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Investigating the Impact of Artificial Intelligence on Ais Efficiency in Indonesian Industrial Companies: A Mediated Moderation Approach

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Abstract

This study aims to examine the role of moderating technological vigilance in industrial companies (Indonesia Stock Exchange) in Indonesia in supporting the relationship between Artificial Intelligence (expert systems, neural networks, genetic algorithms, intelligent agents) and Accounting Information Systems (AIS) efficiency. SmartPLS4 and the Statistical Package of Social Science filter and analyse data collected from number 127 financial managers, accounting managers, and financial facilities managed in industrial companies in Indonesia. Research conducted in industrial companies revealed that expert systems significantly improve accounting information systems and decision-making sustainability, and intelligent agents improve decision-making sustainability. Neural networks, genetic algorithms, and intelligent agents do not provide similar support. These findings guide industry practitioners in adopting effective technologies, inform developers to focus on relevant innovations and assist policymakers in creating supportive regulations. In addition, educational institutions can adjust their curricula to equip students with essential skills for the industry. Overall, the results emphasize the importance of leveraging advanced technologies in accounting to improve operational efficiency and sustainability in the industrial environment.

Keywords: *Artificial Intelligence, Technological Vigilance, Accounting Information Systems, Industrial Companies.*

Introduction

An efficient and integrated system for managing all accounting activities, particularly within modern computing technologies, is paramount for enterprises (Yoshikuni et al., 2023). The role of Strategic Management Accounting (SMA) is substantial in this integration, assisting in the facilitation of effective decision-making within corporate entities (Pedroso et al., 2020). The characteristics of the Information System (IS) and Management Accounting Adaptability (MAA) are pivotal elements that impact the efficiency of management accounting (Yigitbasioglu, 2016). Bai & Krishnan, (2012) moreover, a company's Management Accounting System (MAS) can foster collective learning within firms, especially by establishing a group's transactive memory system (TMS). Hence, harnessing contemporary Accounting Information Systems (AIS) and upcoming technologies is imperative for

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organizations to improve their decision-making processes, strategic adaptability, and overall performance in today's fiercely competitive business landscape.

The advancement of Artificial Intelligence (AI) entails comprehending human intellect, devising algorithms to replicate intelligent actions and effective electronic functions, acquiring essential data, making prompt decisions grounded on thorough data scrutiny, and ensuring ethical and secure progress (Chhillar & Aguilera, 2022). AI's usage extends across diverse sectors, including finance. The repercussions of AI on society and the economy are significant, as its assimilation gives rise to ethical issues such as privacy breaches, discriminatory practices, and security vulnerabilities (Chang, 2023). The integration of AI into software development necessitates the assessment of elements like the competencies of employees, environmental assets, and team proficiencies (He, 2022). The progression of AI from theoretical exploration to commercial utilization has notably impacted society, the economy, and technology. The reciprocal advancement of technology and the economy within the existing economic and technological landscape is pivotal for the progress of AI and the economy. AI is of paramount importance in enhancing the performance of accounting and governance professions (Moll & Yigitbasioglu, 2019). Its various applications, such as expert systems, neural networks, genetic algorithms, and smart agents, are essential for meeting the electronic technology requirements of modern businesses (Huang et al., 2023). The incorporation of AI into public accounting information systems has demonstrated significant advancements, underscoring the significance of aligning intelligent systems with financial goals (Mergel et al., 2023).

The accounting field faces challenges that include: (1) developing an AI-enhanced accounting system; (2) educate accountants about new technologies; (3) manage costs associated with program maintenance and upgrades (Al Ghatrifi et al., 2023; Faulconbridge et al., 2023; Jemine et al., 2024; Kureljusic & Karger, 2024). Organizations are required to invest in staff training, establish relationships with technology suppliers, and develop adaptable frameworks to implement new technologies efficiently. The utilization of AI technology within service provision presents organizations with the opportunity to improve levels of customer service and operational efficiency (Bagozzi et al., 2022; Wirtz et al., 2023; Yang, 2023). Through the utilization of AI for automation, companies can streamline mundane tasks, carry out precise data analysis rapidly, and provide prompt customer service through chatbots and intelligent systems. This automation diminishes the dependence on manual labour, enhances operational efficiency, and boosts customer satisfaction. AI enables the optimization of resource allocation, productivity enhancements, and overall improvement in service quality, allowing organizations to conserve energy, time, and expenses while enhancing their service standards (Czarnitzki et al., 2023).

The focus of this research is to study how AI affects accounting systems and the level of technological awareness in industrial companies in Indonesia, which needs to be addressed in previous research. In addition, the industrial sector plays an important role in the country's economic development and has the power to influence the financial system. Therefore, this sector industry bears a great responsibility to improve the living standards of individuals in terms of absorbing them into the labour market and increasing their skills and experience. Based on the above, this research aims to determine the impact of artificial intelligence on the efficiency of accounting systems in public shareholder companies, considering the importance of the industrial sector and its role in strengthening the Indonesian economy. Based on the arguments above, this research was conducted to explore the moderating role of technological vigilance on the relationship between AI (expert systems, neural networks, genetic algorithms, intelligent agents) and AIS efficiency in industrial companies.

Literature Rewiew

The AI, AIS, and Decision-Making Sustainability

Utilitarianism, a moral theory focusing on maximizing overall well-being, has historical ties to the Enlightenment era and the development of social theory (Eggleston, 2022; Zhao & Gomez Farinas, 2023). In the realm of industrial enterprises, the evolution of Utilitarianism aligns with the advancement of technologies such as Expert Systems, Neural Networks, Genetic Algorithms, and Intelligent Agents, which have been pivotal in addressing sustainability challenges and enhancing decision-making processes (Gomberg, 1989; Karnouskos et al., 2020) . These technologies, particularly Industrial Agents (IAs), have played a crucial role in the digital transformation of industries, contributing to efficiency and sustainability in areas such as smart production, smart grids, logistics, and healthcare (Burns, 1989). To ensure the ethical and sustainable use of these technologies, a harmonized regulatory framework is essential, emphasizing technological neutrality and proportionality to mitigate risks and promote the common good. This approach underscores the importance of technological vigilance in industrial enterprises to achieve accountable and sustainable AI applications while upholding Utilitarian principles.

