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Research paper

Impacts of Artificial Intelligence on Auditing Quality: A Case Study in Chattogram City, Bangladesh

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Abstract

Artificial intelligence (AI) is becoming increasingly valuable in our daily decision-making processes. Therefore, a study was conducted to examine the impact of AI on various aspects such as perception, regulation, organizational structure, and procedural changes, particularly focusing on new competencies in audit procedures. This study utilized closed-ended survey data obtained on a Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The data was gathered through purposeful sampling from experienced professionals in the audit field located in the port city of Chattogram, Bangladesh. The survey response data are categorized into six factors using factor analysis through the principal component analysis extraction method and Varimax rotation with Kaiser Normalization, conducted via IBM SPSS Statistics 26, and validated with Cronbach's Alpha coefficient. Based on factor analysis, the structural equation model (SEM) was developed with IBM SPSS AMOS 22 software, taking application of artificial intelligence as exogenous variable and auditor perception change, audit regulatory change, audit structural change, audit procedural change, and new competencies arise in auditing as endogenous variable and validate with convergent, discriminate and model validity. The finding shows that artificial intelligence has no significant contribution to audit structural change or audit procedural change. Therefore, applying artificial intelligence in the audit procedure, no structural or procedural changes are required. However, the application of artificial intelligence has a positive and significant contribution to perception change, audit regulatory change, and the emergence of new competencies in auditing for auditors. Consequently, applying artificial intelligence to audit procedures may change auditor perception, audit regulations may require modification, and new competencies may arise in auditing to adapt to the environment of artificial intelligence. The study results may be utilized in policy formulation and their impact on implementing artificial intelligence in audit procedures.

Keywords: *Artificial Intelligence; Audit; Chattagram; Policy; Structural Equation Model.*

1. Introduction

Auditing is the process of verifying the financial statements and other accounting information of a business organization. The economic condition of the entity is systematically analyzed in this process. The individual who assumes responsibility for the process is referred to as an "Auditor‘' (Kumar & Sharma, 2015). The term "artificial intelligence" refers to a substitute for human intelligence that is created by combining hardware and software. A human expert system is replaced by an expert system in artificial intelligence, and machine intelligence is used in place of human intelligence. Artificial intelligence assists managers in making decisions by delivering information that is more accurate and by simplifying aspects that are involved in making difficult judgments (Askary et al., 2018). It is a new technology that seeks to imitate human judgments and cognitive abilities, and it offers adopters the opportunity to gain a competitive advantage (Munoko et al., 2020). There is also the possibility of defining artificial intelligence as the intelligence that is displayed by machines. An ideal "intelligent" machine is a flexible, rational agent that senses its environment and makes choices that increase its chances of success in reaching a goal (Adiloglu et al., 2019). This definition comes from the field of computer science. According to the definition provided by the Organization for Economic Co-operation and Development (OECD), artificial intelligence (AI) is a machine-based system that is capable of making predictions, suggestions, or judgments that influence actual or virtual environments for a specific set of human-specified goals (Noordin et al., 2022). There are two types of audit quality: DeAngelo, who defines audit quality as the joint probability that auditors both identify a breach in the client's accounting system and report the breach, and Zhang, who defines audit quality assurance of high financial reporting quality. Both of these definitions fall within the category of audit quality. According to the findings of some researchers, the quality of an audit can be classified as the likelihood that the auditor would identify a security breach and disclose it. In Bangladeshi audit firms, we are examining how artificial intelligence (AI) affects audit quality. This study aims to analyze the influence of AI as a substitute for human intelligence on auditing processes, information risk, and the assurance of financial reporting. This study shows how strong audits and advanced Artificial Intelligence (AI) provide financial management integrity and effectiveness. Auditing financial statements and other accounting data ensures an organization's financial correctness and openness. In wealthy countries, frameworks like the International Standards for the Professional Practice of Internal Auditing (ISPPIA) standardize internal audit quality, but cultural differences make them challenging to adopt in poor countries. Integration of AI into economic-financial data administration, monitoring, and control has improved productivity and risk management. Internal control inefficiencies and poor AI implementation continue to expose organizations to accounting discrepancies and financial reporting fraud. Internal auditing processes and AI's ability to support effective financial management are examined in this study, revealing challenges and opportunities for improvement in different cultural and economic contexts.

1.2. Literature review

In recent years, Artificial Intelligence (AI) has become a transformative force in the field of auditing. The increasing complexity and volume of financial data have made traditional audit methods less effective. Consequently, AI technologies are being adopted more widely to enhance audit procedures and improve audit quality. Existing literature demonstrates that AI impacts various aspects of audit quality in diverse ways, including effectiveness, efficiency, fraud detection, and auditor judgment. For instance, Issa et al. (2016) note that AI reduces human errors and enhances audit efficiency. Brown-Liburd et al. (2015) highlight that AI improves fraud detection through anomaly detection techniques. Moffitt et al. (2018) explain that real-time auditing enabled by AI enhances responsiveness. However, Kokina and Davenport (2017) emphasize the skill gaps that auditors face when adopting AI. Additionally, Richins et al. (2017) raise ethical concerns regarding decision-making processes related to AI.

Recently, Nisarga (2024) explored the multifaceted impact of technology on audit practices, focusing on how technological innovations such as data analytics, AI, RPA, blockchain, and Power BI have reshaped the audit landscape. His research included a survey and employed a Chi-square statistical test to analyze the relationship between technology adoption and the quality and efficiency of audits. The findings reveal a significant connection between the impact of technology and the quality and efficiency of audit reports. This underscores the importance of integrating technological advancements into modern auditing practices to improve both audit quality and operational efficiency.

Taking into account the moderating effect of auditors' and accountants' experience, the research that is being carried out by Almaliki, (2021) from the College of Administration and Economic at the University of Misan aims to construct a measurement model that will evaluate the impact of accounting information system (AIS) characteristics on internal audit effectiveness (IAE). A number of features, including adaptability, relevance, timeliness, dependability, and integration, are being thoroughly investigated. The research makes use of a quantitative methodology, collecting information by means of a questionnaire that was filled out by twenty-five hundred auditors and accountants working for companies that are listed on the Iraqi stock exchange. When it comes to establishing the measurement model, the data analysis is carried out with the help of AMOS and SPSS. Based on the findings, it can be concluded that the values of the measurement model are satisfactory and adequate for the purpose of building a Structural Equation Modeling (SEM) model for the variables considered in the research. The results show significant effects of AIS characteristics on IAE, with experience moderating this relationship. The study validates the measurement model, demonstrating its adequacy for further SEM model development, and highlights the importance of experience in enhancing accounting and auditing processes to aid management decision-making and potentially improve economic performance at the national level.

