminant validity was assessed to determine whether the study constructs were empirically distinct. The Fornell–Larcker criterion was applied by comparing the square roots of the average variance extracted (AVE) values with the inter-construct correlations. The results showed that the square roots of the AVEs for each construct

exceeded their corresponding inter-construct correlations, indicating adequate discriminant validity. The Heterotrait–Monotrait ratio (HTMT) was also used to provide a more comprehensive assessment of discriminant validity. All HTMT values remained below the recommended threshold of 0.85, demonstrating adequate construct distinctiveness among EFF, ACC, and CEF. In addition, the measurement items were carefully reexamined to ensure stronger conceptual alignment with their respective constructs. Theoretically, the retained items within each construct were justified on the basis of their relevance to the EFF, ACC, and CEF dimensions of auditing. Taken together, these findings support the statistical and conceptual distinctiveness of the research constructs.

According to Hair *et al.* (2019), the VIF and tolerance

values are two recommended methods for assessing multicollinearity. Consequently, when examining the collinearity diagnostics, namely VIF and tolerance, for each predictor in this study, the researcher observed no evidence of multicollinearity. According to Hair *et al.* (2019), multicollinearity becomes problematic when the tolerance value is less than 0.10, and the VIF value exceeds 10. In this study, the tolerance values were all above the minimum threshold of 0.10, and the VIF values did not exceed the widely accepted maximum threshold of 10. As shown in Table 2, the VIF values ranged from 2.458 to 5.432, all below 10, while the tolerance values ranged from 0.118 to 0.357, all exceeding the minimum acceptable level of 0.10. Based on these results, there is no indication of multicollinearity in the data.

Table 1. Cronbach's alpha and construct factor analysis

Construct	Item	Cronbach's alpha	AVE	FL	Adopted from
EFF	The automated contouring system will be useful in my job.	0.703	0.735	0.524	Kijisanayotin <i>et al.</i> (2009); Valenzuela <i>et al.</i> (2011); Venkatesh <i>et al.</i> (2003)
	Using the automated contouring system enables me to accomplish tasks more quickly.			0.630	
	Using the automated contouring system increases productivity.			0.513	
	Using the automated contouring system improves the work outcomes.			0.649	
	Learn the skills that enable effective use of artificial intelligence applications			0.863	
	Effectively use artificial intelligence applications			0.591	
ACC	The agreement fraction of decisions is the same as that of the AI system.	0.894	0.770	0.627	He <i>et al.</i> (2023)
	Switch fraction: the proportion of decisions in which the user switched to agree with the system.			0.711	
	Participant ACC of correct final decisions.			0.898	
	ACC-wide correct final decisions with initial disagreement.			0.738	
	positive AI reliance and negative self-reliance.			0.622	
CEF	Investing time and effort to learn artificial intelligence applications.	0.762	0.801	0.984	Tadi (2024)
	The initial setup and implementation costs,			0.648	
	Ongoing operational expenses			0.560	
	Potential long-term savings are achieved through monitoring and reduced manual labor.			0.655	
	Potential long-term savings achieved through improved threat detection and faster response times.			0.568	

Abbreviations: ACC: Accuracy; AVE: Average variance extracted; CEF: Cost-effectiveness; EFF: Efficiency; FL: Factor loading.

The researcher employed Pearson's correlation coefficient to examine the relationships between the independent variables—AI EFF, AI ACC, and AI CEF—and the dependent variable, AUQ. Subsequently, the results of the simple and multiple linear regression analyses were presented for each hypothesized relationship. This was achieved using model summary statistics, analysis of variance, and coefficient models. Table 3 summarizes the Pearson correlations among the independent and dependent variables. As shown in the table, all correlations among the variables were positive and statistically significant. Furthermore, the correlation between AUQ and ACC was the strongest ($r = 0.882$), whereas the correlation between ACC and CEF was the weakest ($r = 0.357$). The Pearson correlation matrix indicates that EFF, ACC, CEF, and AUQ are all positively and significantly associated at the 0.01 significance level.

