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Auditors' Willingness to Learn and Apply Artificial Intelligence Technology in the Auditing Process

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ABSTRACT

The present study focuses on auditors' willingness to learn and their intention to use artificial intelligence technologies in the auditing process. Specifically, it examines how auditors' perceptions of the effectiveness of artificial intelligence in improving performance, their perceptions of the ease of using these technologies, and social influence affect their willingness to learn artificial intelligence technologies. The role of willingness to learn in shaping auditors' intention to use artificial intelligence technologies in the auditing process is also analyzed. The study employed a quantitative, cross-sectional approach based on a survey method. The research data were collected from 209 auditors and financial professionals with at least five years of professional auditing experience using a standardized questionnaire based on a five-point Likert scale. Partial least squares structural equation modeling and SmartPLS software were used to test the conceptual model and research hypotheses. The findings showed that auditors' perceptions of the effectiveness of artificial intelligence, their perceptions of the ease of using this technology, and social influence each had a positive and significant effect on their willingness to learn artificial intelligence technologies. Furthermore, willingness to learn artificial intelligence technologies had a positive and significant effect on the application of these technologies in the auditing process and played a key role in strengthening their acceptance within the auditing profession. The future application of artificial intelligence in the auditing profession depends less on the development of the technology itself than on auditors' readiness and willingness to learn and adopt it. The development of positive attitudes toward the capabilities of artificial intelligence, together with organizational support and the provision of educational opportunities, can facilitate the effective use of this technology in auditing processes. Therefore, audit firms, universities, and professional bodies should consider the development of artificial intelligence-related competencies to be one of their strategic priorities. In addition to facilitating the adoption of emerging technologies, achieving this objective can enhance the quality of professional judgment, increase efficiency, and improve the quality of audit services in data-driven business environments.

Keywords: artificial intelligence, auditing process, willingness to learn technology, performance expectancy, social influence.

Introduction

Artificial intelligence (AI) has emerged as one of the most consequential technological developments reshaping contemporary organizations, professional services, and knowledge-intensive occupations. Its growing capacity to process large volumes of structured and unstructured data, identify complex patterns, generate predictions, automate repetitive activities, and support human decision-making has transformed expectations regarding organizational efficiency and professional performance. Across industries, AI is increasingly integrated into operational, analytical, educational, and managerial processes, thereby redefining the relationship between human expertise and digital technologies [1, 2]. This transformation is closely associated with the broader development of Industry 4.0, in which intelligent systems, advanced analytics, cloud computing, robotic process automation, interconnected information infrastructures, and data-driven decision-making are becoming central to organizational competitiveness and innovation [3, 4]. Digital transformation, therefore, is no longer limited to the adoption of new technological tools; rather, it involves fundamental changes in organizational processes, knowledge systems, employee competencies, and innovation capabilities [5]. Within this environment, accounting and auditing are undergoing a particularly significant transformation because both professions depend heavily on the collection, verification, interpretation, and communication of financial and nonfinancial information.

The auditing profession has traditionally relied on auditors' technical knowledge, professional judgment, sampling procedures, documentary evidence, and compliance-oriented testing. However, the rapid expansion of digital business transactions and the increasing volume and complexity of organizational data have created conditions in which conventional audit methods may no longer be sufficient to provide timely and comprehensive assurance. AI technologies can extend the scope of audit procedures by enabling auditors to analyze entire populations of transactions, detect unusual patterns, assess risk continuously, and identify potential anomalies that may remain undetected through traditional sampling techniques [6, 7]. AI-driven systems may also facilitate automated document review, contract analysis, fraud detection, classification of financial records, predictive risk assessment, and continuous auditing. These developments indicate a transition from periodic, retrospective auditing toward more continuous, intelligent, and data-centered assurance models [8]. Systematic evidence further suggests that AI is transforming both accounting and auditing through changes in process automation, analytical capability, decision support, fraud detection, and the organization of professional work [9]. Accordingly, AI is becoming not merely an auxiliary audit tool but a potentially foundational component of future audit methodologies.

The practical significance of AI adoption in auditing is closely related to its capacity to improve audit quality, efficiency, and the informational value of assurance services. AI applications may enable audit teams to allocate resources more effectively, focus professional attention on high-risk areas, reduce the time spent on routine procedures, and strengthen the consistency of evidence evaluation. Empirical and review-based research has increasingly examined whether such technologies contribute to more accurate risk assessments, more comprehensive testing, and improved audit outcomes [10]. In financial markets, AI adoption has also been associated with audit quality and the broader quality of integrated financial reporting, suggesting that technological capability may influence both the performance of audit procedures and the credibility of corporate reporting systems [11]. In the public sector, AI may enhance the examination of extensive government transactions, improve the identification of irregularities, and strengthen accountability in the use of public resources [12]. At the same time, the use of AI in public-sector auditing introduces risks related to data quality, algorithmic bias, opacity, privacy, and ethical responsibility, which require careful governance and professional oversight [13]. Thus, the potential benefits of AI cannot be separated from the institutional and human conditions under which the technology is implemented.

Despite the technological potential of AI, the success of its implementation in auditing ultimately depends on auditors' readiness, acceptance, knowledge, and willingness to engage with the technology. Audit firms may invest in sophisticated systems, but these investments will not necessarily generate value when auditors lack confidence in the technology, perceive it as difficult to use, resist changes in professional routines, or do not possess the competencies required to interpret AI-generated outputs. Field evidence demonstrates that AI implementation in auditing creates both opportunities and operational challenges, including limitations in data accessibility, integration with existing systems, skill shortages, explainability concerns, organizational resistance, and uncertainty regarding the division of responsibility between auditors and automated systems [14]. Early evidence from accounting practice further indicates that effective outcomes are more likely to emerge through human–AI collaboration than through the complete replacement of professional accountants or auditors [15]. In this collaborative model, AI performs computationally intensive and pattern-recognition tasks, while auditors provide contextual interpretation, skepticism, ethical reasoning, and professional accountability. The strategic challenge, therefore, is not simply whether AI can perform certain audit activities, but whether auditors are prepared to learn how to use it effectively and integrate it into professional judgment.

