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Exploring the moderating role of natural language between the use of AI and auditing and fraud detection in accounting information system: an empirical study in Indonesia

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Article Info	Abstract
Keywords: Artificial Intelligence, Audit, Fraud Detection, Natural Language Processing, Accounting Information System	This study aims to investigate the moderating role of Natural Language Processing (NLP) in the relationship between AI-empowered accounting information systems and audit and fraud detection. The research method used is quantitative analysis with data collection through questionnaires distributed to respondents from finance and accounting departments of companies in Indonesia. This study uses multiple regression analysis and Moderated Regression Analysis (MRA) to test hypotheses. The results show that AI in accounting information systems has a significant effect on audit and fraud detection, with prevention and investigation dimensions as the main contributors. NLP partially moderates the relationship between AI and audit and fraud detection, where NLP significantly strengthens the prevention dimension, negatively moderates the investigation dimension, but does not moderate the dimensions of data gathering, data analysis, risk assessment, and detection. Theoretical Contribution: This study extends the literature on AI and NLP integration in accounting information systems by showing that NLP effectiveness is context-specific and differential depending on the AI dimension being moderated. Practical Contribution: These findings provide guidance for audit practitioners and organizations in prioritizing NLP implementation in preventive audit systems, as well as providing careful considerations in implementing NLP for fraud investigation.

1. INTRODUCTION

The rapid development of digital technology has given rise to various innovations in many areas of life, including accounting and auditing. These dynamics require accounting practitioners and auditors to adapt to technological advances in order to remain relevant in the face of the complexities of the modern business environment. The integration of Artificial Intelligence (AI) in accounting information systems has revolutionized auditing practices and fraud detection techniques. AI's ability to analyze data sets can improve efficiency and accuracy in detecting accounting fraud through machine learning and natural language processing, which are effective in identifying fraud patterns (Iman, 2024).

In addition, AI has the ability to improve the efficiency of the audit process, reduce human error, and increase customer trust (Mediana & Sandari, 2024). By utilizing these capabilities, AI can process unstructured textual data, such as audit reports and financial statements, to identify anomalies and trends that may indicate irregularities or fraud. The application of AI in the audit process not only simplifies operations but also reduces human error, resulting in more reliable results. This, in turn, increases customer confidence in the accuracy and transparency of audits, which ultimately contributes to stronger and more efficient accounting practices.

Financial fraud is a major concern for potential investors, audit firms, and governments themselves. AI is one of the technologies that assists auditors in the audit process, particularly by detecting or analyzing anomalies. AI can automate routine tasks, detect fraud, and identify risks faster and more accurately than traditional methods (Fadilla et al., 2025). One of the features of AI, which is its ability to analyze advanced data, contributes significantly to data-driven decision making, which improves the overall quality of audits. By automating fraud detection and simplifying risk assessment, AI not only improves the efficiency of the audit process but also contributes to more reliable and insightful audits.

The use of AI in auditing and fraud detection is a new trend today. Remarkably, the integration of AI into internal auditing is not just a trend, but a necessary evolution to achieve optimal audit results (Ghafar et al., 2024). Artificial intelligence (AI), or as it is currently called, AI-powered Accounting Information Systems (AIS) in auditing and fraud detection, has gained significant attention in recent years due to its potential to detect fraud patterns faster and with greater accuracy than traditional auditing methods (Bello et al., 2022).

Among the most well-known AI-powered AIS tools is natural language processing (NLP), which provides solutions to challenges such as auditing and fraud detection by enabling computers to understand, interpret, and respond to human language (Munoko, 2022). By processing, analyzing, and decoding natural language data, NLP helps improve the accuracy of AI systems in financial fraud detection. Specifically, NLP can be used to identify keywords in documents that may indicate fraudulent activity and to flag any potentially fraudulent activity based on those keywords (Qatawneh, 2025).

This study attempts to bridge the research gap where this research has not yet been developed in Indonesia. In addition, this study focuses on exploring how NLP moderates the influence of AI on auditing and fraud detection in accounting information systems, where previously there has been no in-depth exploration of the role of NLP. Understanding that the role of NLP can have a significant impact on improving the accuracy and effectiveness of automated audit systems. This study will contribute to the growing literature on AI in accounting, emphasizing the synergistic relationship between AI technology and its ability to process and analyze various forms of data.

Based on the phenomena and differences in the results of previous studies, further research is needed to examine the influence of AI on auditing and fraud detection with NLP as a moderating variable. This study is a replication of the study Qatawneh (2025) that examined the role of AI and NLP in the context of auditing and fraud detection. This study is expected to help accounting practitioners and auditors, especially in Indonesia, to understand the role of AI and NLP technology in improving audit quality and fraud detection effectiveness.