Inferentially, a structural model was constructed in which AUQ served as the dependent variable and EFF, ACC, and CEF as independent variables. This model was used to assess the extent to which each of the three identified audit automation factors individually explained and predicted variations in AUQ. Regression analysis was subsequently conducted to test the three research hypotheses. The regression model was statistically significant and demonstrated substantial explanatory power and model fit ($F = 3567.529$, $p < 0.001$). The model exhibited a high coefficient of determination ($R^2 = 0.887$), indicating that 88.7% of the variance in AUQ among the targeted organizations was explained by the independent variables. As shown in Table 2, the findings provide strong support for H1, H2, and H3, with standardized beta coefficients of 0.785, 0.661, and 0.508, respectively. Furthermore, because the p-values for all relationships were below the

Table 2. Multiple regression analysis

Model	Standard error	Standard coefficients beta	t	Sig.	Result	Collinearity statistics	
Constant	0.387	–	3.382	0.001	–	Tolerance	VIF
EFF	0.069	0.785	5.735	<0.001	Supported	0.226	2.458
ACC	0.078	0.661	4.846	<0.001	Supported	0.357	4.671
CEF	0.074	0.508	3.273	<0.001	Supported	0.118	5.432

Note: Dependent variable: Audit quality (AUQ). Abbreviations: ACC: Accuracy; CEF: Cost-effectiveness; EFF: Efficiency; VIF: Variance inflation factor.

Table 3. Pearson's correlation coefficient

Variables		EFF	ACC	CEF	AUQ
EFF	Pearson's correlation	1	0.427**	0.401**	0.789**
	Significance (2-tailed)	–	<0.001	<0.001	<0.001
	n	207	207	207	207
ACC	Pearson's correlation	0.427**	1	0.357**	0.882**
	Significance (2-tailed)	<0.001	–	<0.001	<0.001
	n	207	207	207	207
CEF	Pearson's correlation	0.401**	0.357**	1	0.699**
	Significance (2-tailed)	<0.001	<0.001	–	<0.001
	n	207	207	207	207
AUQ	Pearson's correlation	0.789**	0.882**	0.699**	1
	Significance (2-tailed)	<0.001	<0.001	<0.001	–
	n	207	207	207	207

Note: **p-value < 0.01 (2-tailed). Abbreviations: ACC: Accuracy; AUQ: Audit quality; CEF: Cost-effectiveness; EFF: Efficiency.

0.05 significance level, the analyses confirmed the study hypotheses, indicating that the three AI-powered factors have a positive and statistically significant impact on AUQ (Table 2 and Figure 2). With an endogenous construct R^2 of 0.887, the proposed model explained approximately 88.7% of the variation in the dependent variable. Although this indicates strong explanatory power, the relatively high R^2 in a cross-sectional perceptual survey necessitated further analysis and discussion. To address this issue, several diagnostic tests were conducted. First, multicollinearity was assessed using VIF values, which remained below the recommended threshold, indicating no serious multicollinearity among the predictor constructs. Second, CMB was evaluated using both procedural and statistical remedies, and the results indicated that the observed associations were unlikely to be substantially distorted by common method variance. Furthermore, the empirical distinctiveness of EFF, ACC, and CEF was supported by confirmatory discriminant validity tests using both the HTMT ratio and the Fornell–Larcker criterion. However, in AI-enabled auditing contexts, where improvements in EFF, ACC, and CEF frequently occur simultaneously and interactively, the relatively strong correlations among these constructs may be partially attributable to their conceptual proximity. The model's high explanatory power may also be attributed to the integrated theoretical framework combining ET, OIPT, and DCV, which collectively capture multiple complementary dimensions of AI-driven audit performance. Additionally, the study's focus on a highly technologically advanced auditing environment may have strengthened the relationships observed among the constructs.