Artificial Intelligence (AI) has greatly altered accounting practices through the enhancement of efficiency and effectiveness in tasks such as the collection and analysis of financial data (Faulconbridge et al., 2023; Malerbi et al., 2023). The utilization of AI in Accounting Information Systems (AIS) has become essential, allowing accountants to save time and perform in-depth calculations rapidly (Kureljusic & Karger, 2024). The introduction of AI in accounting has resulted in enhanced performance and outcomes, as indicated by research demonstrating that AI techniques enhance public accounting information systems (Eulerich et al., 2023) . Furthermore, studies show that AI-based forecasting in financial accounting facilitates proactive management and detailed analysis, underscoring the beneficial impact of AI on forecasting tasks in accounting (Al-Okaily, 2022). In general, the incorporation of AI in AIS has transformed accounting processes, rendering them more efficient and precise, ultimately benefiting accountants and organizations alike.

Efficiency Within Accounting Information Systems (AIS) is of paramount importance for the provision of precise, pertinent, and prompt financial information using minimal resources (Karagiorgos et al., 2022; Luo et al., 2022; Lutfi, Al-Okaily, et al., 2022). The enhancement of AIS efficiency is achieved through the utilization of technologies such as advanced accounting software, system integration, and process automation (Yoshikuni et al., 2023). Designs of AIS that are flexible and easily accessible facilitate swift retrieval of information crucial for decision-making. Effective operations of AIS result in time and cost savings, enhancement of data quality, and assistance to management in making well-informed decisions. Studies underscore the significance of AIS success factors, including system quality, information quality, and user satisfaction, in improving the sustainability of decision-making. In general, an efficient AIS streamlines financial activities, optimizes the utilization of resources, and bolsters the effectiveness of decision-making processes within organizations (Singh et al., 2024).

The incorporation of AI into AIS leads to a significant boost in operational efficiency within a company (Alrfai et al., 2023; Weber et al., 2023). AI plays a key role in automating processes, leading to more precise data analysis, and enabling prompt decision-making (Bao et al., 2023; Cui et al., 2022). The implementation of AI-driven forecasting in financial accounting supports proactive management and in-depth analysis, thereby enhancing the overall performance of AIS (Hariguna & Ruangkanjanases, 2024). Additionally, the utilization of AI in corporate governance has a positive effect on governance standards, with higher levels of AI being associated with enhanced governance. The adoption of AI methodologies in AIS not only improves system efficiency but also ensures that organizational activities are in line with financial goals, underscoring the importance of aligning intelligent systems with financial targets (Cui et al., 2022).

Professionals working in accounting firms are embracing the adoption of AI, resulting in redefined forms of professional activities and services rather than the extinction of professions, thus enhancing the quality of financial information (Faulconbridge et al., 2023). Moreover, AI applications can forecast person-job compatibility and impact job seekers' levels of interest, demonstrating the influence of AI on recruitment processes and information quality (Keppeler, 2024). AI-driven forecasting in financial accounting allows for proactive management and thorough analysis, thereby improving the accuracy and comprehensiveness of financial statements (Kureljusic & Karger, 2024). In general, the utilization of AI in accounting procedures has a positive influence on the precision, comprehensiveness, and uniformity of financial information communicated to public shareholders.

Artificial intelligence (AI) plays a crucial role in decision-making across various industries (Himanshu, 2023; Sheeba, 2023). AI's ability to quickly analyse vast amounts of data, detect patterns, predict outcomes, offer data-driven recommendations, optimize processes, and even automate decisions makes it a powerful tool for enhancing efficiency, reducing risks, and enabling more brilliant strategic moves (Booyse & Scheepers, 2024; Mahajan et al., 2023). However, barriers to AI adoption in decision-making exist, such as human social dynamics, regulatory constraints, lack of transparency, and ethical considerations (H.Bajaj, 2023). Overcoming these barriers is essential for organizations to fully leverage AI's potential in improving decision-making processes and driving overall success. By integrating AI technologies effectively, businesses can harness the benefits of enhanced accuracy, productivity, and strategic decision-making capabilities.

Meanwhile, the following categories of artificial intelligence are included:

Expert System - a type of artificial intelligence that utilizes human expertise to deliver solutions within specific domains. It consists of a knowledge base that stores domain-specific information and an inference engine for interpreting data and generating solutions (Bartmeyer et al., 2022; Caley et al., 2014; Mosqueira-Rey et al., 2008). Expert systems are adept at emulating human decision-making processes through the collection of user data, analysis against stored knowledge, and provision of recommendations based on predefined rules. The knowledge base contains rules, facts, and expertise, while the inference engine processes data to deduce solutions (Ahamad & Mishra, 2024). These systems are highly valuable for their capacity to rapidly offer accurate recommendations in intricate scenarios, rendering them indispensable tools for various applications, such as evaluations of transportation networks, assessments of taxonomic expertise, and rectifying flaws in production plans within seconds.

Neural networks - deriving inspiration from nerve tissue, play a crucial role in multiple domains, including artificial intelligence, machine learning, and finance. They contribute to sales forecasting, budgeting, provision estimation, decision rationalization, and fraud detection within accounting systems (Khan et al., 2023; S. Li et al., 2021). Resembling the neuron clusters in the human brain, these networks are crucial in risk management, particularly in addressing liquidity and financing risks in industrial firms (Rogers, 2020; Yusoff et al., 2019). Their capacity to emulate human brain functions positions them as valuable instruments for decision-making processes, like selecting investment projects and identifying fraudulent activities. In essence, artificial neural networks represent a state-of-the-art model for bolstering business risk management approaches, demonstrating their adaptability and efficacy across various financial applications (Xu et al., 2018).