This issue is particularly important because the introduction of AI changes the nature of auditor judgment. Traditional professional judgment is based on the auditor's ability to evaluate evidence, assess materiality, understand business conditions, and apply professional standards under uncertainty. In AI-enabled environments, auditors must additionally evaluate the quality of data used by algorithms, understand the assumptions underlying models, assess the reliability of automated outputs, and determine when technological recommendations should be accepted, questioned, or overridden. The Fourth Industrial Revolution has therefore altered the informational context in which auditors exercise judgment and has increased the importance of technological literacy alongside conventional accounting expertise [16]. AI-based decision-making also raises normative and ethical questions concerning transparency, accountability, fairness, explainability, and responsibility for errors [17]. Because an algorithm cannot independently assume professional or legal responsibility, auditors remain accountable for the conclusions reached and the evidence relied upon. This condition makes learning and competency development essential, as auditors must understand not only how to operate AI systems but also how to critically evaluate their outputs and limitations.

Research on technology acceptance provides a useful foundation for explaining why some professionals are more willing than others to learn and use new technologies. The Unified Theory of Acceptance and Use of Technology emphasizes that performance expectancy, effort expectancy, social influence, and facilitating conditions shape individuals' behavioral intentions and technology-use behavior. Within auditing, performance expectancy refers to the extent to which auditors believe that AI can improve their performance, accuracy, productivity, or professional effectiveness. When auditors perceive that AI can reduce manual workload, enhance anomaly detection, improve risk assessment, and support better decisions, they may be more motivated to acquire the knowledge required to use it. Effort expectancy concerns the perceived ease of learning and operating AI-based systems. Technologies that appear overly complex, difficult to understand, or incompatible with existing audit routines may discourage learning, even when their potential benefits are recognized. Social influence refers to the extent to which important professional groups, colleagues, supervisors, firms, regulators, and institutional networks encourage or expect the use of AI. Studies applying technology-acceptance models to auditing have demonstrated that these factors can significantly influence auditors' interest in computer-assisted audit techniques and intelligent audit tools [18, 19].

The importance of these variables has also been demonstrated in more recent studies of AI adoption and audit technology readiness. Research based on the UTAUT framework indicates that performance expectancy, effort expectancy, social influence, and organizational infrastructure may shape auditors' acceptance of AI, while the availability of appropriate information technology infrastructure can strengthen or weaken these relationships [20]. Technology readiness is likewise important because auditors differ in their optimism about technology, innovativeness, perceived discomfort, and insecurity. These psychological and professional orientations affect whether they approach AI as a useful opportunity or as a threat to established working practices [21]. Evidence from AI-based audit acceptance models similarly suggests that auditors' readiness to engage with technology is a central antecedent of adoption [22]. Research on internal auditing also confirms that the level of acceptance and behavioral intention to use AI varies according to auditors' beliefs regarding usefulness, ease of use, and perceived professional value [23]. Together, these findings indicate that AI adoption is not an automatic consequence of technological availability; it is a behavioral and organizational process shaped by auditors' expectations, attitudes, and learning orientation.

Willingness to learn is especially important because AI-related competencies cannot be acquired through passive exposure. Auditors must actively develop new forms of knowledge related to data analytics, algorithmic reasoning, information systems, automated controls, cybersecurity, model limitations, and the interpretation of machine-generated evidence. The motivation to learn therefore functions as a bridge between favorable perceptions of technology and actual professional use. Research involving emerging economies has shown that auditors' willingness to learn significantly contributes to their intention to use AI technologies in the audit process, and that this willingness is influenced by beliefs about performance improvement, ease of use, and social expectations [24]. Similar evidence from accounting education indicates that technology-acceptance factors and social-cognitive mechanisms influence intentions to learn audit software, suggesting that perceived capability, expected benefits, and environmental support shape learning motivation even before individuals enter professional practice [25]. More broadly, studies of AI-assisted learning environments show that acceptance is influenced by performance expectations, effort expectations, social influence, and perceived risk [26]. These findings reinforce the proposition that learning intention should be treated as a distinct and theoretically meaningful construct rather than being assumed to arise automatically from general technology acceptance.

Social and cultural conditions may further shape willingness to learn and adopt AI. Auditing is embedded within professional hierarchies, organizational norms, regulatory expectations, and peer networks. Auditors may become more willing to develop AI competencies when senior partners, supervisors, professional associations, universities, and regulators communicate that such competencies are important for career advancement and professional legitimacy. Conversely, weak institutional encouragement may create uncertainty about whether the investment in learning will be rewarded. Cross-cultural research has shown that cultural dimensions, social influence, and personal innovativeness can meaningfully affect technology adoption, indicating that acceptance models should be interpreted within their institutional and cultural contexts [27]. These issues are particularly relevant in developing and emerging economies, where differences in technological infrastructure, organizational resources, professional education, and regulatory support may influence the speed and direction of AI adoption. Evidence from developing countries confirms that AI-related factors can affect the use of information auditing and that organizational and environmental conditions may facilitate or constrain implementation [28]. Consequently, findings derived from highly digitized economies cannot necessarily be generalized without examining local professional conditions.

The implementation of AI in auditing also depends on the perceived feasibility and added value of technology-related recommendations. Research on information technology audits has shown that professionals are more likely to implement recommendations when they perceive the risks as significant, the proposed actions as practical, and the expected benefits as valuable [29]. This logic is directly applicable to AI learning: auditors are more likely to invest time and effort in developing technological competencies when they perceive clear professional benefits and believe the learning process is manageable. Strategic approaches to AI in accounting likewise emphasize that successful implementation requires alignment between technological investments, organizational objectives, professional specializations, and capability development [30]. The quality of data is also central to effective AI use. AI systems depend on reliable, consistent, and relevant data; poor data quality may produce misleading outputs and undermine trust in the technology. Although developed in the context of marketing information, the broader principles of data quality assurance—accuracy, completeness, reliability, and consistency—are equally critical for AI-enabled auditing [31]. Auditors' willingness to learn may therefore be strengthened when organizations provide not only software access but also reliable data environments, technical support, and clear implementation standards.

At the research level, the rapid growth of AI in accounting and auditing has generated an expanding but still fragmented body of literature. Recent reviews identify increasing attention to AI-driven auditing, continuous assurance, algorithmic decision-making, audit analytics, fraud detection, professional judgment, and technology acceptance [32]. Research agendas in accounting information systems also emphasize the need to move beyond descriptive discussions of technological possibilities and toward theoretically grounded studies of how AI changes organizational processes, professional roles, governance structures, and research methods [33]. Although the literature increasingly documents the potential benefits and risks of AI, less attention has been devoted to the learning-related mechanisms through which auditors become willing and able to use these technologies. Many studies focus directly on behavioral intention or adoption, without adequately examining whether individuals possess the motivation to acquire the skills required for meaningful use. This omission is important because willingness to learn may explain why favorable beliefs about AI do not always translate directly into actual adoption.

