Perception of Artificial Intelligence in the Auditing Industry of British Columbia

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Abstract- According to auditing scholarship, Artificial Intelligence (AI) has the potential to reduce errors, mitigate risk, and identify fraud and anomalies in auditing processes. To assess such claims, this research paper uses a quantitative approach to examine survey results from 50 British Columbian accounting and finance practitioners. The results indicate a decline in audit quality and facilitate an inquiry into whether the incorporation of artificial intelligence into auditing procedures would have a positive impact on declining audit quality. Contrary to the research noted above, statistical methods adopted in this study illustrate that there is a strong positive association between audit quality decline and integration of artificial intelligence.

Index Terms- Audit Quality, Auditors, Artificial Intelligence, Risk Prevention and Detection, Survey Analysis, Artificial Neural Networks

I. Introduction

Technological advancements have revolutionized the business sector over the years, and the emergence of artificial intelligence (AI) is expected to be more disruptive than previous innovations. The impact of AI on accounting and auditing is critical to understanding the progress of these industries. AI is the process of automating and replicating human intelligence into intelligent machines, creating augmented intelligence that learns human capabilities, enabling well-defined tasks in real-time [22]. With big data algorithmic capabilities, AI has the potential to enhance the accounting, auditing, and assurance industries' positive competencies. These systems can analyze vast volumes of data in a fraction of the time it would require a team of humans to analyze, reduce data errors and redundancies, shorten the analysis processing cycle for financial statements, increase the reliability and efficiency of information, and enhance anomaly detection and predictive analysis [6][17][18]. Secondary research suggests that AI is known for identifying financial misstatements in annual reports and improving the accuracy and credibility of financial data [6][13][17][18]. The adoption of AI technology is feasible due to the availability of massive amounts of data and virtually limitless processing capacity [14]. Therefore, this study aims to investigate whether AI will positively or negatively impact audit quality decline based on the survey responses of accounting professionals in British Columbia. The study intends to contribute to the existing literature on the potential impact of AI on the auditing industry and provide insights into its implications for the accounting and auditing profession.

The present study aims to extend the existing literature on the impact of artificial intelligence (AI) on the auditing profession by examining the views of accounting professionals operating in the British Columbia region. Specifically, this research seeks to elucidate the implications of AI for the audit process, audit quality, and the skills and competencies that auditors must possess. The findings of this study are expected to be of practical relevance to auditing professionals, audit firm managers, and academic institutions. The results can inform professionals about employment opportunities, required skill sets, and competencies, and ways to add value to their work. The management of audit firms can benefit from the insights provided by this study to stay up to date with industry trends and design training programs to equip personnel with essential technology-related skills. Academic institutions can also restructure their educational programs to prepare students with the necessary abilities to meet the demands of the modern auditor. Ultimately, this research contributes to the literature on AI's impact on the auditing profession and provides practical implications for industry professionals, managers, and educational institutions.

II. Theoretical Framework

A. Disruptive Technology Theory

[3] introduced the concept of disruptive technologies and examined its impact on enterprises. They observed that established companies, which hold a dominant position in their industry, tend to overlook innovations that do not seem to add value to satisfy the needs of their existing clientele. Consequently, these firms become vulnerable to challenges from startups that focus on

developing cutting-edge technological solutions. To stay ahead of the competition, businesses must invest in innovative strategies that are either incremental or radical to meet the requirements of the next generation of customers.

[12] emphasized that disruptive technologies often begin with inferior technology, and although some are unsuccessful, others can disrupt after several months of testing and adaptation. For disruptive technology to impact the market, its "performance trajectory" needs to keep growing until it converges with the performance needs of mainstream customers. This trajectory describes the evolution of the technology's performance over time, and it must exceed the performance requirements of customers for the technology to become disruptive. In the initial stages, disruptive technologies are often low-performing, but as the expected trajectory performance keeps rising faster than the performance required by the mainstream market, it becomes attractive to customers.

[3] also highlight the importance of considering the strategic relevance of disruptive technologies. To integrate disruptive strategic technology with the business models of companies and industries, it is necessary to determine the performance of client demand, as well as the performance trajectory of disruptive technologies. This investigation is crucial to ensure that the performance trajectory of disruptive technology grows at a higher speed than customers' performance requirements. In conclusion, disruptive technologies have the potential to impact the market significantly, and businesses must embrace innovation and invest in strategies that can help them stay ahead of the competition.