2. THEORETICAL REVIEW AND HYPOTHESIS

Artificial Intelligene (AI) in Auditing

Artificial Intelligence (AI) is a field of computer science that focuses on the development of intelligent systems and machines capable of performing tasks that were previously limited to human capabilities (Salehi & Burgueño, 2018; Rumangkit et al., 2025). Artificial intelligence has enormous potential in detecting unusual patterns, analyzing large data sets, and providing more accurate and faster recommendations (Mediana & Sandari, 2024). According to Ghafar et al. (2024), AI has the ability to process large data sets in real-time, not only reducing human error but also speeding up the audit process, thereby saving time and reducing costs. There are several dimensions of AI in the field of accounting information systems. Some dimensions may be related to specific accounting information system practices, but in auditing and fraud detection, the dimensions of AI-enabled accounting information systems include (Han et al., 2022; Casey et al., 2021; Alam et al., 2022). a) Data collection, AI systems can collect large amounts of data from various sources, including financial records, transaction records, and social media feeds. b) Data analysis, AI can analyze this data using machine learning algorithms, identifying patterns, trends, and anomalies that may be evidence of fraud. c) Risk assessment: AI can use predictive analytics to assess the risk of fraud for an organization or a specific set of transactions, allowing auditors and investigators to focus their efforts where they are most needed. d) Detection, AI can be used to detect potential fraud as it occurs by monitoring transaction data in real-time and flagging suspicious activity. e) Prevention, AI can help prevent fraud by identifying potential weaknesses in an organization's internal controls and making recommendations for improvement. f) Investigation, AI can assist in fraud investigations by analyzing large amounts of data quickly and accurately, enabling investigators to identify and track potential suspects.

Natural Language Processing (NLP)

Natural Language Processing (NLP) is a theoretically motivated set of computational techniques for analyzing and representing naturally occurring text at one or more levels of linguistic analysis for the purpose of achieving human-like language processing for various tasks or applications (Liddy, 2001). NLP is the process by which computers can understand, interpret, and communicate in human language. In other words, it is a part of AI, focusing specifically on the interaction between computers and human language, which enables computers to process, interpret, and generate natural language (Pourhabibi et al., 2020).

Natural Language Processing (NLP) plays an important role in enhancing these capabilities, especially in understanding and processing textual data. NLP has emerged as a powerful tool in the field of fraud detection, utilizing large amounts of unstructured text data generated in various sectors, including finance, insurance, and e-commerce (Azlaan, 2024). In recent years, the integration of AI and NLP has significantly changed the audit and fraud detection processes in accounting information systems. NLP techniques enable AI systems to process and analyze large amounts of un d data, such as financial reports and emails, to detect inconsistencies or deviations that may indicate fraudulent activity.

Accounting information systems supported by NLP functions extract data from numerous report texts, extract unusual activity patterns and relationships between accounts, and identify transactions (Qatawneh & Bader, 2021). In addition, NLP is used to understand the context of the text and identify risks associated with trends such as examiner financial gaps, cybersecurity, and areas of potential exposure.

AI supported accounting information systems use NLP to analyze unstructured data such as emails, financial reports, and online comments to extract meaningful findings that support decision-making. AI-supported NLP in AIS helps automate tasks such as report generation, data entry, and data analysis in accounting and financial reporting (Ashraf et al., 2019). Craja et al. (2020) mentions that the use of NLP in accounting can convert natural language information into structured data. This means that auditors can better understand documents and content and analyze them in a more comprehensive and meaningful way.

Meanwhile, Bao et al. (2020) claim that NLP is an important part of AIS and is supported by AI in the world of accounting and finance. NLP plays an important role in tightening the audit process, improving the accuracy and security of financial activities, and improving decision making. Qatawneh (2025) mentions that NLP is a useful tool for developing more efficient methods for detecting fraudulent activities and audit risks.

Hypothesis Development

Resources Based View (RBV) is the use of Artificial Intelligence (AI) in accounting audits, which has a significant and transformational impact on the profession. AI changes the traditional role of auditors by shifting their focus from routine and repetitive tasks to more strategic and data-based analysis (Raschke et al., 1993). This requires auditors to adapt their skills and education, with a greater emphasis on technological expertise and data analysis (Iman, 2024). The integration of AI also opens up new opportunities in auditing. For example, with AI, audits can be conducted continuously, where systems can automatically monitor and analyze data continuously to detect anomalies or indications of fraud.

Research results Qatawneh (2025) show that AI has a statistically significant effect on auditing and fraud decetion. Research results Iman (2024) show that AI can improve efficiency and accuracy in detecting accounting fraud. In addition Mediana & Sandari (2024) mention that the application of AI increases the efficiency of the audit process, reduces human error, and increases customer trust. Fadilla et al. (2025) mentions that the use of AI in auditing contributes significantly to improving the accuracy, efficiency, and reliability of the audit process with its ability to analyze data in depth, identify risks, detect abuse, and optimize audit planning and implementation.