Genetic algorithms - In accounting, GA can tackle intricate tasks like budget planning, investment portfolio optimization, and modelling consumer behaviour based on transaction data (Worring et al., 2021). By leveraging GA, optimal solutions can be derived in vast and complex search spaces by considering multiple influencing factors and criteria crucial for accounting decisions. Moreover, GA can enhance the efficiency of accounting systems by adapting parameters or rules based on historical data trends or evolving market conditions (Lim et al., 2020). Employing GA in AI accounting empowers companies to make better decisions efficiently. It enhances the quality of accounting information produced, ultimately leading to improved decision-making processes and enhanced accounting information quality.

Intelligent agents - play a pivotal role in numerous financial domains, such as monitoring and analysing financial data, detecting fraud, managing risks, and providing recommendations in accounting decision-making. They employ machine learning algorithms for fraud detection, trading automation, and delivering financial guidance to investors (Chand H & J, 2018; Lanny and Wiwik Utami, 2023; Pattnaik et al., 2024). Moreover, intelligent agents have the capability to contribute to the enhancement of the transparency of decision-making processes of artificial agents, thus fostering trust in their dependability and decision-making (Lei et al., 2022). Additionally, agent-based computational economics (ACE) offers prospects for research in management accounting through the utilization of theoretical assumptions concerning economic agents and agent-based modelling (Papagni et al., 2023). Through the utilization of intelligent agents, organizations can boost the effectiveness, precision, and caliber of accounting information, thereby facilitating more knowledgeable and prompt decision-making procedures.

In the realm of Indonesian industrial firms, the utilization of Artificial Intelligence (AI) has the potential to significantly impact Accounting Information Systems (AIS) through the enhancement of decision-making effectiveness (Utami et al., 2023). AI technology can address challenges stemming from incomplete information by equipping the capacity to reason, comprehend, accumulate knowledge, and derive insights from previous encounters to be applied in novel scenarios (Merhi & Harfouche, 2023). Moreover, AI's prompt responsiveness to fresh circumstances, management of intricate scenarios, and ability to adjust to evolving conditions can further bolster AIS within industrial establishments (Mikalef et al., 2023). Integrating AI and AIS can result in heightened operational efficiency, improved decision-making procedures, and enhanced overall performance within Indonesian industrial contexts. Hence, Artificial Intelligence Systems (AISs) are significantly impacted by the utilization of artificial intelligence applications. Consequently, the subsequent hypothesis is as follows:

H1: The AISs’ efficiency in the Indonesia industrial companies affected positively by applying

Artificial Intelligence

From this principal hypothesis, the subsequent sub-hypotheses extend.

H1.1: The AISs’ efficiency in the Indonesia industrial companies affected positively by applying expert systems.

H1.2: The AISs’ efficiency in the Indonesia industrial companies affected positively by applying neural networks.

H1.3: The AISs’ efficiency in the Indonesia industrial companies affected positively by applying genetic algorithms.

H1.4: The AISs’ efficiency in the Indonesia industrial companies affected positively by applying intelligent agents.

H2: The AISs’ efficiency in the Indonesia industrial companies has positively influenced decision making sustainability.

H3: The AISs’ efficiency in the Indonesia industrial companies has a significant mediating effect on the relationship between artificial intelligence and decision-making sustainability.

H4: The artificial intelligence in the Indonesia industrial companies has positively influenced decision making sustainability.

The moderating effect of Technological Vigilance

Technological vigilance in AI and accounting information systems involves understanding the impact on business processes, information security risks, and financial data management paradigms. Implementing AI can enhance accounting information's efficiency and quality but also pose data security and privacy risks (Mishra, 2023; Salman et al., 2019). Companies must monitor regulatory changes related to AI in accounting, like standards for revenue recognition and risk management (Cao et al., 2024). Additionally, considering the social and ethical implications of AI in accounting, such as effects on employment, fairness, and transparency, is crucial (Noreen et al., 2023). Therefore, a comprehensive approach encompassing technical, regulatory, and ethical dimensions is essential for effectively developing and implementing AI-based accounting information systems.

To be technologically vigilant, an entity must possess several key specifications. Firstly, it should exhibit forward-thinking, anticipatory, and proactive behaviors (Ali et al., 2019; Rob Goble et al., 2023; Robert Goble et al., 2018). Second, it must monitor and evaluate both existing and emerging technologies, assessing their risks, benefits, and impacts (Pérez-González & Placer-Maruri, 2011). Additionally, being technologically vigilant involves pre-emptively identifying and assessing potential technological hazards. Moreover, it requires formulating strategies and policies to mitigate risks associated with technology use (Pop et al., 2012). Furthermore, staying technologically vigilant entails recognizing and adapting to shifts in technology trends over time. Mobilizing resources for effective strategy implementation and monitoring is also crucial. Lastly, active engagement with stakeholders to keep them informed and involved in addressing technological risks is vital to technological vigilance.

Technology vigilance plays a crucial role as a moderator in overseeing the integration of AI technology in accounting information systems, ensuring security, sustainability, and usability (Klein et al., 2023; J. Wang et al., 2023). It involves monitoring risks like data security, privacy, and regulatory compliance while addressing social, ethical, and organizational impacts of AI implementation in accounting, such as job implications and CSR concerns (Robles & Mallinson, 2023; Y.-F. Wang et al., 2023). By moderating the interaction between AI and accounting systems, technology vigilance helps maximize the benefits of AI while minimizing associated risks, ensuring sustainable value creation for organizations. This oversight is essential for aligning AI applications with accounting standards and regulations and managing the broader implications on organizational culture and social responsibility.