Furthermore, the use of AI in auditing should be examined as part of a broader transition toward intelligent professional work rather than as a simple substitution of software for manual procedures. The transformation of accounting and auditing practices involves changes in organizational structures, audit methodologies, professional education, knowledge-sharing systems, and the competencies expected from practitioners [8, 9]. The growing integration of AI into public and private auditing also requires continuous professional development, interdisciplinary collaboration, and stronger connections between universities, audit firms, regulators, and professional bodies [12, 13]. Without coordinated learning opportunities, auditors may remain dependent on technical specialists and may be unable to critically evaluate AI-supported evidence. In contrast, when learning is supported through training, experimentation, mentorship, and appropriate technological infrastructure, auditors may develop both operational competence and informed professional skepticism. Thus, learning willingness is likely to be a strategic determinant of whether AI strengthens or weakens audit quality.

The Iranian auditing environment provides a relevant context for examining these relationships. As organizations increasingly digitize financial processes and generate larger volumes of electronic data, Iranian auditors are likely to encounter growing expectations to use data analytics and AI-supported tools. However, the adoption of such technologies may be affected by institutional constraints, differences in organizational resources, uneven access to advanced systems, and variation in professional training. Research from emerging economies indicates that these contextual conditions can substantially influence technology readiness, perceived usefulness, and behavioral intention [22, 24]. Accordingly, examining auditors with substantial professional experience can provide a realistic assessment of how established practitioners evaluate AI-related learning and use. Their perceptions are especially important because experienced auditors are responsible for interpreting evidence, supervising audit teams, and making judgments that may determine whether AI becomes integrated into routine professional practice.

Against this background, the present study aims to examine the effects of auditors' performance expectancy regarding AI, effort expectancy, and social influence on their willingness to learn AI technology and to determine how willingness to learn affects the intention to use AI in the auditing process.

Methodology

This study employed a quantitative, analytical, and cross-sectional research design to investigate auditors' willingness to learn artificial intelligence technologies and their intention to apply such technologies in the auditing process. The study was grounded in an objective methodological orientation and relied on the collection and statistical analysis of numerical data. An inductive approach was adopted, whereby empirical evidence obtained from participants was used to examine the proposed relationships among the research variables and to test the study hypotheses. Data were collected through a survey administered to individuals with substantial professional experience in auditing. Eligibility for participation required a minimum of five years of professional experience in the auditing field. This criterion was established to ensure that respondents possessed sufficient technical knowledge, professional judgment, and practical familiarity with auditing procedures to provide informed assessments of the factors influencing the learning and application of artificial intelligence technologies in auditing. The target population consisted of two principal groups: auditors who were actively employed in the auditing profession and financial professionals who were currently working in other areas of finance or accounting but had previously acquired at least five years of professional auditing experience. Including both groups made it possible to obtain perspectives from individuals with direct and extensive knowledge of auditing processes, regardless of whether they were currently employed as auditors.

The minimum required sample size was determined with reference to the recommendations for partial least squares structural equation modeling. Hair et al. (2019) suggested that survey-based structural equation modeling studies may allocate approximately 10 to 20 observations for each independent observed variable included in the model. Because the measurement model of the present study contained 12 independent observed indicators, the required sample size was estimated to range from 120 to 240 participants. Accordingly, 120 observations were considered the minimum acceptable sample size for conducting the statistical analyses and obtaining sufficiently reliable results. To achieve an adequate number of valid responses, 270 questionnaires were distributed among members of the target population. Following data collection, all returned questionnaires were evaluated for completeness, consistency, response quality, and suitability for statistical analysis. Questionnaires containing substantial missing data, incomplete answers, inconsistent response patterns, or other indications of inadequate completion were excluded. After this screening process, 209 complete and valid questionnaires were retained and included in the final analysis, corresponding to a usable response rate of approximately 77.4%.

Of the 209 respondents, approximately 70% were auditors who were actively employed in the auditing profession, whereas the remaining 30% were financial professionals working in other finance- and accounting-related fields who had at least five years of prior professional auditing experience. The final sample consisted of 187 men and 22 women. Regarding educational attainment, 40 respondents held bachelor's degrees, 138 held master's degrees, 20 held doctoral degrees, and 11 held Doctor of Business Administration degrees with a specialization in finance. In terms of academic discipline, 143 participants had studied accounting in one of its various specializations, 39 had studied financial management, 20 had studied other fields with a financial orientation, and seven had studied financial engineering. The respondents also represented different levels of professional experience. Specifically, 42 participants had between 5 and 10 years of work experience, 117 had between 10 and 15 years, 36 had between 15 and 20 years, and 14 had more than 20 years of professional experience. In addition, approximately 8% of the respondents were university faculty members, whereas the remaining 92% were professionals employed in auditing or in other sectors related to finance and accounting. Regarding professional certification, 21% of the participants held a certified public accountant qualification, whereas 79% did not hold this professional certification. These demographic and professional characteristics indicated that the sample was predominantly composed of experienced and highly educated professionals with substantial familiarity with auditing, accounting, and financial practices.

Data were collected using a structured questionnaire designed to measure the principal constructs included in the conceptual model. The questionnaire was developed through the adaptation of instruments used in previous studies, particularly the measure proposed by Mansour et al. (2025). Because the original instrument had been developed in a context different from that of the present study, its items were localized and revised to ensure their compatibility with the environmental, professional, institutional, and regulatory characteristics of the Iranian auditing profession. The adaptation process involved reviewing the conceptual meaning of each item, modifying terminology where necessary, and ensuring that the statements were understandable and professionally relevant to auditors and financial specialists. Before the main administration, the preliminary version of the questionnaire was submitted to a group of university faculty members and academic experts with relevant knowledge of auditing, management, accounting, and technology adoption. These experts evaluated the clarity, appropriateness, comprehensibility, and wording of the items. Their comments were used to revise the structure, phrasing, and technical language of the questionnaire, after which the final version was prepared for distribution among the target respondents.

The questionnaire employed a five-point Likert response scale to record the extent of respondents' agreement with each statement. The instrument measured five latent constructs: auditors' performance expectancy regarding the capacity of artificial intelligence to improve auditing performance, auditors' effort expectancy regarding the ease of using artificial intelligence technologies, social influence, willingness to learn artificial intelligence technology, and the practical application or intended use of artificial intelligence technology in the auditing process. Performance expectancy was measured using four items coded PE1 to PE4. Effort expectancy was assessed using five items coded EE1 to EE5. Social influence was measured using three items coded SI1 to SI3. Willingness to learn artificial intelligence technology was assessed using five items coded WL1 to WL5. The practical application of artificial intelligence technology in the auditing process was measured using four items coded AU1 to AU4. Higher scores represented stronger perceptions of artificial intelligence effectiveness, greater perceived ease of use, stronger social influence, greater willingness to learn, and a stronger tendency to apply artificial intelligence in auditing activities.