H_1: Artificial intelligence (AI) in accounting information systems has a significant influence on auditing and fraud detection

However, the effectiveness of AI use may not always meet employee expectations. As found by Papagiannidis et al. (2023), AI may fail in various ways, such as adding business value or providing unexpected results. This occurs because AI can be hampered by the quality and complexity of textual data, such as unstructured financial reports, reviews, or customer comments. Additionally, the lack of appropriate algorithms and financial language meaning can undermine its capacity to identify fraud patterns (Mayer et al., 2020).

Therefore, investigating the moderating role of NLP in the relationship between AI and AIS in fraud testing and recognition can determine how the effectiveness of AI can be improved in detecting and preventing fraudulent activities. This theory suggests that AI algorithms related to NLP technology are more effective than AI in detecting fraud patterns, improving testing, and enhancing fraud detection in financial systems (Kumar et al., 2020).

The literature gap in investigating the moderating role of NLP in the approved relationship of AI is that fraud perception is lacking in empirical research, and it is the effectiveness of NLP from Keis that enables AI. Although the use of AI is implemented during fraud detection, there is limited empirical evidence on the effectiveness of NLP in reducing the relationship between certified AI and AIS and the perception of audit and fraud. Furthermore, the literature does not examine the extent to which AI-generated versions of NLP can improve the interpretability of AI-generated editions. Therefore, more empirical research is needed to increase the likelihood that NLP will improve the effectiveness and efficiency of AI enhanced by AI for forensic recognition and auditing or fraud detection.

H_2: Natural language processing (NLP) moderates the relationship between AI in AIS and audit and fraud detection

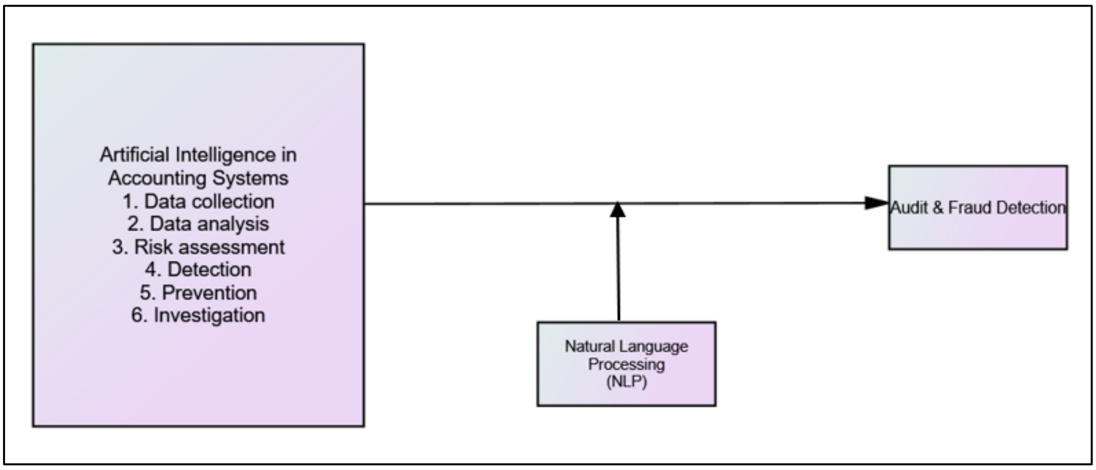

Figure 1. Research Model

3. RESEARCH METHOD

The research population consisted of all employees working for companies in Indonesia. The sample for this study was financial and accounting managers selected to represent the research population. In this sampling method, participants were selected based on their convenience or proximity to the researcher or simply because they were available. Data collection was carried out by contacting the company's HR department via WhatsApp and email. The objectives, goals, and research process were conveyed to HR representatives. The process was carried out by uploading a questionnaire on Google Forms and sending a link to the HR department to send it to respondents and collect the required primary data.

Data collection for this study used a questionnaire distributed via Google Forms. All questions in the questionnaire used a 5-point Likert scale. This study used multiple regression tests to test hypothesis 1 and MRA (Moderated Regression Analysis) tests to test hypothesis 2 using SPSS.

This study adopted an instrument developed by Qatawneh (2024) consisting of 43 questions. Each question item was measured using a 1-5 Likert scale with a score of 1 for "Strongly Disagree," 2 for "Disagree," 3 for "Neutral," 4 for "Agree," and 5 for "Strongly Agree." In the complete instrument, the questionnaire appears in two main sections; the first contains sample demographics, including (age, gender, and qualifications), while the other section presents statements related to the research sub-variables (data collection, data analysis, risk assessment, detection, prevention, and investigation). The results of the validity test are presented in Table 1. All items have a calculated r value greater than the table r, so it can be concluded that all items are valid.