Building on previous frameworks and the existing body of literature on financial auditing, the research that was conducted by Stoel et al. (2012)tries to identify and assess prospective constructs that have an effect on the quality of information technology audits. In this study, a survey instrument is developed, and practitioners of information technology and financial accounting are asked to evaluate the impact of several aspects on the quality of IT audits. In order to further narrow the set of IT audit quality characteristics that have been found, a factor analysis is then utilized. According to the findings, other criteria are significant for the quality of an IT audit, and the relative relevance of these factors varies between auditors who specialize in IT and those who specialize in financial auditing. This research provides insight into the prioritized impact of each factor, offering guidance to IT audit managers for resource assessment and process management, and presents a comprehensive model for researchers to understand how these factors influence IT audit quality. The identified factors also aid in quantifying IT audit quality, essential for communication with stakeholders in the evolving technological landscape.

The study of Al-qatanani (2024) aims to determine the impact of implementing Accounting Information Systems (AIS) on improving internal audit effectiveness in Jordanian pharmaceutical companies. Utilizing a quantitative methodology and SPSS software, the study employs a Likert scale to measure variables. The research involved six pharmaceutical firms listed on the Amman Stock Exchange, with a total of 350 questionnaires distributed to the study sample. The findings indicate that internal audit effectiveness is significantly influenced by the timeliness, flexibility, reliability, and integration of AIS. Statistical analysis revealed significant correlations between these parameters and internal audit levels, with determination coefficients (R^2) ranging from 0.435 to 0.490 and correlation coefficients from 0.426 to 0.701. These results suggest that variations in the AIS characteristics account for 43–49% of the variance in internal audit effectiveness. The study recommends improving audit promptness, ensuring timely reporting, and establishing efficient communication and real-time monitoring systems to enhance internal audit effectiveness in pharmaceutical companies.

Dao et al. (2019) investigate the impact of the Public Company Accounting Oversight Board's (PCAOB) requirement to disclose the names of engagement partners on Form AP and its effect on audit quality. They measure audit quality using two indicators: abnormal accruals and the likelihood of detecting material weaknesses in internal controls. Their findings reveal that disclosing the names of engagement partners is linked to a reduction in abnormal accruals and an increased likelihood that accounting firms will identify material weaknesses in internal controls. This study enhances the existing literature on the disclosure of engagement partner identities by providing further evidence specific to the U.S. context. Additionally, it supports the PCAOB's belief that such disclosures contribute to improved audit quality.

Supriadi (2024) researched the impact of Artificial Intelligence (AI) on detecting accounting fraud in audits. The study aimed to assess the efficiency and accuracy of AI in identifying fraud, as well as to examine the challenges and implications associated with its use in audit practices. The findings indicate that AI significantly enhances both efficiency and accuracy in detecting accounting fraud. Techniques such as machine learning and natural language processing effectively reveal fraud patterns. However, the research also highlights several challenges, including limitations of current AI technology, ethical concerns, data privacy issues, and resistance to adopting AI in the accounting sector. This study contributes to the accounting literature by illustrating how AI can transform audit practices and provides guidance for accounting firms on leveraging AI to improve their auditing processes. Moreover, it suggests potential directions for future research related to the development and integration of AI in accounting.Alawaqleh (2021) investigates the connection between Accounting Information Systems (AIS) and the quality of internal audits, with a specific emphasis on the function that organizational culture plays as a mediator. Within the scope of this study, 183 internal auditors from Jordanian industrial SMEs are analyzed through the use of AMOS and SPSS version 25 for model validation. Despite the fact that AIS directly improves the quality of internal audits, the data indicate that organizational culture only partially mediates the link between the two parameters. According to the findings of the study, audit quality is greatly improved by AIS, and the study also found that organizational culture has a significant influence on this improvement, although a partial one. The research offers useful insights for academics, administrators, and policymakers by stressing the significance of AIS and organizational culture in the process of enhancing the quality of internal audits. Additionally, the research advises that future studies conduct additional research to investigate additional factors and industry comparisons.

Alzeban (2015) evaluates the influence of Hofstede's cultural dimensions—specifically, power distance, uncertainty avoidance, and individualism—on the quality of internal audits (QIA) in Saudi Arabian businesses. Using quantitative analysis, the study examines how these cultural factors affect quality assurance by surveying chief internal auditors from 67 listed companies.

The findings indicate that high power distance and uncertainty avoidance are associated with lower quality of internal audits, while individualism is positively correlated with higher audit quality. This research demonstrates that cultural variables significantly impact the quality of internal audits in Saudi Arabia, with individual accomplishments playing a major role in this influence. Additionally, the study suggests that traditional cultural values and hierarchical structures affect the effectiveness of internal audits, potentially differing from practices in more secular or Western contexts.

Shamsudin et al. (2024) conducted research focusing on the relevance and utilization of various technologies in accounting practices, addressing audit and non-audit firms. Using a quantitative approach, the researchers surveyed ten practitioners responsible for preparing financial statements, requesting them to rank the relevance and usage of 17 technologies identified by the Malaysian Institute of Accountants (MIA). The study found that technologies such as Microsoft Applications, Communication Technology, Mobile Applications, and Fintech are highly utilized and relevant, with scores over 90%. In contrast, emerging technologies like Artificial Intelligence, XBRL, Robotic Process Automation, and Big Data Analytics showed lower relevance and utilization, below 60%. The research highlights that blockchain was given the highest weightage using the Weighted Cooke's Index due to its potential benefits despite its rarity. The study calls for broader research to explore technology adoption across a larger sample and to understand factors influencing technology use in accounting, aiming to improve standardization and effectiveness in financial reporting.