B. Disruptive innovation in audit

In today's rapidly evolving business landscape, companies are continuously modifying their business procedures and methods of operation to meet their clients' requirements. As part of this process, auditors are required to comprehend the business strategy of their clients and the procedures utilized in the creation of value. Process auditing plays a crucial role in the practical completion of any audit, and technological advancements have made it simpler and automated, allowing auditors to focus on other audit elements [2]. Traditionally, auditors were required to obtain pertinent audit evidence by relying on paper documents, such as receipts, payment vouchers, and check duplicates [6][17]. However, technological advancements have led to the phasing out of this traditional method in favor of paperless auditing methods. These methods allow auditors to access any documentary evidence electronically and in real-time, enhancing efficiency and accuracy. The increased and effective storage capacity of current technological gadgets has made it feasible to disrupt and replace the old technique with a paperless system [2]. According to [3], disruption technologies generally underperform current technologies in their early stages. However, if their performance trajectory rises faster than customer demands, they may deliver higher and better performance in the future, attracting customers to the new technology. Moreover, auditors must handle and evaluate massive amounts of data before reaching an audit conclusion. However, performing this operation is costly, and auditors must choose a subset of transactions to investigate. This approach has the drawback of overlooking suspicious deals. Technological advancements, such as artificial intelligence and other specialized technologies, have made it possible to analyze and evaluate all data in surprisingly little time. These technologies eliminate the possibility of overlooking potentially suspicious deals [5].

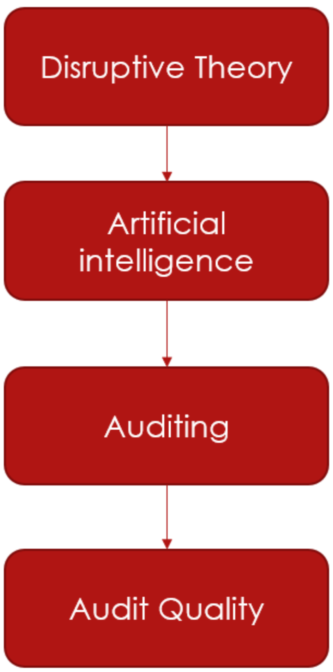

Figure 1: Theoretical Framework

III. Integration of AI in Auditing: An Applied Research

The auditing field in the accounting sector is a highly complex and risky area due to the unstructured nature of tasks involved [16]. The level of audit tests conducted by auditors is based on assessed risk during the auditing phase [16]. Auditors may fail to find material misstatements and provide investors with misleading information, which could be problematic [18]. The problem of auditing lies in the increased volume of unstructured textual documents, which has increased due to technological advancements and the use of social media [6][18]. AI capabilities, such as machine learning, natural language processing, and neural networks, have the potential to effectively detect irregularities and anomalies in financial statements, potentially automating auditor and accounting work [11]. While big data analytics and other automation tools may add value to information provided to financial statement users, they cannot replace auditors' experience, judgment, or professional skepticism [23].

There is a growing body of literature that supports the integration of artificial intelligence in the auditing field. For example, [25] proposed an AI-based auditing framework to assist auditors in decision-making by automating audit procedures. [8] developed an AI-based auditing system that uses a natural language processing technique to analyze text and identify relevant information. Additionally, [4] introduced a machine learning-based auditing system that improves the efficiency and effectiveness of auditing procedures. Overall, there is a need to understand the impact of AI on the accounting and auditing sector, as well as how auditors can adapt their skills to integrate AI into their work effectively. The potential benefits of AI integration in the auditing field cannot be ignored and may lead to increased efficiency and accuracy in the audit process.

The accounting and auditing profession generates an enormous amount of financial data, which increases the risk of presenting misleading information to users of financial statements. However, new technological advances could potentially derive insights easily and streamline the audit process, improving audit quality. In fact, by 2020, three of the four significant audit firms had invested more than $9 million in AI technology [15], anticipating that AI will automate repetitive auditing processes and significantly reduce the hours spent by humans on auditing tasks. For instance, AI systems can replace old-fashioned inventory counting methods, as companies like EY and PwC have already started using intelligent systems with smartphones, image recognition cameras, and computer vision attached to specialized drones to count inventory, identify trends, and flag anomalies, as well as analyze over and short inventory [22].