As a result of this phenomenon, scholarly findings suggest that the successful technology vigilance can alleviate the adverse effects of raw materials on the efficiency of an Accounting Information System (AIS). Consequently, the incorporation of Artificial Intelligence (AI), such as expert systems, neural networks, genetic algorithms, and intelligent agents, will enhance the efficiency of AIS within the context of Indonesian industrial. Moreover, the level of dependence on technology vigilance may lead to either a positive or negative influence on the efficiency of AIS. This has implications for the following research hypotheses.

H5: The effective application of technology vigilance moderates the effect of artificial intelligence on AISs’ efficiency in Indonesia industrial companies. Illustrated in Figure 1, the research model of this investigation comprises three latent variables, specifically: artificial intelligence (e.g., expert systems, neural networks, genetic algorithms, intelligent agents) as the independent variable, AIS efficiency as the dependent variable, and the effectiveness of technology vigilance implementation as the moderator variable.

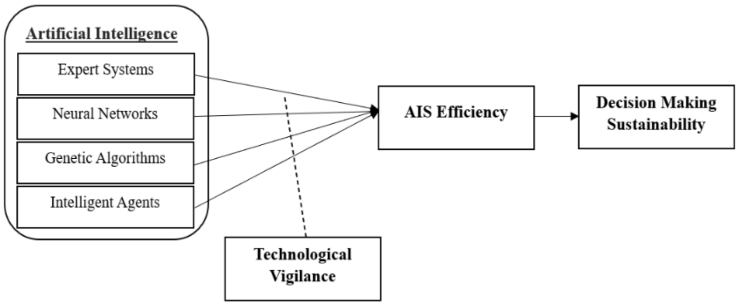

Fig 1. Research Model

Research Methodology

The current study aims to analyses the influence of artificial intelligence on the efficiency of Accounting Information Systems (AIS) in Indonesian public companies within the industrial sector, while also investigating the effects of implementing effective technological awareness as a moderating variable in the relationship between these two factors. The participants of the research were managers from various administrative departments of industrial companies in Indonesia. Surveys were disseminated to 205 financial manager, accounting manager, financial facilities manage within Indonesian public companies, with an average of five questionnaires distributed to each company. A total of 127 usable responses were collected from the participants. The rationale behind selecting Indonesian public companies within the industrial sector as the target population for this research is due to their higher likelihood of utilizing AIS, in contrast to many smaller industrial enterprises that lack such systems due to limitations in size and capital. Questionnaires served as the primary instrument for gathering data pertaining to the study sample and acquiring information that illuminates their perspectives on the variables within the research framework, with the purpose of comprehending and elucidating the connections among each variable.

Questionnaire items were developed based on previously validated and tested surveys. These procedures were employed to evaluate the questionnaire's dependent, independent, mediating and moderator variables. The variable boundary signifies the degree of effectiveness of Artificial Intelligence Systems (AIS) in industrial enterprises in Indonesia. The independent variable indicates the extent of deployment of diverse artificial intelligence applications (such as expert systems, neural networks, genetic algorithms, and intelligent agents) within Indonesian industrial firms. The moderator variable indicates the level of integration of Technology awareness measures within Indonesian industrial enterprises. Table 1 presents the metrics for each variable examined in the study.

Variable items from previous studies were used to ensure the reliability of the measurement items. The items were gauged on a Likert scale, with the extreme scales denoting the following: 1, strongly disagree, and 5, strongly agree. The questions measuring the variables were based on well-established measurements derived from previous research. AI (expert systems with 6 items; neural networks with 7 items; genetic algorithms with 4 items; intelligent agent with 4 items) adopt from Qasaimeh et al., (2022); AIS (5 items): Qatawneh & Al-Okaily, (2024); TV (5 items): Qatawneh & Al-Okaily, (2024) and DMS (4 items): Lutfi et al., (2022).

Result / Finding

Table 1 Respondent’s Demographic Characteristics

Demographics	n = 127	%
Gender		
Male	44	34.65
Female	83	65.35

Age		
20–28 years	15	11.82
29–36 years	19	14.96
37–44 years	32	25.19
>45 years	61	48.03
Occupational Position		
Financial Manager	23	18.11
Accounting Manager	12	9.46
Financial facilities manage	14	11.02
IT Manager	17	13.38
Financing Manager	19	14.96
HR Manager	19	14.96
Marketing Manager	23	18.11
Education Level		
Diploma	10	7.87
Bachelor	36	28.37
Master	77	60.62
PhD	4	3.14
Experience		
2–6 years	14	11.02
7–11 years	28	22.04
12–16 years	15	11.81
17- 21 years	31	24.41
>22 years	39	30.72

The following analysis tested the measurement model's convergent validity (Hair et al., 2017) in table 2. As recommended by Hair et al. (2017), the Average Variance Extracted (AVE), factor loadings, and Composite Reliability (CR) were used to test the convergent validity. To ensure that it meets all the requirements, the AVE, CR, and factor loading values for each item need to be greater than 0.50, 0.60, and 0.50, respectively. The assumption that Variance Inflation Factor (VIF) values below 5 indicate low collinearity and ensure accurate significance assessment and weight estimation is not always correct (O'brien, 2007; Woolston et al., 2010). While VIF values are commonly used to assess multicollinearity, relying solely on this threshold can be misleading. Therefore, it is essential to consider a holistic approach, considering various factors beyond just VIF values, to ensure accurate and reliable model estimation and interpretation. The Coefficient Alpha (CA) is less than 0.60, it represents poor reliability, while fair reliability is between 0.60 to 0.70, good reliability is within 0.70 to 0.08. and 0.80 to 0.95 indicates very good reliability (Hair et al., 2013).