Existing research shows that the quality of accounting information systems (AIS) affects the quality of accounting information. A few years ago, Algrari & Ahmed (2019) conducted research to quantify the effects of these two issues. According to the results, the accuracy of a company's financial records is heavily dependent on the quality of its accounting information systems (AIS). Algrari & Ahmed (2019) found that Iraqi Stock Market firms like Asia Cell Telecommunication Company should upgrade their accounting information systems to keep up with technology developments and put an emphasis on using high-quality accounting data to measure organizational performance. The findings indicate that AIS has a favorable impact on the company's operations and the consistency of financial reporting in accordance with GAAP and IFRS. Accounting information systems (AIS) and their impact on internal auditors in Turkey are the focus of Tan's (2016) research. In order to gauge how 106 internal auditors felt AIS affected their job, researchers used a 12-question questionnaire. The approach centered on learning how AIS, as a database system that stores and retrieves data on computers, aids in internal control, auditing, and the general effectiveness of managing resources and operations. The results show that internal auditors in Turkey think AIS has a beneficial impact on their job by making sure financial reports are reliable according to GAAP and IFRS, strengthening control structures, and increasing compliance with accounting rules and legislation. The paper goes on to say that AIS is important for both preventative and detective controls and that it integrates well with other MIS, like ERP. Nevertheless, it would be beneficial for future studies to expand their scope to include other business roles, such as accountants, managers, and IT auditors, to fully understand the effects of AIS.

The purpose of the study by Almaliki (2021) is to explore the relationship between Accounting Information Systems (AIS) and Internal Audit Efficiency (IAE), particularly examining the influence of the expertise of auditors and accountants. Acknowledging the lack of existing literature that links components of AIS to organizational sustainability and the effectiveness of internal audit development, this study aims to address that gap. The authors investigate their predictions about the links between AIS features and IAE, with experience acting as a moderating variable, by creating a conceptual framework. The interrelationships between the independent, dependent, and moderator variables are illustrated by this framework. In contrast to earlier studies that concentrated on elements like software, governance, and capital, the results highlight the significance of AIS attributes in enhancing IAE and present experience as a substantial new variable in accounting studies. The report gives decision-makers empirical insights by showing how experience may improve internal audit methods and by providing a practical reference for firms to implement a successful solution.

A decade ago, Rapina, R. (2014) investigated the association between Accounting information systems (AIS) and the quality of accounting information. The focus of the research was to identify the impact of organizational variables on AIS quality and the consequences of these factors on accounting information quality. Accounting personnel from 33 Bandung, Indonesia, cooperatives are the subject of this study. The approach included looking at how these organizational characteristics affected the quality of accounting information systems (AIS) and how AIS, in turn, affected the quality of accounting information. Accounting information quality is impacted by AIS quality, which is in turn impacted by management commitment, company culture, and organizational structure, according to the results. Management buy-in, a positive company culture, and a well-designed structure are the three pillars upon which the research rests, all of which contribute to higher-quality accounting and AIS. By highlighting the interdependence of management and organizational variables and their effect on AIS outcomes, these findings give empirical evidence to address problems associated with accounting information quality and AIS. A recent study based on the Chinese economy shows a relationship between blockchain security technology and audit quality control. The study also emphasizes the significance of information security as the basis for audit quality control operations. The results of the experiments show that the implementation of blockchain technology results in a considerable improvement in the quality of audits and a 20% increase in the level of security of audit information (Kravchenko et al., 2023).

From the vantage point of qualified auditors working for Jordanian IT firms, Al-Sayyed et al.(2021) set out to investigate how AI technologies had altered audit evidence. The study surveyed 314 auditors using a tailored questionnaire and used a descriptive analytical methodology. There was a favorable correlation between expert systems and audit evidence collecting, but no correlation between expert systems and neural network technology. The report emphasizes the value of artificial intelligence (AI) in improving audit efficiency and effectiveness and suggests that audit offices in Jordan should prioritize AI adoption for better audit evidence collection.

To better understand how digitization impacts auditing tools and ways of work, Karlsen & Wallberg (2017)conducted research. The study aimed to understand these impacts using fourteen semi-structured interviews with auditors who are currently working in the field. The results showed that the change towards paperless work and greater flexibility had a greater effect on working techniques than on technologies. Notably absent from earlier studies was the study's emphasis on education's increasing significance. To keep up with the changing demands of the auditing profession and prepare students for work in a digitalized world, the authors suggest that schools change their curricula.Investigate how the rise of digital technologies has altered auditing practices and the resources available to practitioners. A recent research based on 235 audit firms that are approved by the POA and studying the transparency reports of 64 organizations that are permitted to conduct audits for public interest entities (PIEs). The results showed that almost every auditing company offers both independent and tax audits, but only the Big Four put a lot of money into digital technology infrastructure and human resources. While IT audit education is offered by 24 organizations, most audit firms have not yet invested in digitalization, and this is despite the importance of information technology. The survey found that although digitization is becoming more important, the Big Four audit firms—which serve bigger customers and are leaders in digital investments—have successfully responded to these changes, whereas the majority of audit companies, particularly those focusing on SMEs, have failed to do so(Adiloglu & Gungor, 2019).

With a focus on both developed (Sweden) and developing (Liberia) countries, a comparative research study investigates how digitalization and new technology have affected the auditing profession in both countries. The study finds that digitalization, including the use of blockchain technology, artificial intelligence, and big data analytics, has greatly improved audit quality and efficiency in both the Swedish and Liberian contexts. This is based on qualitative research that includes semi-structured interviews with four Swedish and five Liberian audit professionals. The findings further emphasize the significance of these new technologies in the auditing industry by demonstrating how digitalization is changing the capabilities and skills needed by audit companies (Melin & Toezay, 2022).

Rodrigues et al. (2023) set out to research how qualified auditors in two different areas of Portugal felt about the influence of AI on their work. Findings from a questionnaire poll show that auditors see AI as a game-changer for the future of their profession, improving audit processes, sample methods, cost-benefit analysis, and the ability to spot significant misstatements. The paper emphasizes that AI is anticipated to revolutionize auditing methods, enabling more consistent and trustworthy auditing procedures. The results indicate that AI will have a major impact on the auditing industry, which might have consequences for productivity, jobs, and auditor independence if these technologies are broadly used. However, there are still concerns about the present level of AI integration in the area.