Table 1. Validity Test

Variabel	Item	r-value	r-table	Result
Data Collection (X1)	X11	0.868	0.266	Valid
	X12	0.783	0.266	Valid
	X13	0.869	0.266	Valid
	X14	0.812	0.266	Valid
Data Analysis (X2)	X21	0.689	0.266	Valid
	X22	0.845	0.266	Valid
	X23	0.712	0.266	Valid
	X24	0.921	0.266	Valid
	X25	0.852	0.266	Valid
	X26	0.885	0.266	Valid
Risk Assessment (X3)	X31	0.822	0.266	Valid
	X32	0.874	0.266	Valid
	X33	0.907	0.266	Valid
	X34	0.802	0.266	Valid
	X35	0.904	0.266	Valid
	X36	0.858	0.266	Valid
	X37	0.676	0.266	Valid
Detection (X4)	X41	0.886	0.266	Valid
	X42	0.888	0.266	Valid
	X43	0.705	0.266	Valid
Prevention (X5)	X51	0.736	0.266	Valid
	X52	0.844	0.266	Valid
	X53	0.819	0.266	Valid
	X54	0.800	0.266	Valid

	X55	0.659	0.266	Valid
	X56	0.854	0.266	Valid
Investigation (X6)	X61	0.777	0.266	Valid
	X62	0.788	0.266	Valid
	X63	0.887	0.266	Valid
	X64	0.886	0.266	Valid
	X65	0.920	0.266	Valid
NLP (X7)	X71	0.752	0.266	Valid
	X72	0.922	0.266	Valid
	X73	0.860	0.266	Valid
	X74	0.878	0.266	Valid
	X75	0.890	0.266	Valid
Fraud Detection (Y)	Y1	0.823	0.266	Valid
	Y2	0.893	0.266	Valid
	Y3	0.895	0.266	Valid
	Y4	0.846	0.266	Valid
	Y5	0.826	0.266	Valid
	Y6	0.613	0.266	Valid
	Y7	0.859	0.266	Valid

The results of the reliability test are shown in Table 2. All variables show a Cronbach's Alpha value above 0.70, which indicates that the research instrument has a good level of internal consistency and is declared reliable.

Table 2. Reliability Test

Variable	Cronbach's Alpha	Result
Data Collection (X1)	0.853	Reliable
Data Analysis (X2)	0.900	Reliable
Risk Assessment (X3)	0.924	Reliable
Detection (X4)	0.772	Reliable
Prevention (X5)	0.876	Reliable
Investigation (X6)	0.901	Reliable
NLP (X7)	0.908	Reliable
Fraud Detection (Y)	0.914	Reliable

4. RESULTS AND DISCUSSION

Respondent Demographic

Frequency and percentage results were calculated based on the research demographics in Table 1. It can be seen that the majority of respondents were female, accounting for 77.8% of the total sample, while male respondents accounted for 22.2%. In terms of educational qualifications, the majority of respondents had a Bachelor's degree, accounting for 85.2%, followed by a Master's degree, accounting for 14.8%. Based on work experience, the distribution of respondents shows that the majority have 2-6 years of experience, accounting for 94.4% of the total sample, while respondents with more than 11 years of experience account for 5.6%.

Table 3. Respondent Profile

Characteristics	Category	F	%
Gender	Male	12	22,2
	Female	42	77,8
Educational Qualifications	Bachelor's Degree	46	85,2
	Master	8	14,8
Experience	2–6 years	51	94,4
	7–11 years	1	1,9
	>11 years	2	3,7
Total		54	100,0

Source: Research results

Descriptive Analysis of the Questionnaire

The mean (μ) and standard deviation (σ) were calculated for respondents' answers to the questionnaire statements. The analysis results show that the highest mean was obtained from the Investigation variable (X5) with a mean of 3.92/5.00, followed by Detection (X4) with a mean of 3.88/5.00, and Risk Assessment (X3) with a mean of 3.86/5.00. The lowest average score but still positive was given to the Data Collection variable (X1), with an average of 3.67/5.00 compared to the maximum average of 5.00. However, all variables obtained average scores higher than the scale average (3.00), indicating that all questionnaire statements and variables were well received by respondents.

It appears that respondents' perceptions of the role of AI in auditing and fraud detection are generally positive, with average scores ranging from 3.67 to 4.58 on a scale of 5.00. This indicates that respondents have a good understanding and appreciation of the implementation of AI technology in auditing practices, although the data collection aspect still requires more attention to improve its effectiveness.