The adequacy of the measurement instrument was examined through the assessment of indicator reliability, internal consistency reliability, and convergent validity. Indicator reliability was evaluated using the outer factor loadings of the observable items on their corresponding latent constructs. All factor loadings exceeded the minimum acceptable threshold of 0.50, supporting the adequacy of the items in representing their intended constructs. Internal consistency reliability was assessed using Cronbach's alpha, composite reliability, and rho_A. The values of all three reliability coefficients exceeded 0.70

for every construct, indicating satisfactory internal consistency among the items. Convergent validity was evaluated using the average variance extracted. All average variance extracted values exceeded 0.50, indicating that each construct explained more than half of the variance in its associated indicators. These results confirmed that the questionnaire possessed acceptable psychometric properties and was sufficiently reliable and valid for evaluating the proposed structural relationships.

Following the completion of data collection, the responses were initially entered into Microsoft Excel for coding, organization, screening, and preparation. During this stage, the dataset was examined for missing values, incomplete records, inconsistent responses, and potential data-entry errors. Only questionnaires that had been fully completed and met the required quality criteria were retained in the final dataset. After the data-cleaning process, the prepared dataset was transferred to SmartPLS for statistical analysis. Partial least squares structural equation modeling was selected because the study aimed to examine a multivariate predictive model involving several latent constructs and multiple observed indicators. This method also enabled the simultaneous evaluation of the measurement model and the structural relationships proposed in the conceptual framework.

The data analysis was conducted in two principal stages. First, the measurement model was assessed to determine whether the observed indicators adequately represented their corresponding latent constructs. This assessment included the examination of outer factor loadings, Cronbach's alpha, rho_A, composite reliability, and average variance extracted. Factor loadings were used to evaluate indicator reliability, while Cronbach's alpha, rho_A, and composite reliability were used to assess the internal consistency of the constructs. Average variance extracted was calculated to examine convergent validity. Threshold values of 0.70 or higher were applied to Cronbach's alpha, rho_A, and composite reliability, whereas an average variance extracted value of at least 0.50 was regarded as evidence of acceptable convergent validity. The results of these assessments demonstrated that the measurement model met the required reliability and validity standards.

In the second stage, the structural model was assessed to test the research hypotheses and determine the model's explanatory and predictive capacity. The coefficients of determination were calculated for the endogenous constructs to indicate the proportion of variance explained by their predictor variables. The coefficient of determination for willingness to learn artificial intelligence technology was 0.760, indicating that the predictor constructs explained approximately 76% of its variance. The coefficient of determination for the practical application of artificial intelligence technology in the auditing process was 0.600, demonstrating that approximately 60% of the variance in this construct was explained by willingness to learn and the other relevant model variables. Model fit was examined using the standardized root mean square residual, the squared Euclidean distance measure, chi-square statistics, and the normed fit index. The standardized root mean square residual values for the saturated and estimated models were below 0.08, indicating an acceptable overall model fit.

The statistical significance of the hypothesized structural paths was evaluated using the bootstrapping procedure available in SmartPLS. Bootstrapping generated standard errors, t statistics, and p values for each proposed relationship. Hypotheses were considered supported when the corresponding path coefficients were statistically significant at the predetermined significance level. The analysis showed that performance expectancy regarding artificial intelligence had a significant positive effect on auditors' willingness to learn artificial intelligence technology. Effort expectancy also had a significant positive effect on willingness to learn, and social influence significantly predicted auditors' willingness to acquire artificial intelligence-related knowledge and skills. In addition, willingness to learn artificial intelligence technology had a statistically significant positive effect on the intention to use and practically apply this technology in the auditing process. All statistical tests were interpreted using two-tailed significance criteria, and p values originally calculated as .000 were reported as $p < .001$ in accordance with APA reporting conventions.

Findings and Results

In the first stage of evaluating the measurement model, the relationships between the latent constructs and their observable indicators were examined, because the validity and adequacy of these relationships provide the basis for confirming the validity of the measurement model and ensuring the accurate measurement of the research constructs. At this stage, the manner in which each latent construct was represented by a set of observable indicators or items was evaluated, and the degree of correspondence between each indicator and its respective construct was assessed. Table 1 comprehensively presents the structure of these relationships and the assignment of the measurement indicators to the research constructs.

Table 1

Factor Loadings and Relationships Between Latent and Observed Variables

Latent Variable	Observed Variable	Factor Loading
Auditors' performance expectancy regarding artificial intelligence for improving performance	PE1	0.759
	PE2	0.776
	PE3	0.740
	PE4	0.781
Auditors' effort expectancy regarding the use of artificial intelligence technologies	EE1	0.785
	EE2	0.786
	EE3	0.713
	EE4	0.760
	EE5	0.764
Social influence	SI1	0.728
	SI2	0.847
	SI3	0.837
Willingness to learn artificial intelligence technology	WL1	0.736
	WL2	0.722
	WL3	0.799
	WL4	0.767
	WL5	0.731
Practical application of artificial intelligence technology in the auditing process	AU1	0.764
	AU2	0.743
	AU3	0.763
	AU4	0.769

The results presented in Table 1 indicate that the factor loadings of all items exceeded the acceptable threshold of 0.50. Accordingly, the convergent validity of the measurement model was confirmed (Kline, 2023). Overall, the findings indicate a satisfactory fit of the measurement model and demonstrate that the items were adequate for measuring the research constructs.

The results for the coefficient of determination (R^2) and adjusted coefficient of determination (adjusted R^2) for the endogenous variables of the model are presented in Table 2. These indices indicate the model's explanatory power in predicting variations in the dependent variables and provide a basis for evaluating the structural adequacy of the model.