Based on interviews with German auditing experts, researchers predict that the field will undergo significant changes in the next 5 to 10 years due to ongoing digitalization. The study employed a two-round Delphi technique to gather opinions from auditors, academics, regulators, and IT specialists. According to the research, no major changes are expected in auditing processes within this time frame, despite the rapid advancements in big data analytics, artificial intelligence (AI), and blockchain technology. Instead, a more continuous auditing approach is anticipated to replace the traditional yearly audit. While these new technologies are expected to be beneficial, experts do not believe they will eliminate the need for auditors or bring about major changes to the industry. However, the report cautions against becoming complacent with small improvements, as emerging technologies, especially those involving blockchain and artificial intelligence, could potentially transform the industry or even reduce the need for human auditors. This creates a paradox between the experts' optimistic outlook and the possibility of disruptive technological impacts, highlighting the need for further research (Tiberius & Hirth, 2019).

With a focus on foreseeing future research paths and software development, Omoteso (2012)examines the present state of research and discussions concerning the application of AI systems in auditing. Outlining the evolution of AI in auditing, the article emphasizes the pros and cons of the technology. Finding research gaps that may be filled by future studies, it focuses on auditing's usage of expert systems and neural networks. Among these areas where knowledge is lacking are the following: weighing the pros and cons of AI adoption; determining how AI will affect audit committees and internal control systems; investigating what this will mean for medium and small audit firms; audit education; audits in the public sector; auditor independence; and the audit expectations-performance gap. Drawing on these indicated research requirements, the study also proposes topics for future software improvements in auditing.

Adeoye et al. (2023) described in their study that artificial intelligence has a positive effect on audit quality, as supported by both descriptive statistics and regression analysis. The results are consistent with previous studies, reinforcing the positive impact of artificial intelligence on audit quality. Survey method using structured questionnaires administered to practicing accountants and staff of the Big Four accounting firms. Taro Yamani's formula is used to determine sample size, and Cronbach’s alpha is used for reliability and validity testing. Descriptive statistics and inferential analysis were used for data analysis. Self-structured perceptional questionnaires administered online. Pre-test conducted for questionnaire relevance and understanding. The study recommended encouraging the use of artificial intelligence in auditing firms to improve audit quality.

Qader et al. (2024) conducted a paper on Blockchain-based technologies and AI's positive impact on audit quality by assisting in the audit process and fraud detection, improving financial reporting. Blockchain and AI create confidence for investors, stakeholders, and legislators. The study delivers implications for investors and policymakers by enhancing the accuracy of financial accounts and governance mechanisms. Data collection is done through Primary sources from 300 respondents collected through random sampling. Data analysis: PLS-SEM was used to investigate relationships between exogenous and endogenous variables.

Another review paper conducted by Mpofu et al. (2023) explored the role of AI in external auditing and evaluated ongoing debates on its implications. It highlights controversies and convergences among researchers on AI adoption in external auditing. The study recommends building strong digital audit teams and increasing training on AI tools for effective integration. The study uses a qualitative research approach, employing a critical literature review. The literature review involved searching peer-reviewed papers and technical reports from databases like Google Scholar, EBSCO host, Web of Science, Scopus, and ProQuest. The search was conducted using specific keywords related to AI and auditing. The literature was reviewed until the saturation point, and thematic analysis was used to identify major patterns in the literature.

1.3. Research gap

As per the above literature, it is observed that traditional auditing systems suffer from various types of limitations, like committing errors, consuming time, and noncompliance with regulatory bodies, etc. The majority of existing literature during this period has focused more broadly on information technology rather than specifically on artificial intelligence. Research has been undertaken to address the problems with traditional systems and to suggest recommendations to solve those. In the reviewed papers lot many ideas were generated to make the auditing process modern, but a few highlighted IT and AI implications in this way, which has been focused on in this paper.

2. Objective of the study

The purpose of the study is to assess the influence that artificial intelligence has on changes in perception, regulations, structures, and procedures, as well as the introduction of new competencies in auditing procedures.

2.1. Conceptual framework

Above, in Figure 1, you can see the conceptual framework that was used for the study.

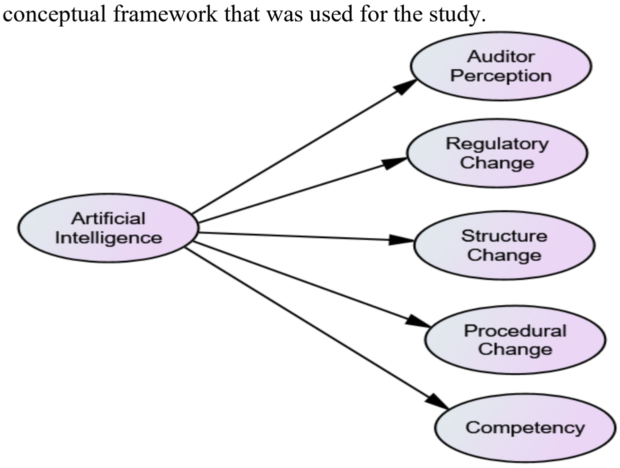

Fig. 1: Conceptual Framework of the Study Shows the Impact of Perception, Regulatory Changes, Structure Change, and Procedural Change on AI, Which Will Increase the Competencies.

2.2. Hypothesis testing

- Hypothesis 1

Null Hypothesis (H0): There is no considerable impact of the use of artificial intelligence on auditor perception alteration.
Alternative Hypothesis (H1): There is a substantial impact that the application of artificial intelligence has on the shift in auditor perception.

- Hypothesis 2

Null Hypothesis (H0): When it comes to auditing regulatory changes, the deployment of artificial intelligence does not have a substantial influence.
Alternative Hypothesis (H1): A substantial impact is brought about by the utilization of artificial intelligence in the process of auditing regulatory change.

- Hypothesis 3

Null Hypothesis (H0): When it comes to auditing structural changes, the deployment of artificial intelligence does not have a substantial impact.
Alternative Hypothesis (H1): A considerable impact can be attributed to the utilization of artificial intelligence in the process of auditing structural transformation.

- Hypothesis 4

Null Hypothesis (H0): It has been determined that the implementation of artificial intelligence in auditing procedures does not have a significant impact.
Alternative Hypothesis (H1): A substantial impact is brought about by the implementation of artificial intelligence in the process of auditing changes in procedures.

- Hypothesis 5

Null Hypothesis (H0): It has been determined that the application of artificial intelligence to new competencies that have emerged in auditing does not have a major influence.
Alternative Hypothesis (H1): The application of artificial intelligence to the development of new abilities in auditing has a significant impact on the future of auditing.