Table 4. Descriptive Statistics of the Questionnaire

Variable/Statement	μ	σ
Data Collection(X1)		
AI collects financial data from various sources, including bank statements, invoices, and receipts	3,85	0,89
AI can extract data from documents such as scanned receipts and manually entered data.	3,81	0,92
AI collects non-financial data, such as customer sentiment, from social media platforms.	3,70	0,85
AI stores and processes large amounts of data to provide a more holistic view of an organization's financial health	3,78	0,91
The use of AI enables accountants to collect data more efficiently, allowing them to use their time more effectively.	3,70	0,88
Average Data Collection	**3,77**	**0,89**
Data Analysis (X2)		
AI support systems reveal hidden relationships between data variables, complementing traditional analysis	3,81	0,93

Variable/Statement	μ	σ
AI can process large data sets in seconds or minutes, while humans require hours or days	3,89	0,96
AI identifies patterns, trends, and anomalies in financial data that may indicate fraud or other irregularities.	3,87	0,88
By using AI combined with NLP, data analysis can be expanded to review unstructured data as well.	3,87	0,94
Algoritma AI menganalisis data keuangan untuk menilai kelangsungan hidup jangka panjang suatu bisnis, dan mengidentifikasi area yang memerlukan perhatian	3,80	0,90
Average Data Analysis	**3,85**	**0,92**
Risk Assessment (X3)		
AI provides accurate assessments of potential fraud or financial crime risks	3,91	0,87
AI helps identify potential ethical issues and conflicts of interest within an organization.	3,85	0,89
Integrating data from various sources to identify potential cybersecurity threats	3,83	0,91
Helping to address risks in accounting and finance and working to reduce risks	3,85	0,88
AI's predictive capabilities effectively anticipate and mitigate future risks based on historical patterns and data analysis	3,83	0,93
Average Risk Assessment	**3,85**	**0,90**
Detection (X4)		
AI detects unusual or suspicious transactions that may indicate fraud	3,94	0,96
AI monitors financial data in real time, identifies potential problems, and notifies the authorities	3,80	0,89
AI also detects non-financial risk areas, such as ethical violations or fraudulent activities.	3,78	0,94
AI-powered tools help identify potential non-compliance in contracts, standards, and financial reporting.	3,83	0,88
AI can identify potential fraud in audit data in real time, enabling auditors to take swift action against any irregularities	3,94	0,91
Average Detection	**3,86**	**0,92**
Prevention (X5)		
AI improves internal control through continuous data monitoring to detect signs of danger and suspicious behavior	3,87	0,90
AI predicts trends that may result in anomalies and supports organizations in ensuring preventive measures are implemented.	3,81	0,88
AI helps organizations transition to preventive audits so that issues can be detected and addressed quickly	3,91	0,93
AI highlights potential vulnerabilities to inform decision-making and minimize fraud risk.	3,87	0,86
AI facilitates the automation of accounting and compliance processes, allowing staff to focus on more strategic tasks	3,94	0,95
Average Prevention	**3,88**	**0,90**
Investigation (X6)		
AI collects evidence based on data analysis and NLP to build a case against suspected fraudsters.	3,91	0,92
AI identifies relationships between members of an organization to reveal potential collusion in criminal activities.	3,87	0,96

Variable/Statement	**μ**	**σ**
AI assists in tracking and recovering stolen assets through digital record and network analysis	3,78	0,94
AI helps determine the identity and location of fraudsters behind transaction fraud	3,89	0,91
AI substantially reduces the time required to conduct investigations and track fraudulent activities by automating the data extraction and analysis process	4,00	0,89
Average Investigation	**3,89**	**0,92**
Audit and Fraud Detection (Y)		
AI investigations are integrated into AIS to improve its ability to detect and prevent fraud	3,87	0,85
AI-supported AIS makes the audit process more efficient and effective by automating routine tasks, improving accuracy, and reducing the risk of human error.	3,91	0,88
AI-supported AIS detects emerging risks, such as cyber attacks and internal threats.	3,96	0,90
AIS that supports AI learns and adapts to historical audit data and develops new analytical models	3,87	0,86
AIS that supports AI uses NLP to automate data extraction from unstructured documents.	3,93	0,92
Average Audit and Fraud Detection	**3,91**	**0,88**
Natural Language Processing/NLP (Z)		
NLP helps AI-powered fraud detection and audit systems extract meaning from natural language data.		
With NLP, AI systems categorize and classify large amounts of unstructured data, transforming it into structured data that is easier for auditors to analyze.	3,87	0,89
NLP enables AI-supported audit responses to customer inquiries more efficiently, without excessive delays and task allocation.	3,85	0,91
NLP identifies and extracts sections of annual reports or company financial statements that require more attention from auditors.	3,91	0,87
NLP detects fraud incidents in areas such as insurance claims, using natural language data to identify suspicious patterns.	3,87	0,93
NLP identifies potential fraudulent activity in financial risk assessments, transactional processes, or investment decisions.	3,81	0,88
NLP automates compliance review processes, improving the sensitivity and accuracy of audit processes.	3,83	0,90
Average NLP	3,89	0,86
Natural Language Processing/NLP (Z)	**3,86**	**0,89**

Source: Research results

Hypothesis Testing

The F test results in Table 5 show a calculated F value of 11.447 with a significance level of 0.000 ($p < 0.05$), indicating that, collectively, all dimensions of AI in accounting information systems have a significant effect on auditing and fraud detection. Thus, hypothesis H1 is accepted, which means that artificial intelligence in accounting information systems has a statistically significant effect on auditing and fraud detection.