AI can eliminate dangerous failures by automating mundane, repetitive manual activities [1]. This technology also enables auditors to concentrate on analyzing and justifying apparent anomalies in financial transactions, such as unexplained entries, deliberate mistakes, and accounting estimation [17][18]. Furthermore, auditing requires the creation of samples to analyze hypotheses about a population, which can be avoided by using big data analytics and AI. These techniques can analyze the entire population while producing valuable insights and eliminating data redundancies and errors [14]. For instance, when auditors perform the tracing procedure, they select a random sample to test the completeness assertion in a transaction cycle. With the help of AI expert systems, auditors can now scan the entire population to check the completeness and accuracy of the transactions conducted by a firm [6]. Therefore, expert systems with intelligent algorithms can analyze and reason the enormous amount of data captured from financial records during the auditing process.

Expert systems that incorporate natural language processing, neural networks, and machine learning techniques have the potential to solve various problems in the accounting field. By implementing expert systems, auditors can shift their focus from routine activities to analyzing irregularities, enabling them to invest their time in activities that enhance audit quality and generate actionable recommendations [17][20]. AI techniques, such as natural language processing, artificial neural networks (ANNs), and machine learning, can easily perform tasks like generating new insights, decision-making, problem-solving, advising, strategy development, relationship building, and leadership [6][9][18].

Natural language processing utilizes AI tools to analyze textual formats, tasks, and applications based on human linguistics. The interpretation and processing of textual formats and tasks are critical steps during the analysis of financial statements and preparation of the audit report. [9] and [8] demonstrate that natural language processing provides meaningful insights and advanced knowledge on textual documents provided by accountants and auditors, such as the firm's financial performance, management's assessment of current and future firm performance, analysts' assessment of firm performance, and compliance with standards and regulations. For instance, natural language processing can be incorporated during the initial acceptance stage of a client, where negative news associated with the client can be automatically filtered with high accuracy through text classification.

In addition to natural language processing, artificial neural networks have proven to be the most beneficial data analysis program in AI. ANNs simulate how the human brain analyzes and processes information and can extract insights and solve issues that are impossible or difficult for humans to solve [10]. ANNs can also produce better results when vast volumes of data are provided, eliminating the risk of performing manual tasks during auditing procedures. ANNs assign weights to data values to approximate multiple processes, minimizing bias and error in data, streamlining the audit test procedures, improving the accuracy of audit judgment, and reducing human error and bias [16][24]. ANNs can handle uncertainty and imprecision, allowing for easier detection of revenue recognition, accounting estimates, and risk and return in auditing and assurance.

Machine learning, a key subset of AI, can allow businesses to examine an entire population to find abnormalities and predict patterns for insights. Machine learning algorithms can develop a model to anticipate outliers or anomalies based on collected data, eliminating the tradeoff between speed and quality [7][19]. Incorporating machine learning techniques will offer audit teams access to the entire data population, enabling targeted and methodical testing [6][17]. Auditors can then focus on analyzing and reducing abnormalities, resulting in higher-quality audits and fewer misstatements and fraudulent activity [6][17]. While these systems have already entered the business sector, their impact on the auditing sector is still under question.

IV. METHODOLOGY

This study aims to see if incorporating artificial intelligence into auditing procedures has a positive impact on deteriorating audit quality. The hypothesis of this study that artificial intelligence could be used to improve the quality of audit reports is tested using the survey responses of 50 accounting and finance professionals working in British Columbia's private sector. A quantitative method was used to analyze the results. To gather data, the researcher used LinkedIn to send an online survey (Microsoft Forms) and phone calls where the researcher asked yes or no questions. Among the 50 accounting professionals surveyed, 36% were CEOs, CFOs, Managers, or Heads of departments, 20% were financial analysts, 10% were audit associates, 8% were accountants, 6% were accounting officers/executives, and 20% were part of other accounting fields. The survey's participants were required to respond to 11 closed-ended questions separated into two portions. The first half of the study asked accounting professionals whether they believed that audit quality had declined in recent years. In contrast, the second segment asked whether they believed that artificial intelligence could be used to enhance audit quality in the future. Moreover, throughout this study, for further analysis purposes, variables are used to represent these questions, such as AQ1, AQ2, AQ3, AQ4, AI1, AI2, AI3, AI4, AI5, AI6, and AI7. The survey questions and the variables to denote these questions are illustrated below in Table 1. Respondents' perceptions of the implications of Artificial Intelligence on Audit Quality were studied using SPSS software, where three statistical techniques were employed: descriptive statistics, correlation analysis, linear regression, and artificial neural network (ANN). Descriptive statistics provides a summary of the data collected to achieve meaningful patterns, but this statistical method does not provide significant conclusions like other statistical methods. Correlation is a statistical method for determining the relationships between two variables and how they are related. A linear regression model is a statistical method where relationships are assessed between a dependent variable and multiple independent variables. An artificial neural network (ANN) is a computerized intelligence system that mimics human intellect and delivers inferences and conclusions for issues or areas humans find difficult to solve. As a consequence, ANN is picked as the fourth statistical approach since it has the potential to deliver superior results and solve difficulties that humans or other statistical standards have struggled to address. These three statistical approaches were explicitly utilized to validate the discovered data. Data triangulation is performed by employing these four methods for analysis to determine whether the methods converge and produce results that reinforce each other.