Table 2. Outer Loading

Variables	Item	Factor Loading	VIF	CA	CR	AVE
Expert Systems (ES)	ES1	0.782	2.222	0.886	0.894	0.636
	ES2	0.764	2.464			
	ES3	0.728	1.848			
	ES4	0.854	2.646			
	ES5	0.819	2.869			
	ES6	0.832	2.853			
Neural Networks (NN)	NN1	0.850	3.044	0.917	0.920	0.671
	NN2	0.865	3.252			
	NN3	0.805	2.342			
	NN4	0.859	3.297			
	NN5	0.845	2.859			
	NN6	0.827	2.330			
	NN7	0.666	1.560			
Genetic Algorithms (GA)	GA1	0.842	2.091	0.853	0.863	0.694
	GA2	0.880	2.527			

	GA3	0.835	2.166			
	GA4	0.772	1.803			
Intelligent Agents (IA)	IA1	0.848	2.426	0.854	0.865	0.703
	IA2	0.915	3.648			
	IA3	0.886	2.735			
	IA4	0.686	1.357			
AIS Efficiency (AIS)	AIS1	0.841	2.053	0.879	0.879	0.734
	AIS2	0.885	2.828			
	AIS3	0.883	2.785			
	AIS4	0.817	1.889			
Decision Making Sustainability (DMS)	DMS 1	0.774	1.878	0.885	0.887	0.686
	DMS 2	0.812	2.033			
	DMS 3	0.880	2.839			
	DMS 4	0.825	2.630			
	DMS 5	0.846	2.641			
Technological Vigilance (TV)	TV1	0.865	2.691	0.882	0.885	0.680
	TV2	0.768	1.742			
	TV3	0.819	2.023			
	TV4	0.799	2.096			
	TV5	0.869	2.912			

Discriminant validity shows in table 3 the extent a construct in terms of degree essentially differs from the others. On the other hand, its measures are not theoretically related to each other (Hair et al., 2013). The most common method of assessing the effectiveness of discriminant validity is the Fornell-Larcker criterion. Furthermore, it is identified when each construct's AVE square root value is greater than its highest correlation with any other latent construct (Hair et al., 2013).

Table 3 Discriminant Validity

	AIS	DMS	ES	GA	IA	NN	TV
AIS	**0.857**						
DMS	0.842	**0.828**					
ES	0.792	0.809	**0.798**				
GA	0.601	0.606	0.766	**0.833**			
IA	0.733	0.750	0.701	0.600	**0.839**		
NN	0.743	0.738	0.721	0.623	0.782	**0.819**	
TV	0.832	0.828	0.803	0.660	0.751	0.709	**0.825**

The Normalized Fit Index (NFI) in table 4 is a measure commonly used in psychometric applications to assess model fit, calculated as 1 minus the Chi² value of the proposed model divided by the Chi² values of the null model, resulting in values between 0 and 1. A higher NFI value closer to 1 indicates a better fit, with NFI values above 0.9 typically considered indicative of an acceptable fit (Lorenzo-Seva & Ferrando, 2023).

Table 4. Model Fit Test Result

	Saturated model	Estimated model
SRMR	0.073	0.073
d_ ULS	3.364	3.383
d_ G	1.857	1.871
Chi-square	1.179.722	1.178.784

NFI	0.720	0.720

in table 5 shows statistical analysis, the preference for higher R-squared or R-squared adjusted values as indicators of better model fit must be balanced with the context and trade-off between model complexity and explanatory power (Xingruo Zhang & Hedeker, 2022). Ultimately, while higher R-squared values are desirable, considering the nuances of model complexity and interpretability is essential in statistical analysis (Piepho, 2023).

Table 5. Coefficient Determination Test Result

	R-square	R-square adjusted
AIS	0.774	0.757
DMS	0.784	0.775

This test was conducted to determine the predictive ability with the blindfolding procedure in table 6. This must be greater than 0 (Chin & Newsted, 1999). When a value is obtained between 0.02 to 0.15 then the predictive capability model is small. If the value obtained is between 0.15 to 0.35 then the model has the ability to predict medium, and if the value obtained is above 0.35 then the model has great predictive ability (Hair et al., 2017).

Table 6. Blindfolding Test Result

	SSO	SSE	Q^2 (=1-SSE/SSO)
AIS	508.000	233.789	0.540
DMS	635.000	305.319	0.519
ES	762.000	762.000	0.000
GA	508.000	508.000	0.000
IA	508.000	508.000	0.000
NN	889.000	889.000	0.000
TV	635.000	635.000	0.000

Table 7 provides support for some hypotheses with P-values less than 0.05 and rejection of others with P-values higher than 0.05. Therefore, 5 hypotheses were supported, and 12 hypotheses were not supported.

Table 7. Hypotheses Testing Result

Hypotheses	Symbol	O	Std Dev	T-stat	P-values	Conclusion
H1.1	ES→AIS	0.325	0.102	3.179	0.001	supported
H1.2	NN→AIS	0.205	0.106	1.936	0.053	not supported
H1.3	GA →AIS	-0.122	0.079	1.547	0.122	not supported
H1.4	IA →AIS	0.083	0.108	0.769	0.442	not supported
H2	AIS →DMS	0.415	0.092	4.537	0.000	supported
H3.1	ES →DMS	0.349	0.102	3.418	0.001	supported
H3.2	NN →DMS	0.079	0.079	0.993	0.321	not supported
H3.3	GA →DMS	-0.069	0.071	0.970	0.332	not supported
H3.4	IA →DMS	0.180	0.075	2.397	0.017	supported
H4.1	ES → AIS →DMS	0.135	0.050	2.697	0.007	supported
H4.2	NN → AIS →DMS	0.085	0.050	1.706	0.088	not supported
H4.3	GA → AIS →DMS	-0.051	0.034	1.485	0.137	not supported
H4.4	IA → AIS →DMS	0.035	0.045	0.763	0.445	not supported
H5.1	TV x ES - AIS	-0.027	0.118	0.231	0.818	not supported
H5.2	TV x NN - AIS	-0.109	0.112	0.973	0.331	not supported
H5.3	TV x GA - AIS	0.126	0.098	1.283	0.199	not supported