2.3. Methods

To ensure that the research is carried on, a survey is carried out at the port city of Chattogram, which is located in Bangladesh. The application of artificial intelligence, auditor perception change, audit regulation change, audit structure change, audit procedural change, and new competences that arise in auditing as a result of the authors' experience and literature review are the factors that have been identified in accordance with the purpose of the study. In the closed-ended survey questionnaire, each of the variables is evaluated using a Likert scale with five points, ranging from 1 (strongly disagreeing with the opinion) to 5 (strongly agreeing with the opinion). The questionnaire for the survey is pre-tested with ten respondents who have previous experience. Following the completion of the modifications and corrections made by them, the survey questionnaire was completed. After that, the questionnaire for the survey was sent out to experienced respondents through an intentional sampling strategy, including e-mail, WhatsApp, and hand-to-hand communication. The sample size is 80, which seems small, but the respondents were selected to represent all crucial stakeholders of the auditing process and AI implications. So the sample size comprised representation of all concerned of both AI and auditing, as a result, it will not lack perfect responses, though the sample size is 80. It will work in future research, as within this 80 representation of every area is ensured, who will be able to contribute. Following the elimination of respondents who answered all of the questions with the same rank and who did not answer a significant number of questions, a total of eighty opinions were ultimately chosen for further examination. Both the normality test and the descriptive analysis were performed on the data that was chosen, and it was entered into Microsoft Excel 2016 and IBM SPSS Statistics 26. Through the use of factor analysis, principal component analysis extraction method, and Varimax with Kaiser normalization rotation method, the survey response values are categorized into six distinct groups. The factor analysis is validated by applying the Cronbach's Alpha value of each factor as well as the Kaiser-Meyer-Olkin measure for determining whether or not the sampling is adequate. Using the IBM SPSS AMOS 22 software, a structural equation model (SEM) was developed based on the factor analysis. The application of artificial intelligence was used as an exogenous variable, and auditor perception change, audit regulatory change, audit structural change, audit procedural change, and new competencies that arise in auditing were used as endogenous variables.

For the model that was chosen, the average variance extracted (AVE) is computed in order to test the convergent validity, the maximum shared variance (MSV) is computed in order to test the discriminant validity, and the model validity is computed. In conclusion, we put the hypothesis to the test for our conclusion.

2.4. Ethical considerations

To guarantee the integrity of the study and the preservation of participants' rights, this research was carried out strictly in accordance with accepted ethical standards. Throughout the course of the study, the following ethical principles were noted:

- Knowledgeable Consent

All participants received a thorough description of the study's goals, methods, possible dangers, and advantages before their involvement. Before the start of data collection, each participant's formal agreement was obtained, and participation was completely optional. Participants were told there would be no repercussions if they chose to stop taking the survey at any time.

- Confidentiality and Anonymity

Every respondent's privacy and confidentiality were strictly protected. There was no request for or storage of personal identifiers. To guarantee that no specific participant could be recognized during the analysis or reporting phases, the data were aggregated and anonymized. Only the research team had secure access to all of the data that was gathered.

- Non-maleficence and Beneficence

The study was designed to avoid any harm to participants. Questions were framed to be respectful and non-invasive. The research aimed to contribute positively to the academic and professional understanding of AI's role in audit practices, potentially benefiting audit professionals, firms, and regulatory bodies.

- Voluntary Participation and Right to Withdraw

Participants were informed of their right to decline participation or withdraw from the study at any time without explanation or penalty. No coercion or undue influence was used to secure participation.

- Data Integrity and Honesty

The researchers ensured that all data were collected and analyzed objectively. There was no fabrication, falsification, or misrepresentation of data at any stage of the research process. The findings presented reflect an honest and accurate account of the collected data.

By upholding these ethical standards, this research seeks to maintain academic integrity and contribute responsibly to the field of audit quality and artificial intelligence.

3. Results and discussion

3.1. Descriptive statistics

The descriptive statistics and normality test of the respondent measured values for Application of Artificial Intelligence, Auditor Perception Change, Audit Regulatory Change, Audit Structural Change, Audit Procedural Change, and New Competencies Arise in Auditing are shown in Table 1.

Table 1: Descriptive Statistics and Normality Test Result

Sl. No.	Questionnaire	Variable name	N	Min	Max	Kolmogorov–Smirnov Test (Sig)	Shapiro–Wilk Test (Sig)	Median
A	Artificial Intelligence							
A1	It is possible to employ artificial intelligence (AI) to take care of the recording of accounting transactions automatically.	AIntelligence1	80	1	5	0.287 (0.000)	0.856 (0.000)	3
A2	As a further means of enhancing fraud detection, the development of models based on sophisticated machine learning auditors	AIntelligence2	80	1	5	0.279 (0.000)	0.876 (0.000)	3
A3	Artificial intelligence can analyze unstructured data such as emails, broadcasts on social media, and audio conference files.	AIntelligence3	80	2	5	0.294 (0.000)	0.847 (0.000)	3
A4	By utilizing their human judgment to assess a more comprehensive and in-depth collection of data and documents, auditors will be able to optimize their time with the assistance of artificial intelligence.	AIntelligence4	80	1	5	0.293 (0.000)	0.862 (0.000)	3
A5	Artificial intelligence enables auditors to evaluate the accuracy of financial accounts more efficiently and effectively.	AIntelligence5	80	2	5	0.261 (0.000)	0.858 (0.000)	3
A6	Artificial intelligence will allow you to undertake an audit on an ongoing basis	AIntelligence6	80	2	5	0.276 (0.000)	0.862 (0.000)	3
B	Auditor Perception							
B1	Increased valuation freedom will result in audits providing audit addressees with less information than they already do.	Perception1	80	1	4	0.178 (0.000)	0.866 (0.000)	2
B2	Addressees of audits will have a greater level of trust in automated auditing techniques than in manual ones.	Perception2	80	1	4	0.220 (0.000)	0.877 (0.000)	2
B3	The management report has a significant increase in the number of future-oriented risk statements concerning the expectation gap.	Perception3	80	1	4	0.220 (0.000)	0.876 (0.000)	2
B4	Artificial intelligence will reduce audit risk	Perception4	80	1	4	0.199 (0.000)	0.876 (0.000)	2
C	Regulatory Changes							
C1	There will be a significant regulatory gap between the	ReguChange1	80	2	5	0.215 (0.000)	0.872	4