Table 1: Survey Questions and their Variables

Two Measures	Questions asked to accounting professionals	Variable to denote survey questions
Audit Quality Decline	Do you agree with the following statement? "Auditors find immense difficulty in performing internal control tasks such as inventory counting, document review etc. due to its physical nature."	AQ1
	Do you agree with the following statement? "Auditors spend an enormous amount of time analyzing financial statements."	AQ2
	Do you agree with the following statement? "Auditors do not notice the majority of the material misstatements caused by concealment or falsification of accounting records and supporting documents."	AQ3
	Do you agree with the following statement? "Auditors have been wasting majority of their time in conducting manual tasks rather than analysis and professional judgment."	AQ4
Integration of Artificial Intelligence	Do you agree with the following statement? "Artificial intelligence will play a "significant" role in the corporate accounting departments."	AI1
	Do you agree with the following statement? "Artificial intelligence has the ability to automate internal control	AI2

	tasks such as inventory counting, document review etc."	
	Do you agree with the following statement? "Artificial intelligence will automate the scanning of financial statements hence helping auditors to reduce time in analyzing financial statements."	AI3
	Do you agree with the following statement? "Artificial intelligence will reduce financial errors and material misstatements caused by concealment or falsification of accounting records and supporting documents."	AI4
	Do you agree with the following statement? "Artificial Intelligence has the capability to reduce fraudulent activities and reduce the chances of a financial crisis."	AI5
	Do you agree with this statement? "By incorporating artificial intelligence, auditors will be focusing on analysis and professional judgment rather than wasting majority of their time in conducting manual tasks."	AI6
	Do you agree with this statement? "Professional judgment can be performed by artificial intelligence systems."	AI7

V. Data Analysis

A. Descriptive Statistics

Descriptive statistics generate patterns and insights by illustrating and summarizing data in an accessible manner. However, these patterns do not make any inferences or conclusions beyond the data, or the hypothesis predicted. Table 2 below contains the descriptive statistics of the variables of this study. The first section of the survey assessed the participants' views on the decline in audit quality. The results showed that 40% of the participants strongly agreed, and 46% agreed that auditors encountered difficulty in performing internal control tasks. Moreover, 40% strongly agreed, and 50% agreed that auditors spent most of their time analyzing financial statements. Additionally, 58% agreed that auditors did not accurately notice material misstatements and overlook concealment and fraud, and 48% strongly agreed that auditors were wasting too much time on manual audit tasks. About 10% to 20% of the respondents were neutral regarding the decline in audit quality, while all respondents stated that auditors' performance had remained the same.

The second section of the survey examined the participants' beliefs on the potential positive impact of integrating AI systems in the auditing process. The findings indicated that 46% strongly agreed, and 40% agreed that AI would play significant roles in accounting departments. Additionally, 40% strongly agreed, and 50% agreed that AI would automate internal control tasks. Moreover, 36% strongly agreed, and 48% agreed that AI would automate the scanning of financial reports and reduce auditors' time in analyzing financial statements. Furthermore, 52% agreed that AI would reduce financial errors and material misstatements, while 32% strongly agreed that it could reduce fraudulent activities and future financial crises. Additionally, 54% agreed that AI would allow auditors to focus on analysis and professional judgments rather than wasting time on manual tasks, and 52% believed that professional judgment could be provided by auditors alone and not by intelligent systems. Only 2% to 4% of the participants believed that the integration of AI would not improve auditor performance and would not reduce financial errors and misstatements. The reliability of the survey instrument was assessed using Cronbach's Alpha, and the integration of AI data sets used in the analysis process had a score of 0.704, indicating a high degree of reliability among all the items. However, further analysis showed that if AI7 were deleted from the analysis, Cronbach's alpha reliability analysis would increase to 0.760. The descriptive statistics demonstrate that the majority of the participants believe that integrating AI systems would positively impact auditing procedures and the auditing field as a whole.