H5.4	TV x IA - AIS	0.033	0.133	0.248	0.804	not supported

Discussion

The results of hypothesis 1.1 is ES play a crucial role in enhancing AIS systems in industrial companies by automating decision-making processes with expert knowledge (Prasad & Green, 2015). These systems can be utilized in various accounting aspects like cost analysis, financial forecasting, risk management, and performance evaluation, leading to improved efficiency, reduced errors, and faster accounting procedures (Suhel et al., 2020). By implementing ES, companies can access more accurate financial information, aiding in strategic decision-making. Moreover, ES enable the detection of hidden patterns and trends, facilitating quicker responses to market changes, ultimately enhancing the overall performance and competitiveness of industrial enterprises (Karagiorgos et al., 2022).

The outcome of hypothesis 1.2 is NN play an important role in improving AIS in industrial companies, enabling companies to utilize advanced technologies to increase efficiency, accuracy, and predictability in accounting and decision-making processes (Kureljusic & Karger, 2024; Lei et al., 2022; Yan, 2022). Without the integration of NN, companies may struggle to harness the potential of this technology for predictive analysis, pattern recognition, and complex data processing, thereby limiting their ability to optimize financial operations, identify opportunities or risks, and adapt to market changes quickly and effectively. If NN do not take effect, companies may rely more on traditional methods that may be less efficient and accurate in managing financial information and making strategic decisions. Relying on traditional methods without neural networks can hinder companies from managing financial information efficiently and making strategic decisions accurately, highlighting the importance of incorporating neural networks into accounting systems to improve performance and competitiveness in the modern business landscape (Lehner et al., 2022).

Research hypothesis (H1.3) is GA play a crucial role in enhancing computational approaches for optimization and portfolio management in financial contexts (Lim et al., 2020; Majeed et al., 2021; Passos & Barrenechea, 2020). They offer the capability to find optimal or near-optimal solutions for intricate and unstructured problems, which are prevalent in accounting and financial systems. Failure to incorporate GA in industrial companies may lead to missed opportunities for efficient resource allocation, risk management, and strategic decision-making processes. Traditional optimization methods may prove less effective in handling the complexity of modern financial challenges, potentially limiting companies' abilities to capitalize on advanced computational tools for financial information management and strategic planning (C.-H. Chen et al., 2019). Embracing GA can empower companies to tackle complex business problems and optimize their operations effectively.

In the H1.4 hypothesis test IA play a crucial role in enhancing AIS in industrial companies by automating tasks, improving operational efficiency, and providing real-time financial insights (Ng et al., 2021) . Without IA, companies may face barriers in adopting AI for decision-making, leading to reliance on manual tasks prone to errors and inefficiencies (Booyse & Scheepers, 2024). Additionally, the use of AI techniques, including intelligent agents, significantly contributes to the improvement of public accounting information systems, aligning activities with financial targets and enhancing overall performance. Furthermore, AI, including intelligent agents, has been shown to positively impact firms' productivity, with a 1% increase in AI penetration leading to a 14.2% increase in total factor productivity, highlighting the importance of AI in fostering economic sustainability within Industry 4.0 (Gao & Feng, 2023). Therefore, the absence of IA influence can hinder companies from leveraging technology to enhance efficiency, reduce costs, and make informed decisions based on accurate financial data, potentially impeding their competitiveness and growth.

The latter supports hypothesis 2 Efficient AIS play a crucial role in enhancing DMS within a company by improving the speed, accuracy, and relevance of financial data collection, processing, and reporting. This efficiency provides management with timely and reliable information, enabling better decision-making to support the company's long-term sustainability goals (Hamed, 2023). Moreover, optimized AIS can help in resource allocation, cost reduction, and process enhancement, all contributing to the overall sustainability of the enterprise (Qatawneh, 2023). Additionally, management awareness of organizational goals and financial information, facilitated by AIS, is vital for achieving desired outcomes and ensuring efficient system utilization (Abdelhalim et al., 2023). Therefore, the significant relationship between efficient AIS and DMS underscores the importance of leveraging technology to drive sustainable business practices and achieve long-term success.

Test Hypothesis H3.1 concludes that ES has a significant effect on DMS in industrial enterprises by leveraging the knowledge of industry experts to analyses complex data and offer real-time recommendations (Z. Chen et al., 2023). By using ES, companies can enhance the speed, accuracy, and relevance of their decisions, ultimately optimizing operational performance and working towards long-term sustainability objectives (Z. Chen et al., 2023). The adoption of ES can strengthen enterprises' abilities to consider sustainability aspects such as operational efficiency, risk management, and environmental impact, thereby aiding in the achievement of sustainable sustainability goals in the future (Pistolesi & Lazzerini, 2023). Additionally, the use of expert systems aligns with the broader trend in AI towards addressing sustainability challenges and promoting responsible AI development (Lazaroiu et al., 2022; Zhao & Gomez Farinas, 2023).

In the H3.2 hypothesis test, NN play a crucial role in DMS processes within industrial enterprises, particularly in enhancing sustainability efforts. They are used for predictive analysis, pattern recognition, and data processing, offering valuable insights into operational performance, energy efficiency, and resource management (Sult et al., 2024). The integration of neural networks in sustainability strategies is essential for driving long-term sustainability goals and improving overall performance (Z. Chen et al., 2023). However, if NN do not significantly impact DMS, it may suggest a lack of effective integration of these technologies or a perception that their outputs are not robust enough to influence substantial sustainability decisions. This highlights the importance of evaluating the utilization of NN in sustainability strategies and exploring alternative solutions to ensure that companies can effectively meet their sustainability objectives (Z. Chen et al., 2023).