This study further provides a more comprehensive explanation of the model's explanatory capacity. First, we acknowledge that conceptually related constructs, such as EFF, ACC, and CEF, may share some common variance because they represent complementary dimensions of AI-enabled auditing performance. However, prior to hypothesis testing, construct validity was assessed through convergent and discriminant validity analyses. The findings alleviated concerns regarding substantial construct overlap by confirming that each construct represented a distinct theoretical domain and satisfied the established criteria for discriminant validity. Second, because all responses were collected from the same respondents at a single point in time, we acknowledge that a cross-sectional perceptual survey may introduce common-method bias. This potential issue was assessed through both procedural and statistical remedies. The findings indicated that CMB did not pose a serious threat to the validity of the results. Nevertheless, we recognize that common-source variance cannot be completely eliminated and therefore acknowledge this as

a limitation of the study. Third, the implications of the high R^2 value have been clarified. The strong explanatory power suggests that the integrated theoretical framework combining ET, OIPT, and DCV captures important organizational mechanisms through which AI contributes to AUQ, rather than indicating redundancy among the constructs. Therefore, the high R^2 reflects the substantial combined influence of EFF, ACC, and CEF on AUQ within the study. Nevertheless, readers are encouraged to interpret the findings within the specific organizational and industry setting examined. Future research is recommended to further validate the model using longitudinal designs or multi-source data.

5. Findings and discussion

Regression analysis results indicate that AUQ has been positively and significantly impacted by EFF, ACC, and CEF. These findings clearly indicate that considerable efforts have been made to improve audit EFF through automation. EFF had a statistically significant positive impact on AUQ ($\beta = 0.785$; $p < 0.001$). This finding reinforces the fact that a highly efficient level of automation—characterized by faster data processing, reduced labor, and shorter audit cycles—significantly enhances performance. It also supports previous research indicating that automation reduces discrepancies more quickly and effectively. ACC also had a significant and positive impact on AUQ ($\beta = 0.661$; $p < 0.001$). The more auditors trust and rely on accurate automated tools for calculation, anomaly detection, and evidence extraction, the greater their confidence in audit results. This, in turn, strengthens professional judgment and enhances assurance in audit findings derived from audit evidence. CEF also demonstrated a significant impact, with a large effect size ($\beta = 0.508$; $p < 0.001$). These findings clearly indicate that automation tools, by reducing operational costs and improving audit productivity, play a crucial role in enhancing AUQ. Automation not only generates cost savings but also enables auditors to focus on higher-risk areas. Therefore, it can be concluded that all three hypotheses are strongly supported, as EFF, ACC, and CEF each have a significant positive impact on AUQ. The implications of these findings suggest that audit automation is not only a methodological tool for improving productivity but also a highly influential factor in enhancing overall AUQ, primarily by reducing human error and operational costs. The existing literature supports the findings of this study. Reducing the time spent on audit functions can significantly increase their effectiveness. Due to the multiple manual processes involved, such as data collection, sampling, and testing, traditional audit procedures are considered time-consuming. By using automated audit systems, auditors can examine all