Table 2: Descriptive Statistics

Variables	N	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
AQ1	50	40%	46%	14%	-	-
AQ2	50	40%	50%	10%	-	
AQ3	50	16%	58%	22%	4%	-
AQ4	50	48%	36%	16%	-	-
AI1	50	46%	40%	14%		
AI2	50	40%	50%	8%	2%	
AI3	50	36%	48%	16%	-	-

AI4	50	36%	52%	8%	2%	2%
AI5	50	38%	30%	26%	4%	2%
AI6	50	38%	54%	4%	2%	2%
AI7	50	4%	6%	22%	52%	16%

B. Correlation

Correlation is a statistical approach for identifying the relationship between the dependent and independent variables and the percentage of effect the independent variable has on the dependent variable. In this research, the dependent variable used in the analysis is Audit Quality Decline (AQdecline), and the independent variable is Integration of Artificial Intelligence (AIeffect_auditing). An average of the four variables AQ1, AQ2, AQ3, and AQ4 was derived to determine the variable AQdecline, and an average of the seven variables AI1, AI2, AI3, AI4, AI5, AI6, and AI7 was derived to determine a variable AIeffect_auditing. After employing this statistical method, the correlation between Audit Quality decline and Integration of Artificial Intelligence was 29.2%, as shown below in Table 3, which proves that the association is positive and has medium strength. This inference means that the integration of artificial intelligence will have a positive but not a substantial impact on audit quality decline. Moreover, the correlation obtained from the data is significant at the 0.05 level because the p value is less than 0.05. Even though the correlation between the two is of intermediate strength, the positive association between the two variables proves that artificial intelligence will positively affect declining audit quality. The medium strength between the two variables might be due to the influence of other factors not incorporated in the study.

Table 3: Correlation

		AIeffect_auditing	AQdecline
AIeffect_auditing	Pearson Correlation	1	.292*
	Sig. (2-tailed)		.039
	N	50	50
AQdecline	Pearson Correlation	.292*	1
	Sig. (2-tailed)	.039	
	N	50	50

C. Linear Regression

Regression analysis assesses the influence of independent variables on the dependent variable. The analytical choice is based on the Multiple R, R Square, Adjusted R, Intercept, and Coefficient values. The intercept of the regression reveals the value of the dependent variable when the independent variable or variables are equal to zero. The regression coefficient indicates how many units of the dependent variable will change for each unit of the independent variable. Multiple R of the output indicates the degree and direction of the link between the independent and dependent variables. R Squares value indicates the proportion of instances in which the independent variable best describes the dependent variable. Based on the linear regression analysis, a correlation of r = 0.973 suggests a strong, positive association between two variables. The r squared value of 0.946 in the model explains 94.6% of the variation in the response variable around its mean. In other words, 94.6% of the variation in audit quality decline can be explained by the integration of artificial intelligence, which means that AI integration will have a strong response on audit quality decline.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.973a	.946	.945	.15421

a. Predictors: (Constant), AIeffect_auditing

Figure 1: Linear Regression Summary

D. ANN Multilayer Perceptron

An Artificial neural network (ANN) method was also used to analyze the training data's performance to understand the entire population's behavior. Because it simulates the way a human brain examines and processes information, ANN analysis is employed because it can produce better findings than other statistical techniques. Consequently, ANN is a better model than regression and models input with relation to the output. ANN incorporates a multilayer perceptron that generates insights by creating three layers of connectivity; input layer, hidden layer, and output layer. The hidden layer classifies features given by the input layer to form a better and more accurate relationship between the independent and dependent variables. ANN Multilayer Perceptron analysis is used to determine the importance and effect of each independent variable, AI1, AI2, AI3, AI4, AI5, and

AI6, on the dependent variable AQdecline, as shown below in Figure 3. AI7 was unused by the ANN analysis as it was considered as instances that would distort the results of the analysis based on the results of the Cronbach Alpha test. In ANN, 60% of the instances are used in the training phase, 20% of the data is used in the selection phase, and 20% of the instances are used in the testing phase [21]. The remaining 10% is considered unused instances as they are considered outliers or instances that will distort the results derived from the analysis.