Figure 1

Factor Loadings and Relationships Between Latent and Observed Variables

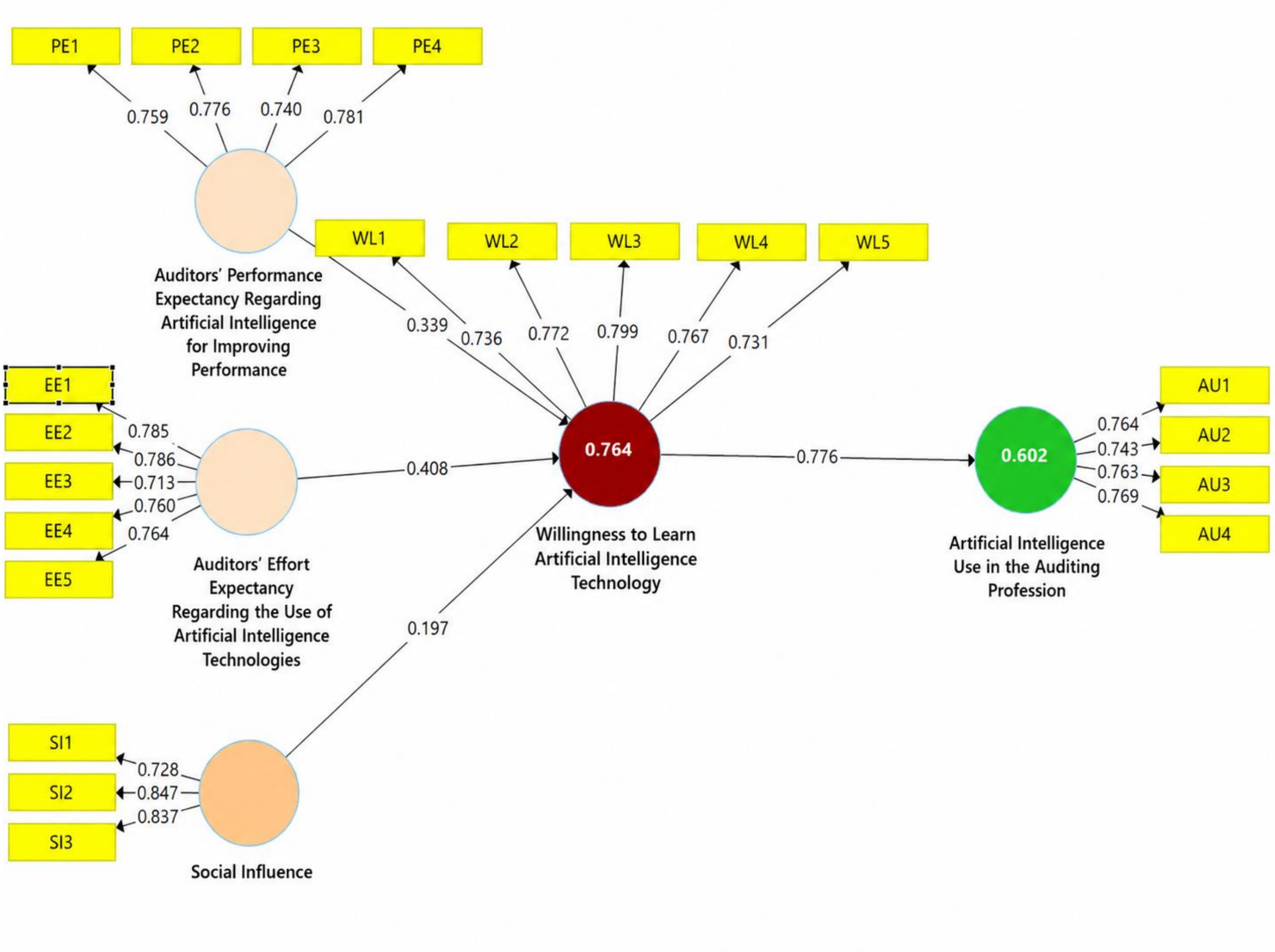

Table 2

Results of the Evaluation of the Structural Model's Explanatory Power Based on the Coefficients of Determination

Variable	Adjusted R²	R²
Willingness to learn artificial intelligence technology	0.764	0.760
Practical application of artificial intelligence technology in the auditing process	0.6002	0.600

The results presented in Table 2 demonstrate that the model possesses satisfactory explanatory power for the endogenous variables. The coefficient of determination for willingness to learn artificial intelligence technology was 0.760, indicating that approximately 76% of the variance in this variable was explained by the predictor constructs included in the model. This value represents a high level of explanatory power. In addition, the coefficient of determination for the practical application of artificial intelligence technology in the auditing process was 0.600, indicating that 60% of the variance in this variable was explained by the model's independent variables. Overall, these results demonstrate that the structural model has satisfactory explanatory power and adequately accounts for the relationships among the research constructs.

Table 3

Reliability and Convergent Validity Indices of the Research Constructs

Variables	Cronbach's α	ρA	Composite Reliability (CR)	Average Variance Extracted (AVE)
Auditors' performance expectancy regarding artificial intelligence for improving performance	0.763	0.765	0.849	0.584
Auditors' effort expectancy regarding the use of artificial intelligence technologies	0.819	0.821	0.874	0.581
Social influence	0.728	0.741	0.847	0.649
Willingness to learn artificial intelligence technology	0.818	0.819	0.879	0.580
Practical application of artificial intelligence technology in the auditing process	0.757	0.759	0.845	0.578
Assessment criterion	> 0.70	> 0.70	> 0.70	> 0.50

The results presented in Table 3 indicate that all research constructs demonstrated satisfactory reliability and convergent validity. The values of Cronbach's alpha, composite reliability, and ρA for all variables exceeded the threshold of 0.70, indicating satisfactory internal consistency and stability among the items measuring each construct. Furthermore, the average variance extracted values for all variables were greater than 0.50, indicating that each construct explained a substantial proportion of the variance in its corresponding indicators and possessed acceptable convergent validity. Among the constructs, social influence demonstrated the highest level of convergent validity, with an AVE value of 0.649, whereas the other constructs also remained within the acceptable range, with AVE values ranging from 0.578 to 0.584. Overall, the findings indicate that the measurement model was of satisfactory quality and that the reliability and validity indices confirmed the adequacy of the measurement instrument for testing the structural model.

Model fit assessment is one of the fundamental stages of structural equation modeling and evaluates the extent to which the conceptual research model corresponds with the empirical data. Model fit is assessed using a set of statistical indices, each of which examines a particular aspect of model quality. Obtaining acceptable values for these indices indicates that the proposed model is sufficiently adequate to represent the structure of the relationships among the research constructs and has an appropriate capacity to explain the observed data and test the proposed conceptual relationships.

Table 4

Results of the Overall Model Fit Evaluation

Fit Index	Saturated Model	Estimated Model
Standardized root mean square residual (SRMR)	0.061	0.072
d_ULS	0.872	1.026
Chi-square	455.066	494.649
Normed fit index (NFI)	0.805	0.788

The model fit indices indicate that the proposed model had an acceptable fit. The SRMR values for both the saturated model (0.061) and the estimated model (0.072) were below the threshold of 0.08, indicating a satisfactory model fit. The d_ULS values also indicated an appropriate correspondence between the model and the empirical data. The normed fit index values of 0.805 and 0.788, although slightly below the ideal threshold of 0.90, were considered acceptable within the context of partial least squares structural equation modeling. Overall, these indices demonstrate that the model had an adequate fit and was sufficiently appropriate for testing the relationships among the research constructs.