The partial t-test results show that not all AI dimensions have a significant individual effect on auditing and fraud detection. The t-value of data collection is 0.091 with a significance of 0.927 ($p > 0.05$), indicating that data collection does not have a significant effect on auditing and fraud detection. The t-value of data dnalysis is -2.448 with a significance of 0.018 ($p < 0.05$), indicating that data analysis has a significant negative effect on auditing and fraud detection. The t-value of Risk Assessment is 1.001 with a significance of 0.322 ($p > 0.05$), indicating that risk assessment has no significant effect on auditing and fraud detection. The t-value of is -1.053 with a significance of 0.298 ($p > 0.05$), indicating that detection has no significant effect on auditing and fraud detection. The t-value of Prevention is 2.877 with a significance of 0.006 ($p < 0.05$), indicating that prevention has a significant positive effect on auditing and fraud detection with the highest beta coefficient (0.762). The t-value of Investigation is 2.445 with a significance of 0.018 ($p < 0.05$), indicating that investigation has a significant positive effect on audit and fraud detection with a beta coefficient of 0.540.

Table 5, Hypothesis Testing

Model	Unstandardized Coefficients		Standardized Coefficients	T	Sig.
	B	Std. Error	Beta		
1(Constant)	5,559	1,971		2,821	,007
Data Collection	,021	,232	,020	,091	,927
Data analysis	-,572	,234	-,558	-2,448	,018
Risk assessment	,194	,193	,196	1,001	,322
Detection	-,239	,227	-,251	-1,053	,298
Prevention	,670	,233	,762	2,877	,006
Investigation	,508	,208	,540	2,445	,018

Source: Data processing results

To test the second hypothesis, *a* Moderated Regression Analysis (MRA) was conducted by including the NLP variable as a moderating variable. The t-test results in Table 6 show the moderating effect of NLP on the relationship between AI dimensions and audit and fraud detection. The t-value for the interaction of Data Collection*NLP is -0.811 with a significance of 0.422 ($p > 0.05$), indicating that NLP does not moderate the relationship between data collection and audit and fraud detection. The t-value for the interaction of Data Analysis*NLP is 0.218 with a significance of 0.828 ($p > 0.05$), indicating that NLP does not moderate the relationship between data analysis and audit and fraud detection. The t-value for the interaction of Risk Assessment*NLP is 0.581 with a significance of 0.565 ($p > 0.05$), indicating that NLP does not moderate the relationship between risk assessment and audit and fraud detection. The t-value for the interaction between Detection*NLP is -0.867 with a significance of 0.391 ($p > 0.05$), indicating that NLP does not moderate the relationship between detection and auditing and fraud detection. The t-value for the interaction between Prevention*NLP is 3.035 with a significance of 0.004 ($p < 0.05$), indicating that NLP significantly moderates the relationship between prevention and audit and fraud detection. The very high beta coefficient value (9.284) indicates that NLP substantially strengthens the effect of prevention on audit and fraud detection. The t-value for the Investigation*NLP interaction is -2.480 with a significance of 0.017 ($p < 0.05$), indicating that NLP significantly negatively moderates the relationship between investigation and audit and fraud detection. This negative result may indicate that at a high level of investigation, the addition of NLP does not provide proportional added value.

Based on these results, hypothesis H2 is partially accepted. NLP is proven to moderate the relationship between AI in AIS and audit and fraud detection, particularly in the prevention and investigation dimensions, albeit with different directions. NLP is not proven to moderate the relationship in the data collection, data analysis, risk assessment, and detection dimensions.

Table 6. Moderated Regression Analysis (MRA)

	Unstandardized Coefficients		Standardized Coefficients		
Model	B	Std. Error	Beta	T	Sig.
1 (Constant)	3,548	7,445		,477	,636
Data Collection	1,150	1,363	1,074	,844	,404
Data analysis	-,466	1,332	-,454	-,350	,002
Risk assessment	-,586	1,207	-,592	-,485	,630
Detection	,918	1,163	,960	,789	,435
Prevention	-4,454	1,486	-5,064	-2,996	,005
Investigation	4,330	1,621	4,601	2,671	,011
NLP	,455	,277	,616	1,641	,109
Data Collection*NLP	-,040	,050	-1,875	-,811	,422
Data analysis*NLP	,011	,050	,513	,218	,828
Risk assessment*NLP	,026	,044	1,283	,581	,565
Detection*NLP	-,036	,042	-1,825	-,867	,391
Prevention*NLP	,160	,053	9,284	3,035	,004
Investigation*NLP	-,146	,059	-7,516	-2,480	,017

Source: Data processing results

The Influence of AI in Accounting Information Systems on Auditing and Fraud Detection

The results of this study prove that artificial intelligence (AI) in accounting information systems has a statistically significant effect on audit and fraud detection. This finding is in line with previous studies conducted by Qatawneh (2025) and Munoko (2022) which state that the adoption of AI in accounting information system practices can result in more effective anomaly identification, predictive analytics, real-time monitoring, risk assessment, and fraud analysis.