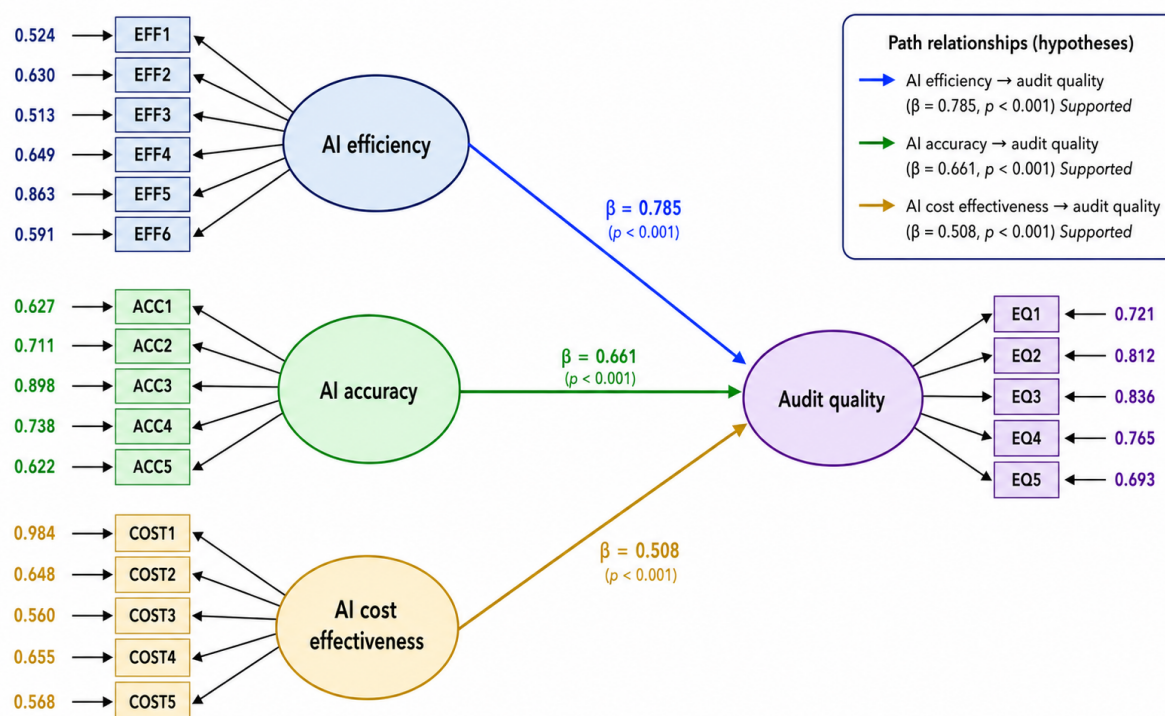


Figure 2. The measurement and structural model analysis. Image created by the authors.

available data, thereby significantly reducing the repetitive nature of manual operations and accelerating the audit process (Vasarhelyi *et al.*, 2015). According to Kokina and Davenport (2017), automated audit systems enable auditors to focus primarily on higher-level analysis and interpretation rather than data processing, resulting in significant time savings. Additionally, integrating AI and data analytics enables auditors to conduct continuous audits rather than routine audits, thereby improving EFF and overall responsiveness. Furthermore, Appelbaum *et al.* (2017) demonstrated that audit automation systems can process a continuous flow of data in real time, enabling auditors to quickly identify abnormalities. Similarly, Zhang *et al.* (2021) showed that attended process automation systems facilitate immediate data validation, thereby reducing turnaround times. Therefore, it can be concluded that automation enhances responsiveness and flexibility in audit firms, thereby maximizing resource utilization.

Accuracy is one of the most critical components of AUQ, as it ensures the reliability of financial data. Audit automation eliminates the risk of human error in results, as it relies on programmed processes based on predefined logic. Khaled and Oweis (2022), in their study on AI-driven solutions for audit automation, demonstrated that data validation outcomes achieved high ACC without inconsistencies. By reducing the burden

of persistent human errors, such as those in data entry, reconciliation, and sampling, professionals can focus on high-risk and complex areas, thereby improving the ACC of audit outcomes. Furthermore, studies have shown that automation enhances auditors' ability to detect hidden errors. For example, Schmitz and Leoni (2019) found that technologies such as blockchain, AI, and traceability improve audit trail verification and ACC. In a related study, Manson *et al.* (1998) found that the adoption of audit automation positively affects both risk assessment and reporting ACC in the U.S. and the United Kingdom. Therefore, it can be concluded that audit automation contributes to a more accurate audit process.

Cost-effectiveness is one of the main arguments in favor of audit automation. Audit automation reduces the need for manual execution, thereby lowering labor costs and increasing EFF (Manson *et al.*, 1998). According to Vasarhelyi *et al.* (2015), technology-enabled continuous auditing reduces reliance on extensive manual audits, thereby lowering costs. Appelbaum *et al.* (2017) also reported cost savings, showing that audit automation reduces data processing costs by eliminating the need for additional human labor, making firms more cost-efficient. Additionally, automation reduces rework caused by human errors and omissions, thereby increasing CEF. Kokina and Davenport (2017) noted that it minimizes the need

for costly corrections by ensuring a higher level of ACC in data collection and processing. Furthermore, Zhang *et al.* (2021) observed that it maximizes human resource utilization by enabling flexibility in handling varying workloads without requiring additional staff. As a result, audit automation not only reduces operational costs but also enhances overall financial EFF.