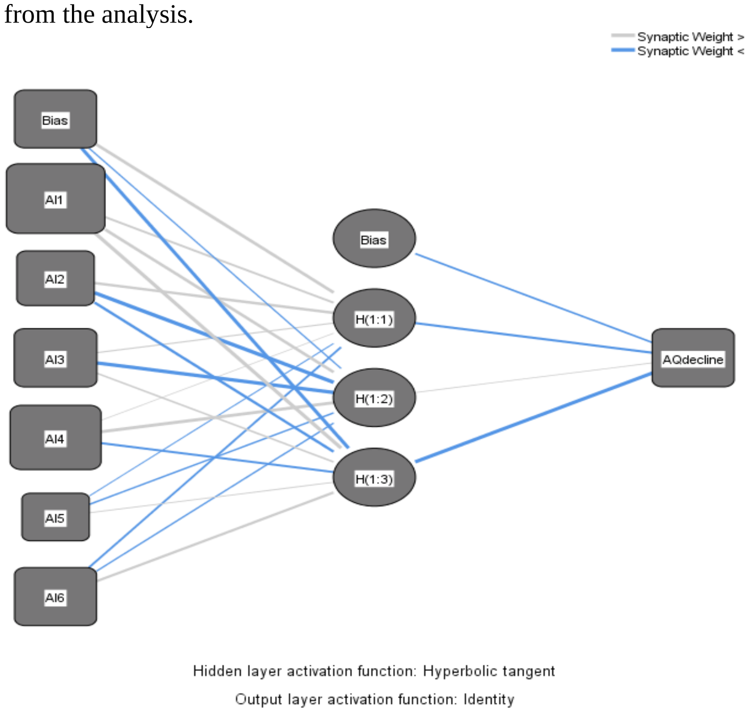

Figure 3: Integration of AI and AQdecline multilayer perceptron

According to the case-processing summary of the ANN model analysis, 72% of survey responses were used in the training phase to determine the weights. In the ANN analysis, as shown in Figure 3, the network includes three nodes with one hidden layer. The lines passing from the input layer to the hidden layer determine the strength of the relationship. The darker and fatter the line is, the stronger the relations. Moreover, a bias or error term is included in the input layer and the hidden layer "to adjust the output along with the weighted sum of the inputs to the neuron, which helps the model in a way that it can fit best for the given data" [21]. In Figure 3, multiple lines are passed from the AI variables to the hidden layer, depicting that various association patterns are considered during the analysis procedure. Moreover, a model summary was also generated from the ANN analysis to understand the error factor while testing the data, as shown in Table 4.

Table 4: Error term through ANN

Model Summary		
Training	Sum of Squares Error	20.206
	Relative Error	1.155
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.00
Testing	Sum of Squares Error	4.714
	Relative Error	.867

According to the model summary, as shown in Table 4, the model error terms for the training and testing phase are 1.155% and 0.867%, respectively, which are significantly small. The model proves that it performed well. The ANN multilayer model also helps to determine the most important independent variables concerning AQdecline, as shown below in Table 5.

Table 5: Importance of variables from ANN analysis

Independent Variable	Importance	Normalized Importance
AI1	.313	100.0%
AI2	.111	35.5%