Overall, the results of the study show that AI in AIS can be a very powerful tool in fraud detection for accounting. AI is capable of analyzing large amounts of financial data to identify patterns, anomalies, and inconsistencies that may indicate fraudulent activity. AI's ability to process large data sets in real-time not only reduces human error but also speeds up the audit process, saving time and reducing costs (Ghafar et al., 2024).

In the context of auditing, the research results also confirm that the adoption of AI in AIS assists in the auditing process by ensuring automated audit procedures, anomaly identification, fraud detection, risk assessment, and reconciliation procedures. In general, the results indicate that by using AI, auditors can perform tasks quickly and efficiently and focus on more strategic tasks, leading to an efficient and effective auditing process. AI can improve the accuracy and quality of audits and provide better insights into the financial health of an organization.

Analysis of AI Dimentions in SIA

The research results indicate that not all AI dimensions have the same influence on auditing and fraud detection. The results show that the prevention dimension has the strongest and most significant influence on auditing and fraud detection. This finding is in line with research Bello et al. (2022) which states that prevention is the most effective sub-variable in auditing and fraud detection. This shows that AI is highly effective in improving internal controls through continuous real- e data monitoring to find warning signs and suspicious behavior. AI is capable of predicting trends that may result in anomalies and supporting organizations in ensuring that countermeasures are implemented. AI's ability to help organizations shift to preventive auditing so that problems can be detected and addressed quickly is a significant added value in modern auditing practices.

The investigation dimension has also been proven to have a significant positive effect on auditing and fraud detection. This indicates that AI is very helpful in gathering evidence based on data analysis to build cases against suspected fraudsters, identifying relationships between members of an organization to reveal potential collusion in criminal activities, and assisting in tracking and recovering stolen assets through digital analysis and network records. AI substantially reduces the time required to manually investigate and track fraudulent activities by automating the data extraction and analysis process.

The results of the study show a significant negative effect of data analysis on auditing and fraud detection. Dimensions data Collection, Risk Assessment, and Detection do not show a significant individual influence on fraud audit and detection. This may indicate that these dimensions play a greater role as supporters or enablers for other dimensions (especially prevention and investigation) in an integrated AI system, rather than as stand-alone factors.

The finding that the prevention dimension has the strongest influence is in line with the modern audit paradigm that emphasizes the importance of early fraud prevention (*preventive audit*) over fraud detection after it has occurred (*detective audit).* AI enables organizations to shift from a reactive audit approach to a proactive audit approach that can identify and prevent potential fraud before it causes significant losses.

Moderating Role of NLP in the Relationship between AI and Auditing and Fraud Detection

The main objective of this study is to investigate the moderating role of Natural Language Processing (NLP) in the relationship between AI in accounting information systems and audit and fraud detection. The results show that NLP has a significant moderating role, but with complex and varying patterns depending on the AI dimension being moderated.

NLP Moderation in the Prevention Dimension

The results show that NLP positively and significantly moderates the relationship between prevention and audit and fraud detection. This very high beta coefficient value indicates that NLP substantially strengthens the effectiveness of the prevention dimension of AI in audit and fraud detection. These findings have important theoretical and practical implications. The use of NLP enables AI tools to process unstructured data, that can provide valuable additional information for auditing and fraud detection. This combination can provide audit professionals with more complete and accurate information for decision making. NLP in accounting is a time-saving solution that empowers auditors and fraud detection professionals to focus on strategic activities, leaving routine tasks to computer systems. This is in line with the findings (Qatawneh, 2025) which state that NLP helps auditors to be more efficient in analyzing documents and content. NLP can support the automation of various types of audit documents, enabling the efficient delivery of final reports, client letters, and financial statements.

In the context of prevention, NLP enables AI systems to automatically monitor internal communications, transactions, and documents to identify *red flags* or suspicious patterns that may indicate potential fraud. NLP in AI can provide automatic and instant discrimination against individuals or information trends, thereby protecting organizations from potential fraudulent activities. NLP's ability to understand context and sentiment in text allows the system to detect more subtle patterns that may be missed by traditional quantitative analysis. The combination of AIS-powered AI and NLP can provide data audit professionals with higher quality data in the most efficient way to make informed decisions and reduce errors.

These results confirm previous research findings that NLP frameworks integrated with AI significantly improve the accuracy and precision of analysis in various contexts (Meenakshi et al., 2024). In the context of fraud prevention, NLP enables AI systems to not only analyze numerical data, but also understand and interpret textual information that often contains important indicators of potential fraud.