6. Theoretical and practical contributions

This study adds empirical evidence to both managerial and academic understanding in several ways. By improving understanding of how AI enhances AUQ, the findings contribute to the existing body of literature. Overall, this work addresses the limited research on the impact of AI on AUQ from an information processing perspective. AI integration and automated decision-making systems can enhance the information processing EFF of organizations. This study proposes that the EFF, ACC, and CEF of AI systems can significantly improve AUQ, using the theoretical framework of ET, OIPT, and DCV.

In particular, the results help quantify perceptions of AI's contribution, which may support both researchers and practitioners in integrating this disruptive technology into auditing processes. By analyzing the perceived contribution of AI to the quality of internal and external audits and identifying notable differences between domestic and international audit firms in the U.S., this study contributes to emerging knowledge in the field. The detailed measurement of AI's impact on AUQ among both internal and external auditors in the U.S. makes this study distinctive. Consequently, it expands research on AI and AUQ.

This study examines the relationship between AI and AUQ in the U.S. services industry from the perspectives of internal and external auditors, building on prior research. It is among the first studies to examine AI and AUQ constructs in service industries of developed countries while incorporating the perspectives of both internal and external auditors. AI research has been more concentrated in manufacturing sectors than in service industries, particularly in both developed and emerging economies. This study validates the AI model within the U.S. service industries using the proposed framework. In addition to the widely accepted view that AI can enhance organizational performance, this work provides a new perspective on knowledge processes and operational engagement variables. The AUQ process in the U.S. service sector is significantly influenced by AI infrastructure, EFF, ACC, and CEF. Consequently, this study provides a more comprehensive understanding of these components, which may assist future researchers in developing more robust

and empirically validated models. Additionally, the study framework provides a foundation for further research in this area, including potential applications in finance, hospitality, and education.

Regardless of audit type or organizational context, auditors can enhance their technical skills and utilize AI in auditing processes by understanding how internal and external auditors perceive and adopt AI technologies. The practical implications of the findings are important for company executives and accounting professionals. Managers in both the public and private sectors should consider the benefits and importance of AI adoption to improve productivity and quality. However, organizations must carefully plan and structure AI implementation to avoid undesirable outcomes. Managers should also select qualified accounting professionals who can effectively interact with AI systems to improve business EFF and reduce the risk of misuse.

The empirical findings offer practical insights for managers and senior executives in the service sector seeking to use AI to improve business processes. First, AI integration should focus on enhancing EFF, ACC, and CEF to improve AUQ. Managers should view AI not only as an EFF tool but also as a strategic component of business development. By leveraging capabilities such as autonomous learning and predictive analytics, AI should be strategically applied in risk management, decision-making, and process optimization. This approach can strengthen organizational resilience and continuously improve operational performance.

Second, managers should prioritize building collaborative relationships with various stakeholders, as this enhances the effectiveness of AI systems. AI implementation does not eliminate the need for external input; rather, timely, relevant data often depend on close collaboration with partners. Effective collaboration improves the quality of real-time data, enhances AI outputs, and strengthens the overall audit process, enabling more precise and efficient management of stakeholder relationships.

Finally, although AI adoption offers substantial benefits, organizations should avoid premature or poorly planned investment decisions. Firms must assess their existing AI infrastructure and readiness, as these factors significantly influence the success of implementation. Before undertaking large-scale AI integration, managers should evaluate the organization's digital maturity, including data availability, IT infrastructure, supporting technologies, and workforce capabilities, to ensure sustainable and high-quality outcomes.