AI3	.162	51.7%
AI4	.241	77.0%
AI5	.017	5.4%
AI6	.156	49.9%

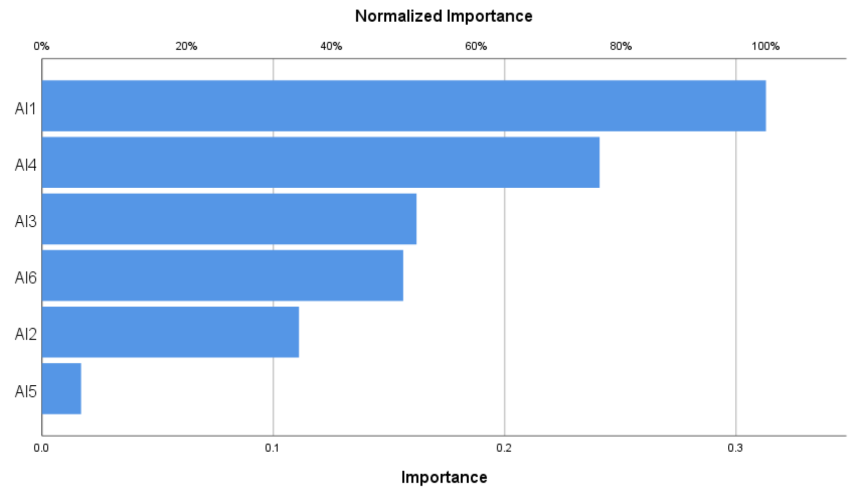

Figure 2: Importance variables that affect AQdecline

According to the ANN analysis, as shown in Table 5 and Figure 4, AI1, AI4 and AI3 are the most important independent variables, respectively, that positively affect AQdecline, whereas AI5 has the most negligible effect on the AQdecline. AI5 has a negligent effect as an independent variable because the variable focuses on the reduction of financial crisis due to the integration of AI, which is unlikely as the effect of AI is still being explored in the auditing industry. Therefore, artificial intelligence will play a significant role in accounting departments. It will reduce financial errors and material misstatements caused by concealment and falsification and will automate the scanning of financial statements, which will help auditors to reduce time in analyzing financial statements. These are the significant effects of the integration of artificial intelligence that will enhance the decline in audit quality. The least influencing factor in improving audit quality due to the integration of artificial intelligence is the reduction in the chances of financial crisis due to fraudulent activities.

VI. Conclusion and Recommendation for Further Research

The findings of this study provide valuable insights into the impact of integrating artificial intelligence on audit quality. The survey results indicated that accounting and finance professionals in British Columbia perceived a decline in the quality of financial audits in recent years. Specifically, 70% of the respondents agreed or strongly agreed that audit quality has declined, while only 4% disagreed or strongly disagreed. The reasons cited for the decline in audit quality included increased complexity and diversity of financial reporting standards, pressure to complete audits within tight deadlines, and a lack of training for auditors. However, respondents believed that integrating AI into the financial auditing process would improve audit quality. Specifically, 72% of respondents agreed or strongly agreed that AI integration would improve audit quality, while only 2% disagreed or strongly disagreed. The main reasons cited for this belief were that AI can automate mundane manual audit tasks, analyze large amounts of data effectively and efficiently in real-time, and reduce or eliminate the falsification and concealment of financial information. Respondents also believed that AI integration would reduce the time required for audits and allow auditors to focus on analyzing data and providing informed judgment. The statistical analysis of the survey data confirmed a significant relationship between AI integration and improved audit quality. Specifically, all the statistical and analytical tests revealed that there was a strong association between respondents who perceived a decline in audit quality and those who believed that AI integration would improve audit quality

Despite the statistically significant findings, this study has several limitations. First, the sample size of 50 accounting and finance professionals is relatively small, and the results cannot be generalized to other countries or regions. Second, the survey was conducted in a single industry (i.e., accounting and finance), and other industries may have different perceptions of the impact of AI on audit quality. Third, the survey did not explore the specific types of AI technologies that would be most beneficial for improving audit quality, and future research could address this gap. Finally, the study did not investigate the potential downsides or risks associated with AI integration, such as the potential for errors in AI algorithms or the loss of human judgment in the audit process.

In conclusion, this study provides evidence that AI integration has the potential to improve audit quality in the accounting and finance industry. While there are limitations to the study, the statistically significant findings suggest that further research is warranted to explore the specific ways in which AI can be used to enhance audit quality, as well as the potential risks and downsides of AI integration. By doing so, the accounting and finance industry can leverage AI technology to reduce audit risks and improve the quality of financial reporting.