Figure 2

Bootstrap Results for the Structural Model

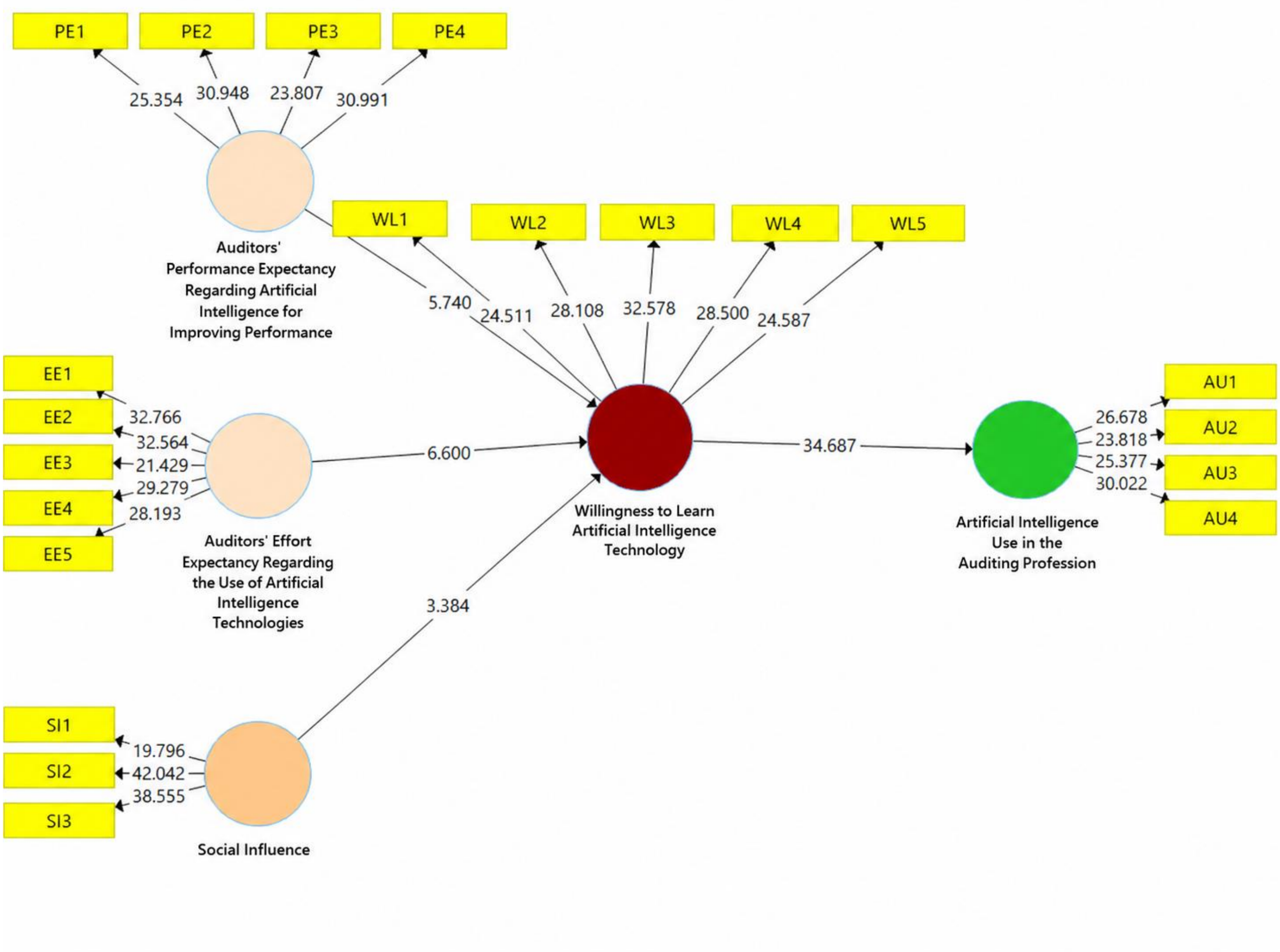

Table 5

Results of Hypothesis Testing

Hypothesis	Hypothesis Statement	t Statistic	p Value	Confidence Level	Result
H1	Auditors' performance expectancy regarding the ability of artificial intelligence to improve performance has a significant effect on their motivation to learn artificial intelligence technology for auditing.	5.700	< .001	99%	Supported
H2	Auditors' effort expectancy regarding the use of artificial intelligence technologies has a significant effect on their willingness to learn these technologies in the auditing profession.	6.600	< .001	99%	Supported
H3	Social influence has a significant effect on auditors' willingness to learn artificial intelligence technology.	3.384	.001	99%	Supported
H4	Willingness to learn artificial intelligence technology has a significant effect on the intention to use this technology in the auditing process.	34.687	< .001	99%	Supported

Discussion and Conclusion

The present study examined the factors influencing auditors' willingness to learn artificial intelligence technologies and the effect of this willingness on their intention to apply AI in the auditing process. The results supported all four research hypotheses. Auditors' performance expectancy regarding AI had a positive and statistically significant effect on their willingness to learn AI technology, with a t value of 5.700 and $p < .001$. Auditors' effort expectancy regarding the use of AI technologies also positively and significantly affected their willingness to learn, with a t value of 6.600 and $p < .001$. Social influence had a positive and significant effect on willingness to learn AI technology, with a t value of 3.384 and $p = .001$. Finally, willingness to learn AI technology had a strong positive and significant effect on the intention to use AI in the auditing process, with a t value of 34.687 and $p < .001$. The model also demonstrated substantial explanatory power. Performance expectancy, effort expectancy, and social influence jointly explained approximately 76% of the variance in auditors' willingness to learn AI technology, while willingness to learn explained approximately 60% of the variance in the practical application of AI in auditing. These findings indicate that auditors' adoption of AI depends not only on the availability of technological systems but also on their perceptions of usefulness and usability, the expectations of their professional environment, and their motivation to acquire the necessary knowledge and skills.