Using the H3.3 hypothesis test, GA play a crucial role in DMS with industrial enterprises, as they offer a method to optimize solutions based on multiple criteria (Kırda & Aytekin, 2023). However, the effectiveness of GA in enhancing DMS can be influenced by various factors, including the precision of parameters, input data quality, and external influences such as policy and economic aspects (Zhao & Gomez Farinas, 2023). While GA can contribute to improving DMS efficiency and effectiveness, their impact may vary based on implementation and contextual factors. The integration of AI-based approaches, such as deep learning models, can further enhance sustainability performance in manufacturing activities (Jamwal et al., 2022). Therefore, a comprehensive evaluation of methods and consideration of alternative approaches are essential to ensure the successful achievement of sustainability goals in industrial settings (Krol & Sierpinski, 2022).

Using the H3.4 hypothesis examination IA play a crucial role in enhancing DMS within industrial enterprises by leveraging AI capabilities to analyses vast amounts of data efficiently and accurately, optimize resource management, predict outcomes of decisions, and simulate scenarios for selecting the most sustainable options (Stecyk & Miciuła, 2023). These technologies facilitate quick adaptation to changing conditions, leading to improved efficiency, reduced waste, and lower operating costs (X. Wang et al., 2023). Moreover, the application of Intelligent Agents has been shown to significantly impact DMS processes in industrial settings, contributing to environmental, economic, and social sustainability goals (Behrooz et al., 2023; Shen & Yang, 2023; Xiekui Zhang & Zhu, 2023) . By enabling companies to make informed and sustainable choices, IA is instrumental in driving progress towards a more sustainable future across various dimensions.

Test Hypothesis 4.1 concludes that The integration of ES and AIS in industrial enterprises plays a crucial role in enhancing DMS by providing accurate financial data and strategic recommendations (Al-Hattami, 2022; Behrooz et al., 2023). ES leverage the data processed by AIS to improve the quality and effectiveness of decisions, ultimately supporting sustainability goals across environmental, economic, and social aspects (Lutfi, Al-Okaily, et al., 2022). This synergy between ES and AIS enables companies to make informed decisions based on comprehensive data, reducing uncertainty and facilitating the achievement of sustainability objectives in a more holistic and scalable manner (Yoshikuni et al., 2023). Additionally, the use of AI in addressing sustainability challenges underscores the importance of a proactive regulatory framework to ensure the ethical and sustainable deployment of these technologies in decision-making processes (Zhao & Gomez Farinas, 2023).

According to Test Hypothesis 4.2, Suppose NN do not have a significant effect on DMS and are unable to function as an intervening variable for accounting information systems in industrial companies. In that case, this means that the application of NN in this context does not make a significant contribution to improving the quality or effectiveness of decisions that support sustainability. This suggests that NN may need to be more suitable or optimal for dealing with the complexity or specificity of the data required for sustainable decision-making. In addition, NN also fail to act as an effective link between accounting data and DMS, which inappropriate implementation, insufficient data, or incompatibility with existing

AIS may cause. Overall, this indicates the need to re-evaluate the technology used and consider other approaches that are more appropriate for the context and needs of the industrial company. The application of NN in industrial enterprises plays a crucial role in DMS by improving the quality and effectiveness of decisions (Wen et al., 2023). NN aid in predicting Key Performance Indicators (KPIs) deviations and identifying contextual variables that influence decision-making processes, ensuring consistency and early decision-making (García-Esparza et al., 2023). Therefore, NN serve as valuable tools in addressing the complexity of data required for continuous decision-making and act as effective links between accounting data and ongoing decisions, emphasizing the need for their continued utilization and potential re-evaluation of technologies in industrial settings.

It is concluded via Test Hypothesis H4.3 that Suppose GA do not have a significant effect on DMS and are unable to function as an intervening variable for accounting information systems in industrial companies. In that case, the meaning is that the application of GA does not make a significant contribution to improving the quality or effectiveness of decision-making. Sustainable. This shows that GA may need to be more suitable or optimal for dealing with the complexity of data required for DMS. Additionally, the inability of GA to serve as an effective link between accounting data and sustainable decisions indicates the need for a re-evaluation of the technology used and the possibility of considering alternative approaches that better suit the needs and context of the industrial company. Research has shown that GA can significantly impact market structures by influencing firms' investment decisions in innovative R&D (Passos & Barrenechea, 2020). Moreover, genetic algorithms have been utilized in model predictive control to optimize real-time environmental systems efficiently, such as reducing combined sewer overflow volumes in sewer systems (Zhao & Gomez Farinas, 2023). Additionally, GA have been proven to be effective in optimizing management procedures for data-limited fisheries, enhancing the performance of catch rules and ensuring compliance with sustainability objectives (Zimmer et al., 2015).

Test Hypothesis 4.4 states that, IA as part of AIS, play a crucial role in automating decision-making processes and financial analysis within organizations (Booyse & Scheepers, 2024). AISs significantly impact the operational performance of industrial companies by providing relevant information for decision-making, aiding in adapting to external environmental changes and improving decision-making based on generated information (Behrooz et al., 2023). The integration of IA into AIS is essential for enhancing operational performance and adapting to dynamic business environments. If IA do not significantly influence DMS and cannot act as intervening variables for AISs in industrial companies, it represents a missed opportunity to leverage advanced technology for operational excellence and adaptability in the face of changing business landscapes (Gao & Feng, 2023).