NLP Moderation on the Investigation Dimension

The results of the study show that NLP significantly moderates the relationship between investigation and audit as well as fraud detection. These un t results require careful interpretation and can be explained through several perspectives. At advanced stages of investigation, where AI is already highly effective in analyzing structured data and complex fraud patterns, the addition of an NLP layer may create additional complexity that is disproportionate to the added value it provides. In-depth fraud investigations often require highly specific and structured data analysis, where the presence of NLP can actually create noise or irrelevant information. This negative coefficient may also indicate that at certain levels of investigation, too much automation through NLP can reduce the critical human judgment involved in fraud investigations. Fraud investigations often require intuition, complex contextual considerations, and an understanding of nuances that are difficult to fully automate.

Although NLP can assist in analyzing investigative documents, in practice, implementing NLP for investigations may require extensive tuning and customization, which can reduce relative efficiency compared to well- established traditional investigative methods. These negative results may also reflect the implementation phase of NLP technology, which is still in the adjustment stage, where organizations are still in the process of learning how to optimally integrate NLP into their fraud investigation processes. However, it is important to note that even though the moderating effect of NLP on the investigation dimension is negative, the main effect value of the investigation itself remains positive and significant, indicating that the AI investigation dimension remains important for fraud auditing and detection.

Moderating Effect of NLP on Other Dimensions

The results of the study show that NLP does not moderate the relationship between the dimensions of data collection, data analysis, risk assessment, and detection with auditing and fraud detection. These findings can be interpreted as follows:

Data Collection

At the data collection stage, the process generally involves the extraction of transactional and structured data from various systems. NLP may not provide significant added value at this stage because most of the data collected is already in a format that can be processed directly by AI systems without the need for natural language processing.

Data Analysis

Although NLP can assist in analyzing textual data, the results of the study show that in the overall dimension of data analysis, NLP does not significantly moderate its relationship with auditing and fraud detection. This may be because data analysis in the context of auditing and fraud detection focuses more on quantitative analysis and numerical patterns, where NLP has a more limited role.

Risk Assessment

Risk assessment in auditing and fraud detection generally uses predictive models and scoring based on historical data and quantitative risk factors. Although NLP can help identify risks from textual sources, the results of the study show that its moderating effect is not significant, possibly because existing risk assessment methodologies are already robust enough without the need for additional NLP.

Detection

The results showing no moderating effect of NLP on the detection dimension are quite interesting, considering that NLP is often thought to improve fraud detection through text analysis. This finding may indicate that in practice, fraud detection relies more on transactional and behavioral pattern analysis, which is already handled well by AI without the need for an additional NLP layer, or that the implementation of NLP for detection is still not optimal.

5. CONCLUSION AND RECOMMENDATIONS

This study successfully explored the moderating role of *Natural Language Processing* (NLP) in the relationship between AI use and fraud detection and auditing in accounting information systems in Indonesia, with respondents consisting of managers and financial and accounting staff. The results show that AI has a significant influence on auditing and fraud detection, with the prevention dimension having the strongest influence followed by investigation, while NLP was found to moderate positively and very significantly on the prevention dimension but moderated negatively and significantly on the investigation dimension, indicating that the role of NLP is differential and context-specific. These findings provide empirical support for the preventive audit paradigm and answer the research question that the effectiveness of NLP is highly dependent on the specific dimensions of AI implementation. Based on these results, practitioners are advised to prioritize the implementation of NLP in preventive audit systems with a focus on monitoring internal communications and proactively identifying red flags, but to be cautious in implementing NLP for investigations by not completely replacing the professional judgment of auditors, as well as developing AI and NLP systems that are holistically integrated with adequate investment in employee training and change management. Regulators need to develop clear frameworks and standards for the implementation of AI and NLP in auditing, including guidelines on ethical aspects and data privacy, develop capacity building programs to improve practitioners' capabilities, and provide incentives for organizations, especially small and medium-sized enterprises, to adopt this technology.

Further research should expand the sample to include more companies from various industry sectors, conduct longitudinal studies to understand the dynamics of implementation over time, combine perceptual data with objective data on audit performance, explore why the data analysis dimension shows negative results, conduct comparative analysis between industries, investigate contextual factors that influence the effectiveness of NLP, use mixedmethods for deeper understanding, explore integration with other emerging technologies such as blockchain and big data analytics, and conduct studies on the ethical and privacy implications of using AI and NLP. Higher education institutions, especially accounting study programs, need to integrate learning about AI and NLP into the curriculum to prepare graduates who are ready to face the era of digital auditing, develop collaboration with industry to provide practical exposure, and encourage AI-based research oriented towards the development of a people-centered economy and shared prosperity. so that the implementation of all these recommendations is expected to improve audit quality and fraud detection effectiveness in Indonesia and contribute to increased transparency and accountability in organizational financial reporting, which will ultimately support healthier and more sustainable economic development.

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