	new realities of digital business and the criteria for auditing.						(0.000)	
C2	Using artificial intelligence, standards for accounting and auditing will be defined.	ReguChange2	80	2	5	0.216 (0.000)	0.845 (0.000)	4
C3	There will be very little room for discretion under the auditing requirements.	ReguChange3	80	2	5	0.261 (0.000)	0.795 (0.000)	4
C4	AI enhances compliance with laws and accounting standards	ReguChange4	80	2	5	0.230 (0.000)	0.868 (0.000)	4
D	Structural Changes							
D1	Auditors will be freed from routine chores and able to focus on more difficult jobs because of automation.	StruChange1	80	1	5	0.379 (0.000)	0.770 (0.000)	2
D2	The auditor's profession will have completely shifted from classic auditing to consulting	StruChange2	80	1	5	0.367 (0.000)	0.779 (0.000)	2
D3	The new standard will be continuous auditing, as opposed to annual audits, which is currently the norm.	StruChange3	80	1	5	0.357 (0.000)	0.802 (0.000)	2
D4	Most auditing businesses that are small and medium-sized will be displaced by technological advancements.	StruChange4	80	1	5	0.347 (0.000)	0.800 (0.000)	2
E	Procedural Changes							
E1	AI will be able to make auditing decisions with a high degree of discretion	ProcChange1	80	2	5	0.221 (0.000)	0.875 (0.000)	4
E2	In the future, full audits, as opposed to random audits, will be the norm.	ProcChange2	80	2	5	0.261 (0.000)	0.855 (0.000)	3
E3	Auditing risks will be eliminated completely	ProcChange3	80	1	5	0.254 (0.000)	0.860 (0.000)	3
E4	It is anticipated that the application of artificial intelligence will be a part of the future of the auditing profession.	ProcChange4	80	2	5	0.263 (0.000)	0.846 (0.000)	3
F	New Competencies							
F1	Skill sets required to perform audits with information technology	Competency1	80	2	5	0.281 (0.000)	0.834 (0.000)	3
F2	Skill sets required to perform audits with advanced digital technology	Competency2	80	2	5	0.286 (0.000)	0.851 (0.000)	3
F3	Need to redesign the academic curriculum for Auditors	Competency3	80	2	5	0.234 (0.000)	0.833 (0.000)	3
F4	Paperless technology will make auditors' personal judgments obsolete	Competency4	80	1	5	0.252 (0.000)	0.862 (0.000)	3

The minimum, maximum, and median values of application of artificial intelligence, auditor perception change, audit regulatory change, audit structural change, audit procedural change, and new competencies arise in auditing 1 to 2, 4 to 5, and 2 to 4, respectively. The Kolmogorov– Smirnov Test and Shapiro–Wilk Test statistics of application of artificial intelligence are 0.261 to 0.294 and 0.847 to 0.876, auditor perception change are 0.178 to 0.220 and 0.866 to 0.877, audit regulatory change are 0.215 to 0.261 and 0.795 to 0.872, audit structural change are 0.347 to 0.379 and 0.770 to 0.802, audit procedural change are 0.221 to 0.263 and 0.846 to 0.875 and new competencies arise in auditing are 0.234 to 0.286 and 0.833 to 0.862 respectivelyat the significance level 0.000. As a result, the survey response values are not normally distributed, and we consider the median for mean rank comparison as a nonparametric test.

3.2. Factor analysis

Following this, a factor analysis is carried out using the principal component analysis extraction method and the Varimax with Kaiser normalization rotation method. The results of this analysis indicate that the Kaiser-Meyer-Olkin Measure of Sampling Adequacy value is 0.687 (p = 0.000). This allows the respondent's values to be classified into the various variables. As a result, we can categorize the responses to the survey questionnaire into six different groups according to the Impact of Artificial Intelligence on Audit (IAIA) model, which is presented in Table 2.

Table 2: Convergent Validity Test of the IAIA Model, Factor Analysis, and Cronbach's Alpha Evaluation

Rotated Component Matrix									Convergent	Square
	Component						Variable	Cronbach's	Validity	Root of
	1	2	3	4	5	6	Name	Alpha	(AVE)	AVE
AIntelligence1	0.903						Artificial Intelligence	0.950	0.747	0.864
AIntelligence3	0.901									
AIntelligence2	0.880									
AIntelligence4	0.877									
AIntelligence5	0.869									
AIntelligence6	0.752									
Competency1		0.928					New Competencies	0.924	0.770	0.878
Competency4		0.906								
Competency2		0.898								
Competency3		0.817								
ReguChange3			0.903				Regulatory Changes	0.908	0.703	0.838
ReguChange2			0.900							
ReguChange1			0.830							
ReguChange4			0.825							
StruChange2				0.887			Structural Changes	0.914	0.678	0.823
StruChange4				0.887						
StruChange1				0.883						
StruChange3				0.883						
ProcChange2					0.944		Procedural Changes	0.906	0.722	0.850
ProcChange1					0.941					
ProcChange3					0.873					

ProcChange4	0.747					
Perception1		0.923	Auditor Perception	0.886	0.679	0.824
Perception2		0.857				
Perception4		0.830				
Perception3		0.747				

Now from the above table, the survey response values are classified into six factor classes as (i) Application of artificial intelligence (factor loading 0.752 to 0.903), (ii) Auditor perception change (factor loading 0.747 to 0.923), (iii) Audit regulatory change (factor loading 0.825 to 0.903), (iv) Audit structural change (factor loading 0.883 to 0.887), (v) Audit procedural change (factor loading 0.747 to 0.944) and (vi) New competencies arise in auditing (factor loading 0.817 to 0.928). Here, all the factor loadings are greater than 0.04. So, each factor of the response variables has good reliability.

The Cronbach's Alpha value of the factor, application of artificial intelligence is 0.950, auditor perception change is 0.886, audit regulatory change is 0.908, audit structural change is 0.914, audit procedural change is 0.906, and new competencies arising in auditing is 0.924, respectively. All the Cronbach's Alpha values are greater than 0.7. So, the classified factors of the survey response variables are reliable, valid, and consistent.