The first finding showed that auditors' performance expectancy regarding AI significantly increased their willingness to learn the technology. In other words, auditors were more motivated to develop AI-related competencies when they believed that AI could improve their professional performance. This result is theoretically reasonable because professionals are more likely to invest time and cognitive effort in learning a technology when they expect it to produce meaningful improvements in productivity, accuracy, decision quality, or career effectiveness. In auditing, the perceived performance benefits of AI may include faster analysis of large datasets, more comprehensive transaction testing, enhanced anomaly detection, improved risk assessment, and a reduction in the time devoted to repetitive procedures. The result is consistent with the evidence reported by Mansour et al., who found that performance-related beliefs significantly influenced auditors' willingness to learn and subsequently use AI technologies in the audit process [24]. It is also compatible with studies showing that perceived usefulness and expected performance gains are central determinants of auditors' acceptance of AI and computer-assisted auditing systems [18-20].

The significance of performance expectancy can also be explained by the changing informational requirements of contemporary auditing. Traditional audit procedures are increasingly challenged by the volume, velocity, and complexity of organizational data. AI provides the possibility of analyzing broader transaction populations, recognizing patterns that may not be immediately visible to human auditors, and supporting continuous or near-continuous assurance. Empirical evidence suggests that AI can improve aspects of the audit process by increasing analytical capacity and enabling auditors to direct attention toward higher-risk transactions and judgments [6]. Reviews of AI and audit quality similarly indicate that advanced technologies can strengthen the comprehensiveness and efficiency of audit procedures when they are appropriately integrated into professional practice [10]. The positive relationship identified in the present study therefore suggests that auditors' learning motivation is strongly connected to their expectation that AI will create identifiable professional value. When AI is perceived as an instrument for enhancing rather than undermining professional performance, auditors are more likely to regard learning as a worthwhile investment.

This finding is also aligned with research showing that AI adoption can contribute to audit quality and financial reporting outcomes. Khan et al. reported that AI adoption was associated with audit quality and integrated financial reporting in Gulf Cooperation Council markets, indicating that technological implementation can influence both audit execution and reporting credibility [11]. Moreover, field evidence indicates that AI can create substantial opportunities in auditing through automation, data analysis, and decision support, although the benefits depend on organizational conditions and implementation quality [14]. The current result extends these studies by emphasizing that anticipated performance benefits operate before actual adoption through auditors' willingness to learn. Therefore, communicating concrete and occupation-specific benefits may be essential for encouraging auditors to participate in AI training and capability-development programs.

The second finding demonstrated that effort expectancy had a positive and significant effect on auditors' willingness to learn AI technologies. This means that auditors were more willing to acquire AI-related knowledge when they perceived the technology as understandable, accessible, and relatively easy to use. Although learning any advanced technology requires effort, perceived complexity may discourage engagement when auditors believe that AI systems require highly specialized programming knowledge or are incompatible with established audit practices. Conversely, intuitive interfaces, clear documentation, user-oriented training, and integration with familiar audit software may reduce psychological and practical barriers to learning. This result is consistent with UTAUT-based studies indicating that effort expectancy is a significant determinant of auditors' behavioral intentions toward computer-assisted auditing techniques and AI-supported systems [18, 19]. It also supports findings that the perceived ease of AI use contributes to internal auditors' acceptance and behavioral intention [23].

The effect of effort expectancy may be particularly important in auditing because practitioners frequently work under time pressure, budget constraints, regulatory deadlines, and substantial professional responsibility. Even when auditors acknowledge the potential value of AI, they may hesitate to learn it if they expect the learning process to disrupt existing assignments or impose excessive cognitive demands. Technology-readiness research has shown that optimism and innovativeness can facilitate auditors' readiness, whereas discomfort and insecurity may inhibit their engagement with new systems [21]. Similarly, AI-based audit acceptance has been associated with auditors' technology readiness and their confidence in interacting with digital tools [22]. The current findings suggest that improving perceived usability may therefore have effects beyond immediate system acceptance. It can motivate auditors to begin the learning process, experiment with AI applications, and develop confidence through repeated use.

The result is also consistent with evidence from AI-assisted learning contexts. Wu et al. found that willingness to accept AI-supported learning environments was influenced by technology-acceptance factors, including effort expectancy and perceived risk [26]. Although that study was conducted in an educational context, its underlying implication is relevant to professional learning: users are more willing to engage with AI when the learning environment appears manageable and when uncertainty about the technology is reduced. The present study accordingly indicates that audit organizations should not assume that technological sophistication itself will motivate learning. Highly capable systems may remain underused when their interfaces, terminology, or operational procedures are perceived as difficult. The usability of AI tools and the design of training environments are therefore central components of auditors' learning willingness.

The third finding indicated that social influence positively and significantly affected auditors' willingness to learn AI technology. Although the magnitude of this relationship was lower than those associated with performance and effort expectancy, it remained statistically meaningful. This result implies that auditors' willingness to learn is affected by the expectations, encouragement, and behavior of individuals and institutions that are important within their professional environment. Audit partners, supervisors, colleagues, clients, professional associations, universities, and regulatory bodies can signal whether AI competence is regarded as valuable, legitimate, and necessary. When respected professional actors support AI use, auditors may interpret technological learning as an emerging professional norm rather than an optional activity. This interpretation is consistent with UTAUT-based research in auditing, which identifies social influence as a determinant of interest in adopting computer-assisted and AI-based audit technologies [19, 20].

The role of social influence can also be understood through the collective and hierarchical nature of audit work. Audit procedures are generally performed within teams and under formal supervision. Individual auditors may have limited authority to introduce new technologies independently, especially when firm policies, partner preferences, or client systems determine the available tools. Consequently, support from organizational leaders may legitimize the time and effort required for learning. Evidence from cross-cultural technology-adoption research indicates that social influence interacts with cultural values and personal innovativeness in shaping AI adoption [27]. In institutional environments where conformity to professional expectations and senior authority is important, social influence may be particularly relevant. The finding also corresponds with evidence that accounting students' intentions to learn audit software are shaped by technology-acceptance and social-cognitive factors [25]. Accordingly, the development of AI competencies should be approached as an organizational and professional process rather than being assigned exclusively to individual auditors.

The positive effect of social influence may additionally reflect uncertainty surrounding AI's professional implications. Auditors may be unsure whether AI will improve their careers, reduce the demand for certain tasks, or alter the distribution of professional responsibility. Under conditions of uncertainty, individuals frequently rely on the views of trusted colleagues and institutions. Public endorsement by audit firms and professional organizations can reduce perceived uncertainty and establish AI learning as a recognized component of professional development. However, social influence should not be understood merely as pressure to conform. It can also operate through knowledge sharing, mentoring, peer learning, and the observation of successful technology use. Organizational knowledge-management systems are therefore likely to strengthen AI learning when they facilitate the exchange of experience, technical guidance, and practical solutions [4]. This interpretation is consistent with the broader argument that digital transformation depends on changes in organizational knowledge and human capability, not simply on the acquisition of technologies [5].