REFERENCES

[1] Acemoglu, D., & Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. Journal of Economic Perspectives, 33(2), 3-30. https://doi.org/10.3386/w25684
[2] Bierstaker, J. L., Burnaby, P., & Thibodeau, J. (2001). The impact of information technology on the audit process: an assessment of the state of the art and implications for the future. Managerial Auditing Journal, 16(3), 159–164. https://doi.org/10.1108/02686900110385489
[3] Bower, J. L., & Christensen, C. M. (1995). Disruptive technologies: catching the wave. Harvard Business Review, 73(1), 43–43.
[4] Chen, Y., Wu, Z., & Yan, H. (2022). A Full Population Auditing Method Based on Machine Learning. Sustainability, 14(24), 17008. MDPI AG. Retrieved from http://dx.doi.org/10.3390/su142417008
[5] Crosley, G., & Anderson, A. (2018). The audit of the future: daring, disruptive and data-driven but poised to add significant value to firms and clients. Public Accounting Report, 42(2).
[6] Dbouk, B., & Zaarour, I. (2017). Towards a Machine Learning Approach for Earnings Manipulation Detection | Semantic Scholar. Asian Journal of Business and Accounting, 10(2), 215–251. https://www.semanticscholar.org/paper/Towards-a-Machine-Learning-Approach-for-Earnings-Dbouk-Zaarour/d9fdeab8fbd6c697549cc8f84d1284f1ec2d1c9c
[7] Dickey, G., Blanke, S., & Seaton, L. (2019, June). Machine Learning in Auditing – Current and Future Applications " Machine Learning Times. Machine Learning Times. Retrieved from: https://www.predictiveanalyticsworld.com/machinelearningtimes/machine-learning-in-auditing-current-and-future-applications/10568/.
[8] Ding, D. (2022). Design of computer economic audit system and intelligent language implementation based on SURF algorithm. Journal of Control Science and Engineering, 2022, Article ID 4362870. https://doi.org/10.1155/2022/4362870
[9] Fisher, I. E., Garnsey, M. R., & Hughes, M. E. (2016). Natural language processing in accounting, auditing and finance: a synthesis of the literature with a roadmap for future research. Intelligent Systems in Accounting, Finance and Management, 23(3), 157–157.
[10] Frankenfield, J. (2020, August 28). Artificial Neural Network (ANN). Investopedia. Retrieved from: https://www.investopedia.com/terms/a/artificial-neural-networks-ann.asp.
[11] Frey, C., & Osborne, M.A. (2017). The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change, 114, 254-280.
[12] Habtay, S. R. (2012). A firm-level analysis on the relative difference between technology-driven and market-driven disruptive business model innovations. Creativity and Innovation Management, 21(3), 290–303. https://doi.org/10.1111/j.1467-8691.2012.00628.x
[13] Issa, H., Sun, T., & Vasarhelyi, M. (2016). Research Ideas for Artificial Intelligence in Auditing: The Formalization of Audit and Workforce Supplementation. Journal of Emerging Technologies in Accounting, 13, 1-20.
[14] Kokina, J., & Davenport, T. H. (2017). The Emergence of Artificial Intelligence: How Automation is Changing Auditing. Journal of Emerging Technologies in Accounting, 14(1), 115–122. doi:10.2308/jeta-51730
[15] Kooper, M. (2020, January 2). Big Four Invest Billions in Tech, Reshaping Their Identities. Bloomberg Law. Retrieved from: https://news.bloomberglaw.com/us-law-week/big-four-invest-billions-in-tech-reshaping-their-identities.
[16] Lin, J. W., & Hwang, M. I. (2010). Audit quality, corporate governance, and earnings management: A meta-analysis. International Journal of Auditing, 14(1), 57-77. doi:10.1111/j.1099-1123.2009.00403.x
[17] Liu, Q., & Vasarhelyi, M. A. (2014). Big Questions in AIS Research: Measurement, Information Processing, Data Analysis, and Reporting. Journal of Information Systems, 28(1), 1–17. https://doi.org/10.2308/isys-10395
[18] Lokanan, M. E., & Sharma, K. (2022). Fraud prediction using machine learning: The case of investment advisors in Canada. Machine Learning with Applications, 8, 100269. https://doi.org/10.1016/J.MLWA.2022.100269
[19] Lu, H. (2020, July 29). Why Machine Learning an Audit? Medium. Retrieved from: https://medium.com/swlh/why-machine-learning-an-audit-66ca65c5fc76.
[20] Murad, H. (2017, November 29). Artificial intelligence: A reality check for professional accountancy. Retrieved February 06, 2021. Retrieved from: https://www.linkedin.com/pulse/artificial-intelligence-reality-check-professional-hasan-murad
[21] Neural networks tutorial: Data set. Neural Designer. (n.d.). Retrieved from: https://www.neuraldesigner.com/learning/tutorials/data-set.
[22] Raphael, J. (2017, June 13). How artificial intelligence can boost audit quality. Retrieved January 10, 2021. Retrieved from: https://www.cfo.com/auditing/2015/06/artificial-intelligence-can-boost-audit-quality/
[23] Technology and the Audit of Today and Tomorrow. (2017, April 20). PCAOB. Retrieved from: https://pcaobus.org/news-events/speeches/speech-detail/technology-and-the-audit-of-today-and-tomorrow_644.
[24] Ujjwalkarn. (2016, August 10). A quick introduction to neural networks. Retrieved February 02, 2021. Retrieved from https://ujjwalkarn.me/2016/08/09/quick-intro-neural-networks/
[25] Zhang, A., Cho, S., & Vasarhelyi, M. (2022). Explainable artificial intelligence (xai) in auditing. International Journal of Accounting Information Systems, 46. https://doi.org/10.1016/j.accinf.2022.100572

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