7. Limitations and future research

This study examined the impact of artificial intelligence on AUQ processes in the U.S. business services sector, a sector that has received limited empirical attention from local scholars. As with other studies, this research has several limitations that should be considered when identifying directions for future research. This section acknowledges the study's limitations, which may affect the generalizability and interpretation of the findings.

Due to time and budget constraints, the study was limited to a single state in the U.S. Therefore, further empirical research is required to validate the findings across different contexts and settings. In addition, the data used in this study were collected only from service-sector organizations in the U.S. to test the theoretical model, limiting the generalizability of the findings. Different results may have been obtained if the study had been conducted across multiple sectors and business contexts, such as healthcare, hospitality, and others. Consequently, future studies are encouraged to replicate this research in diverse contexts.

Although AI has a broader meaning that encompasses various organizational stakeholders, this study focused only on the perceptions of senior employees within the selected organizations. In the services sector, the term "customers" includes both internal and external users: external customers are business-to-business clients, and internal customers are employees across professional, technical, administrative, and support roles. Therefore, the study would have been more comprehensive if it had included perspectives from all stakeholder categories and organizations.

It was also observed that the survey's anonymous distribution prevented the researcher from following up with non-respondents to encourage participation. As a result, the sample may not fully represent the views of different departments within the participating organizations. Moreover, the study relied primarily on a survey questionnaire administered to senior staff members. To reduce subjectivity in data collection, future research is recommended to incorporate data triangulation methods, such as interviews with audit managers and direct observations.

Furthermore, more robust analytical insights could be obtained by applying alternative methodologies. For example, previous studies have used logistic regression and multi-criteria decision-making techniques such as Analytic Hierarchy Process and Technique for Order Preference by Similarity to Ideal Solution to evaluate the impact of AI in various contexts, including small and medium-sized

enterprises and AUQ (e.g., Boonmee *et al.*, 2025; Pasi *et al.*, 2026). Therefore, future research is encouraged to adopt and compare such methodologies to enhance analytical rigor, originality, and practical value.

Finally, this study employed a cross-sectional design, capturing data at a single point in time. As a result, conclusions regarding changes over time should be drawn with caution. Future research is recommended to adopt longitudinal designs to better examine causal relationships and capture changes in variables over time.

8. Conclusion

Artificial intelligence has brought significant changes and developments to organizational processes and operations across various sectors, including the auditing sector, due to its rapid growth. AI-based audit automation represents a major innovation in the sector, enhancing AUQ by increasing EFF and ACC while reducing operational costs. The primary objective of this study is to investigate how AI-powered automation affects AUQ in the U.S. A structured, self-administered questionnaire was used to collect empirical data from auditors within the U.S. audit sector. A total of 207 responses were collected for analysis. MRA and correlation analysis were employed as inferential statistical techniques to test the proposed hypotheses. The results indicate that EFF significantly improves AUQ by reducing the time and effort required for audit procedures. ACC also has a significant positive effect, as automation tools enhance the credibility of audit evidence and help reduce the risk of material misstatements. CEF emerged as an influential factor, as resource-efficient tools directly improve audit performance. Overall, the findings demonstrate that audit automation is an effective strategy for enhancing AUQ, and organizations seeking improved audit outcomes should prioritize adopting efficient technological tools. Future research may extend these findings by examining the longitudinal effects of automation adoption or by comparing the relative effectiveness of different automation platforms. Such studies would provide deeper insights into how technological advancements continue to shape AUQ over time.

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Conflict of interest

Ahmad Aburayya is a Guest Editor of this journal, but was not in any way involved in the editorial and peer-review

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Ethics approval and consent to participate

Ethical approval was obtained from Alfa Plus USA (Reference Number: ID 18-643-2025). Informed consent was obtained from all individual participants included in the study.

Consent for publication

All participants provided informed consent for the publication of the findings derived from this study. Where applicable, participants gave explicit permission for the publication of any data, images, or information that could potentially reveal their identity. The authors affirm that all relevant consent forms have been obtained and are available upon reasonable request.

Availability of data

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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