Based on the aforementioned factor analysis, the factor variables are delineated as follows: (A) The application of artificial intelligence is characterized by (A1) AI's capability to autonomously record accounting transactions (AIntelligence1), (A2) the enhancement of fraud detection through advanced machine learning models created by auditors (AIntelligence2), (A3) AI's ability to analyze unstructured data, including emails, social media posts, and audio conference files (AIntelligence3), (A4) AI's facilitation of auditors in optimizing their time, thereby allowing for the application of human judgment to a more extensive and profound array of data and documents (AIntelligence4), (A5) AI's provision for auditors to assess the authenticity of financial statements with greater efficacy and efficiency (AIntelligence5), and (A6) AI's capacity to enable continuous auditing (AIntelligence6). (B) Changes in auditor perception are delineated as (B1) Increased valuation flexibility diminishes the informativeness of audits for audit addressees (Perception1), (B2) Audit addressees exhibit greater trust in automated auditing procedures compared to manual methods (Perception2), (B3) The expectation gap and future-oriented risk disclosures in management reports significantly escalate (Perception3), and (B4) Artificial intelligence mitigates audit risk (Perception4). Audit regulatory change is characterized by (C1) a significant regulatory gap between the contemporary digital business landscape and existing auditing standards (ReguChange1), (C2) the establishment of accounting and auditing standards through AI (ReguChange2), (C3) auditing standards featuring limited discretion (ReguChange3), and (C4) AI improving adherence to legal and accounting standards (ReguChange4). Audit structural change is characterized by (D1) Automation alleviating auditors from routine tasks, allowing focus on more complex responsibilities (StruChange1), (D2) A complete transition of the auditor's profession from traditional auditing to consulting (StruChange2), (D3) The establishment of continuous auditing as the new norm, superseding annual auditing (StruChange3), and (D4) Technological advancements displacing the majority of small and midsized auditing firms (StruChange4). Audit procedural changes include (E1) AI's capacity to make auditing decisions with significant discretion (ProcChange1), (E2) the establishment of full audits as the new norm rather than random audits (ProcChange2), (E3) the complete eradication of auditing risks (ProcChange3), and (E4) the integration of artificial intelligence into the future of the auditing profession (ProcChange4). New competencies in auditing are identified as (F1) skill sets necessary for conducting audits utilizing information technology (Competency1), (F2) skill sets required for audits employing advanced digital technology (Competency2), (F3) the necessity to reformulate the academic curriculum for auditors (Competency3), and (F4) the obsolescence of auditors' personal judgments due to paperless technology (Competency4).

After this factor analysis, the classification IAIA structure equation model is developed from the application of artificial intelligence as an exogenous variable and auditor perception change, audit regulatory change, audit structural change, audit procedural change, and new competencies arising in auditing as endogenous variables, as shown in Figure 2.

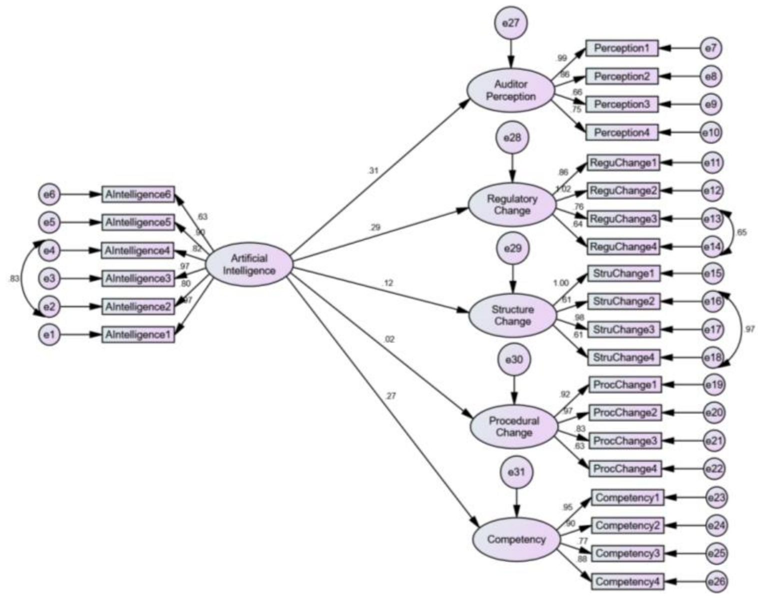

Fig. 2: IAIA Structure Equation Model.

From the above IAIA structure equation model, the standard regression weight for application of artificial intelligence is 0.63 to 0.97, for auditor perception change is 0.66 to 0.99, for audit regulatory change is 0.64 to 1.02, for audit structural change is 0.61 to 1.00, for audit procedural change is 0.63 to 0.97 and for new competencies arise in auditing is 0.77 to 0.95 respectively (which are nearly between –1 to 1). So, each of the factor loadings is extremely high and statistically significant ($p < 0.05$). The correlation between e2 and e4 is 0.83, between e13 and e14 is 0.65, and between e16 to e16 is 0.97, which are also statistically significant ($p < 0.05$).

The observed IAIA structure equation model index values are χ^2/df is 1.681 (< 3), comparative fit index (CFI) value is 0.914 (which is > 0.9), incremental fit index (IFI) is 0.916 (which is> 0.9) and Tucker Lewis index (TLI) is 0.904 (which is > 0.9), which also satisfy the standard requirement of the model. So, the IAIA structure equation model is well-fitted.
The average variance expected (AVE) to test convergent validity (from Table 2) forapplication of artificial intelligence is 0.747, for auditor perception change is 0.679, for audit regulatory change is 0.703, for audit structural change is 0.678, audit procedural change is 0.722 and for new competencies arise in auditing is 0.753, which are greater than standard value 0.5. So, the IAIA structure equation model achieved convergent validity.
Now, to test the discriminant validity, maximum shared variance (MSV) is calculated, and the IAIA structure equation model regression coefficients are shown in Table 3.