It is concluded via Test Hypothesis 5.1 that TV is unable to moderate the relationship between ES and efficiency within industrial enterprises. ES such as AIS, are essential for organizational performance (Callen, 1990; Choe, 1996). The impact of ES on organizations can be multidimensional, affecting efficiency, effectiveness, expertise, education, and the overall environment of the organization ("Editorial Policy," 2022). Additionally, the level of vigilance and vigilance decrement in tasks can influence the effort invested and the efficiency of processing, highlighting the importance of TV in maintaining performance levels (Baldwin-Morgan & Stone, 1995). Therefore, if TV fails to moderate between ES and AIS efficiency in industrial enterprises, it could lead to decreased performance, potential inefficiencies, and a lack of optimization in using expert systems for organizational success.

Test Hypothesis 5.2 concludes that If TV fails to moderate between NN and Efficiency in AIS within industrial enterprises, it implies a potential risk of decreased operational productivity and performance. The integration of AI in risk management and operational efficiency can influence the relationship between Corporate Social Responsibility (CSR) and idiosyncratic risk, showcasing a U-shaped curve where CSR initially reduces risk but can later have adverse effects, especially when AI innovation weakens the positive impact of CSR on risk management (Lutfi, Alkelani, et al., 2022). Additionally, the application of Artificial Neural Networks (ANN) in technological networks highlights the importance of joint and individual performance in enhancing efficiency, considering the significance of partner contributions and perceptions within networks (G. Li et al., 2021). Therefore, without effective moderation by TV, the synergy between NN and Efficiency AIS may not be optimized, potentially leading to suboptimal performance in industrial enterprises.

Test Hypothesis 5.3 states that TV, as a key aspect of monitoring and adapting to technological advances, plays a crucial role in industrial enterprises. In the context of GA and Efficiency in AIS , the integration of GA techniques, such as in the Total Resource Management (TRM) approach, can significantly enhance operational efficiency and effectiveness in industries such as rubberwood processing (Bross, 1999). However, without proper TV to moderate and align these advances, enterprises may face challenges in leveraging the full potential of AI innovations like GA, as seen in the study on the relationship between CSR and idiosyncratic risk moderated by AI innovation and operational efficiency in Chinese firms (G. Li et al., 2021). Therefore, the absence of effective TV to balance and optimize the utilization of GA and Efficiency in AIS could lead to missed opportunities for performance improvement and sustainable transitions in industrial settings.

Finally, Test Hypothesis 5.4 states that TV plays a crucial role in moderating the interaction between IA and efficiency in AIS within industrial enterprises. Research by Thielicke highlights the importance of verifiable information in decision-making processes (Kuvalekar et al., 2023), while Kipp, Curtis, and Li emphasize the ethical considerations surrounding the use of computerized IA in financial reporting decisions (Karnouskos et al., 2020). Additionally, Kwon and Lee discuss the application of multi-agent intelligent technology in adjusting ERP systems to environmental changes, showcasing the significance of autonomous cooperation among agents in monitoring and analyzing system performance (Kwon & Lee, 2001). Furthermore, Choe's study underscores the influence factors on the performance of accounting information systems, indicating the need to consider factors such as user involvement and organization size, especially in relation to the evolution level of intelligent agents (Kipp et al., 2020). Therefore, if TV fails to moderate between IA and efficiency in industrial enterprises, it could lead to compromised decision-making processes, ethical concerns in financial reporting, and inadequate adaptation to environmental changes, ultimately impacting the overall performance of accounting information systems.

Utilitarianism in accounting, as discussed in the research papers, underscores the importance of expert systems in enhancing operational efficiency and the quality of accounting information, benefiting companies, stakeholders, and society (Fulop et al., 2023; Sebo, 2023). Additionally, Utilitarianism stresses the significance of efficient AIS in generating precise and relevant accounting data to facilitate improved decision-making and sustainability (Patil & Framling, 2023). However, when considering NN, GA, IA, DMS, and TV, Utilitarianism suggests that these technologies may not play a significant role as moderating variables in maximizing benefits for industrial enterprises, prompting companies to explore alternative solutions for more direct advantages in technological decision-making (Habeeb, 2022; Samarghandi et al., 2023).

The integration of ES in industrial enterprises can indeed enhance the efficiency and accuracy of accounting processes, leading to more precise and rapid accounting decisions, thereby improving operational and financial performance. ES play a crucial role in capturing and utilizing professional knowledge, especially in risk and reliability analysis (Yazdi et al., 2019). Additionally, efficient AIS play a crucial role in ensuring DMS by providing accurate and timely data for considering long-term impacts and balancing economic, social, and environmental factors (Yoshikuni et al., 2023). However, if technologies like NN, GA, and IA, along with AIS efficiency and DMS, do not act as significant moderating or intervening variables, companies should focus on proven technologies to avoid ineffective investments and prioritize solutions that have demonstrated tangible benefits (Al-Okaily, 2022; Karagiorgos et al., 2022; Lutfi, Al-Okaily, et al., 2022). This underscores the importance of implementing effective technologies to enhance accounting and decision-making processes while being cautious about unproven technologies.

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Conclusion and Recommendation

These findings demonstrate the importance of adopting advanced technologies to improve information system performance. The practical implications encourage companies to integrate AI into accounting processes for better results, improved operational efficiency, and more informed decision-making. In addition, companies are also advised to pay attention to aspects of technological awareness to manage risks associated with the implementation of AI and maximize the benefits obtained from this innovation. Thus, investment in technology and human resource training are key to achieving success in digital transformation in the industrial sector. Based on the research findings, industrial companies in Indonesia are advised to prioritize investment in expert systems to improve AIS efficiency and support sustainable decision-making. Although neural networks and genetic algorithms have not been proven significant, evaluating their implementation remains relevant according to organizational needs. Optimizing intelligent agents is also important, especially in customer service and fraud detection. Increasing technological awareness through training, periodic evaluations, and security policies is essential. In addition, educational institutions need to adjust their curriculum so that graduates are ready to face the integration of AI in accounting. Digital transformation will be successful if supported by the readiness and development of human resources on an ongoing basis.

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