The fourth and strongest finding showed that willingness to learn AI technology had a substantial positive effect on auditors' intention to apply AI in the auditing process. The exceptionally high t statistic indicates that learning willingness was a central mechanism linking auditors' perceptions of AI to their intended professional use. This result closely supports the findings of Mansour et al., who demonstrated that auditors' willingness to learn significantly predicted their intention to use AI technologies in emerging economies [24]. The result suggests that positive attitudes toward AI are insufficient unless they are translated into an active willingness to acquire competence. Auditors may recognize the usefulness of AI yet remain unable or unwilling to use it when they lack knowledge of how the technology operates, how its outputs should be interpreted, or how it can be integrated into audit procedures. Learning willingness provides the motivational foundation for overcoming this gap.

This finding has important implications for the human–AI relationship in auditing. Current evidence suggests that AI is more likely to complement professional accountants and auditors than to eliminate the need for human expertise [15]. AI systems can identify patterns and automate data-intensive tasks, but auditors remain responsible for contextual interpretation, professional skepticism, ethical evaluation, and the final audit opinion. As auditing becomes increasingly technology-enabled, the quality of human–AI collaboration will depend on whether auditors understand the capabilities and limitations of automated systems. The transformation of auditor judgment during the Fourth Industrial Revolution therefore requires continuous learning and the acquisition of interdisciplinary competencies [16]. Willingness to learn may enable auditors to retain meaningful control over AI-supported decisions rather than becoming passive recipients of algorithmic recommendations.

The strong relationship between willingness to learn and intended AI use is also significant in light of the ethical and governance risks associated with intelligent technologies. AI-generated outputs may be affected by biased data, inappropriate model assumptions, insufficient transparency, or unreliable information. Auditors who lack relevant knowledge may be unable to recognize these weaknesses. Ethical analyses emphasize that AI-based decision-making in accounting and auditing raises questions regarding accountability, fairness, explainability, and professional responsibility [17]. Similarly, public-sector auditing research highlights both the opportunities and the ethical and operational risks of AI implementation [13]. Therefore, willingness to learn should include more than operational software training. It should encompass critical understanding of data quality, model validation, cybersecurity, privacy, and the appropriate boundaries of algorithmic assistance.

The explanatory power of the model further confirms the importance of the selected variables. The finding that performance expectancy, effort expectancy, and social influence explained 76% of the variance in willingness to learn indicates that these factors collectively provide a strong account of auditors' learning motivation. The 60% explained variance in AI application likewise demonstrates that willingness to learn is a major predictor of intended use, although other organizational, technological, and institutional factors may also be involved. These may include facilitating conditions, information technology infrastructure, management support, resource availability, regulatory guidance, data accessibility, and perceived risk. Previous research has shown that IT infrastructure can moderate AI adoption in auditing [20], while studies in developing countries have identified environmental and organizational conditions as important influences on information-audit usage [28]. The present model should therefore be interpreted as explaining a substantial behavioral component of AI adoption while recognizing that actual implementation also depends on the surrounding organizational system.

Overall, the findings show that the future of AI-enabled auditing depends substantially on the development of auditors' human and professional capabilities. Recent reviews describe AI as a major force transforming accounting and auditing through automation, continuous auditing, advanced analytics, and intelligent decision support [8, 9]. Nevertheless, technological capability alone cannot guarantee successful implementation. Auditors must perceive AI as useful, believe that it can be learned and operated with reasonable effort, receive support from their professional environment, and become motivated to acquire the required competencies. The findings consequently position willingness to learn as a critical intermediate construct between technology perceptions and intended use. This perspective contributes to current research agendas that call for greater attention to the organizational and human dimensions of AI in accounting and auditing [32, 33].

This study has several limitations that should be considered when interpreting its findings. First, the cross-sectional design measured auditors' perceptions, willingness, and intended technology use at a single point in time and therefore did not permit direct conclusions about changes in these variables or definitive causal relationships. Second, the study relied on self-reported questionnaire data, which may have been affected by social desirability, differences in respondents' interpretations of AI, or an inclination to present favorable attitudes toward technological development. Third, although all participants had at least five years of professional auditing experience, the sample included both currently practicing auditors and financial professionals with previous auditing experience, and these groups may differ in their current exposure to audit technologies.

Fourth, the study examined intended or practical AI application rather than objectively recorded usage behavior. Finally, the concentration of the sample within one national and institutional environment may limit the generalizability of the findings to auditing systems with different regulatory, technological, cultural, and professional characteristics.

Future research should employ longitudinal designs to determine how auditors' willingness to learn and AI-use behavior change as they gain practical experience with intelligent auditing systems. Experimental or intervention-based studies could assess whether structured training programs, hands-on workshops, or supervised AI use produce measurable changes in technology readiness, confidence, professional judgment, and actual adoption. Future models should also incorporate additional variables such as facilitating conditions, technological infrastructure, perceived risk, trust in AI, algorithmic transparency, organizational support, digital self-efficacy, professional skepticism, and ethical awareness. Comparative studies could examine differences between external auditors, internal auditors, public-sector auditors, forensic accountants, and financial professionals, as well as variations across audit-firm sizes and levels of professional seniority. Cross-national research would be valuable for identifying whether cultural, regulatory, and economic conditions alter the effects of performance expectancy, effort expectancy, and social influence. Researchers should also distinguish between general AI use and specific applications such as fraud detection, automated document review, continuous auditing, risk prediction, and generative AI-assisted reporting.

In practice, audit firms should treat AI competency development as a strategic component of workforce planning rather than as an optional technical initiative. Training should be designed around realistic audit tasks and should demonstrate how AI can improve efficiency, evidence evaluation, risk identification, and professional judgment. Organizations should select user-friendly systems, provide continuous technical support, allocate protected time for learning, and establish mentoring arrangements through which experienced users can assist colleagues. Senior partners and supervisors should communicate clear expectations regarding responsible AI use and visibly support participation in training, as their endorsement can strengthen the professional legitimacy of learning. Universities and professional bodies should integrate AI, data analytics, algorithmic accountability, cybersecurity, and technology-assisted auditing into accounting and auditing curricula. At the same time, practical guidance should emphasize that auditors retain responsibility for critically evaluating AI outputs and should not substitute automated recommendations for professional skepticism or independent judgment.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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