Table 3: Discriminant Validity and Path Coefficient of IAIA Structure Equation Model

Correlation			Estimate MSV	Path Co-efficient			Estimate	P
AIntelligence	<-->	Perception	0.297	AIntelligence	--->	Perception	2.778	0.005
AIntelligence	<-->	ReguChange	0.313	AIntelligence	--->	ReguChange	2.652	0.008
AIntelligence	<-->	StruChange	0.118	AIntelligence	--->	StruChange	1.080	0.280
AIntelligence	<-->	ProcChange	0.018	AIntelligence	--->	ProcChange	0.213	0.832
AIntelligence	<-->	Competency	0.280	AIntelligence	--->	Competency	2.356	0.018

To test the discriminant validity, the maximum shared variance (MSV) of the application of artificial intelligence and auditor perception change is 0.297, which is less than the square root of AVE for the application of artificial intelligence (0.864) and the square root of AVE for auditor perception change(0.824) (from Table 2). Again, the maximum shared variance (MSV) of application of artificial intelligence and audit regulatory change is 0.313, which is less than the square root of AVE for application of artificial intelligence (0.864) and the square root of AVE for audit regulatory change (0.838)(from Table 2). Also, the maximum shared variance (MSV) of application of artificial intelligence and audit structural change is 0.118, which is less than the square root of AVE for application of artificial intelligence (0.864) and the square root of AVE for audit structural change (0.823)(from Table 2). Again, the maximum shared variance (MSV) of application of artificial intelligence and audit procedural change is 0.018, which is less than the square root of AVE for application of artificial intelligence (0.864) and the square root of AVE for audit procedural change (0.850)(from Table 2). Moreover, the maximum shared variance (MSV) of application of artificial intelligence and new competencies arising in auditing is 0.280, which is less than the square root of AVE for application of artificial intelligence (0.864) and the square root of AVE for new competencies arising in auditing (0.878)(from Table 2). So, the selected IAIA structure equation model has achieved the discriminant validity.
The path co-efficient of application of artificial intelligence to auditor perception change is 2.778 (p = 0.005), application of artificial intelligence to audit regulatory change is 2.652 (p = 0.008), application of artificial intelligence to audit structural change is 1.080 (p = 0.280), application of artificial intelligence to audit procedural change is 0.213 (p = 0.832) and application of artificial intelligence to new competencies arise in auditing is 2.356 (p = 0.018).

3.3. Discussion

- Hypothesis 1

In the IAIA structure equation model, the path coefficient of application of artificial intelligence to auditor perception change is 2.778 (p = 0.005). As the p-value is less than 0.05, application of artificial intelligence has a significantly positive significant impact on auditor perception change, and null hypothesis 1 is rejected. The application of artificial intelligence has a significant positive contribution to auditor perception change. So, the perception of the auditor would change with the application of artificial intelligence.

- Hypothesis 2

According to the IAIA structural equation model, the path coefficient of applying artificial intelligence to audit regulatory change is 2.652 (p = 0.008). This value is statistically significant. Considering that the p-value is lower than 0.05, it may be concluded that the use of artificial intelligence has a positive and significant impact on audit regulation reform. Therefore, the null hypothesis cannot be accepted. The implementation of artificial intelligence has made a materially favorable and important contribution to the modification of audit regulations. Therefore, the deployment of artificial intelligence would result in a change to the audit regulatory environment.

- Hypothesis 3

The IAIA structural equation model has a path coefficient of 1.080 (p = 0.280) for the application of artificial intelligence to audit structural change. This value is based on the IAIA structural equation model. Because the p-value is higher than 0.05, it can be concluded that the implementation of artificial intelligence does not have a substantial impact on audit structural change. Furthermore, there is not sufficient evidence to reject the null hypothesis. 3. There is no major contribution that the application of artificial intelligence has made to the structural reform of auditing. Therefore, the structure of the audit would not suffer any changes because of the implementation of artificial intelligence.

- Hypothesis 4

The route coefficient of using artificial intelligence to audit procedural modification is 0.213 (p = 0.832) in the IAIA structural equation model. This value indicates that the application of AI led to the change. Because the p-value is higher than 0.05, it can be concluded that the implementation of artificial intelligence does not have a substantial impact on the modification of audit procedures. Furthermore, there is not sufficient evidence to discard the null hypothesis. 4. The implementation of artificial intelligence does not make a major contribution to the modification of audit operational procedures. Considering this, the auditing process would not be altered in any way by the implementation of artificial intelligence.

- Hypothesis 5

According to the IAIA structural equation model, the route coefficient of the application of artificial intelligence to new skills that evolve in auditing is 2.356 (p = 0.018). This is the best estimate of the potential benefits of this application. Given that the p-value is less than 0.05, it is possible to draw the conclusion that the utilization of artificial intelligence has a positive and significant impact on the development of new competencies in auditing through the usage of this technology. Because of this, the fifth null hypothesis is not accepted. With regard to auditing, the implementation of artificial intelligence has made a contribution that is both beneficial and significant to the creation of new competencies. It is for this reason that the implementation of artificial intelligence has the potential to call for the creation of new skills within the realm of auditing.

As the above discussion AI doesn't have any impact on the structural or procedural change because the procedures are fixed and not flexible. The perception, economics, cultural, and other factors of the concerned of this region are mostly rigid. In that case, the perception may be considered to moderate to comply with the AI blended old systems. Necessary steps may be taken to adopt the automated systems with the major stakeholders, like revenue officers, taxpayers, etc. The mass taxpayers are not technically sound to understand the systems that may create a disinterest among them to practice with the AI blended systems, which should also be promoted effectively to accept it by them.

4. Conclusion

In the present study, it is observed that the application of artificial intelligence has no significant contribution to audit structural change or audit procedural change. So, it is concluded that to apply artificial intelligence in audit procedures, no structural or procedural changes are required. It is also observed that the application of artificial intelligence has a positive and significant contribution to auditor perception change, audit regulatory change, and new competencies arising in auditing. So, it is concluded that to apply artificial intelligence in audit procedures, auditor perception would be changed, audit regulations may require modification, and new competencies would arise in auditing to adapt to the environment of artificial intelligence. The study results may be utilized in policy formulation and their impact on implementing artificial intelligence in audit procedures.

5. Recommendation

1) Application of artificial intelligence has no significant contribution to audit structural change or audit procedural change. So, no structural or procedural changes are required to apply artificial intelligence in the audit procedure.
2) Application of artificial intelligence has a positive and significant contribution to auditor perception change, audit regulatory change, and new competencies arise in auditing. So, the perception of the auditor should change to adopt artificial intelligence with digital technology. Artificial intelligence applications also require some regulatory changes in audit procedures. Finally, to apply the artificial intelligence in auditing new competencies (information technology, digital technology, redesign academic curriculum, paperless technology, etc.)would arise. In future research may be undertaken to apply AI tools and algorithms to make auditing dynamic, meaning it auto changes if necessary.

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