The Impact of the Quality of Corporate Governance and Accounting Information System on Non-Financial Performance: The Mediating Role of Non- Financial Information Quality

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Abstract: This paper explores how corporate governance (CG), accounting information system (AIS), and non-financial information (NFI) quality influence decision-making effectiveness (DME) and non-financial performance (NFP). Using partial least squares structural equation modeling (PLS-SEM), data from 344 publicly listed Saudi Arabian companies were analyzed, collected via questionnaires from managers, accountants, department heads, and board members. Results show that CG and AIS quality positively impact NFI quality, which in turn mediates their effect on DME and NFP. NFI quality directly influences both DME and NFP, with DME acting as a significant mediator between NFI and NFP. Additionally, NFI acts as a key mediator between CG and AIS quality, and subsequently DME and NFP. The findings emphasize NFI's role in linking CG and AIS to performance outcomes, offering new insights into the importance of non-financial metrics within an integrated stakeholder and decision-usefulness framework—particularly relevant in the Middle Eastern context.

Key-Words: - Corporate governance quality, accounting information system quality; non-financial information quality; decision-making effectiveness; non-financial performance quality; stakeholder theory; decision-usefulness theory; Saudi Arabia

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1 Introduction

Decision-making in today's business world heavily depends on access to effective and complete information systems and proper corporate governance characteristics. A quality accounting information system (AIS) facilitates the collection, processing, storage, and dissemination of quality information, enabling management to respond swiftly to market changes and stakeholder expectations [1]. At the same time, quality corporate governance (CG) ensures the creation of an appropriate framework for corporate transparency, responsibility, and ethical choices [2], [3]. Thus, quality AIS and quality CG form a whole consistent structure allowing enterprises to strengthen their resilience. They together contribute to reliable disclosure of financial and non-financial information (NFI) necessary for stakeholders' decision-making and sustainable development of business activities [4].

Only recently have scholars identified a need to incorporate NFI into reporting methods throughout organizations [5], [6], [7]. By measuring sustainability, employee engagement, and customer satisfaction levels, a company can determine its non-financial performance. When NFI is incorporated into AIS with good governance frameworks, such as transparent reporting methods, adequate internal controls, and oversight by independent parties, it allows for organizations to become more transparent when reporting NFI. With transparent reporting standards embedded in the corporate culture, organizations are more likely to collect verified and accurate NFI that reflects their sustainability initiatives, social responsibility performance, and value creation [8], [9], [10], [11]. This helps the organization become more transparent and accountable [12], [13] to stakeholders by allowing decision makers to look at other indicators when determining organizational performance [5], [14], [15], [16]. With more and better information reported on a routine basis, organizations with NFI incorporated into the reporting process experience greater levels of decision-making effectiveness (DME) and non-financial performance (NFP), which ultimately leads to a sustained competitive advantage [17], [4], [15],[16].

Although previous research has acknowledged the importance of NFI, few studies have investigated how NFI affects DM performance and NFP in developing countries [18]. Furthermore, prior studies have explored how CG quality and AIS quality affected financial information and outcomes [19], [20]. Limited research attempted to examine how NFI contributes to improving DME and NFP [5], [15]. These relationships have not been empirically tested in the Saudi Arabian context; thus, little is known about how NFI affects business practices there [9]. Saudi Arabia provides a critical environment to conduct this research because the Kingdom is quickly growing and changing economically and socially. As Saudi organizations begin to implement international best practices, understanding how CG quality, AIS quality, and NFI quality affect decision-making will be critical to improving performance.

To address the existing gap, this study aims to develop a comprehensive model that assesses the impact of CG quality, AIS quality, and NFI quality on two critical business outcomes: DME and NFP within the context of Saudi Arabia. This study extends prior literature in several key ways. First, it addresses the limited empirical evidence on the interplay between CG quality, AIS quality, and NFI in shaping non-financial organizational outcomes within Saudi Arabia. By placing these frameworks in the context of a developing economy, this study attempts to build on current literature that has been conducted in developed economies. Ultimately, this study attempts to provide empirical insight to fill gaps associated with NFP in a developing economy and provide practitioners with frameworks they can implement to better operate within their changing business environment and make informed strategic decisions to advance their organizations. Secondly, this study is novel as it attempts to apply an integrated theoretical framework of stakeholder theory and decision usefulness theory to shed light on these relationships.

The remainder of this paper is structured as follows: Section 2 presents the theoretical framework, relevant literature, and the development of hypotheses. The methodology used in this study is described in Section 3. Section 4 presents the proposed model results. Finally, sections 5 and 6 provide a discussion and conclusion, highlighting possible avenues for future research.

2 Theoretical Framework and Hypothesis Development

2.1 Integrated theoretical framework

On a theoretical level, stakeholder theory and decision-usefulness theory have been employed throughout this research. These two theories were combined to create a more integrated holistic approach when discussing how CG quality, AIS quality, NFI quality, DME, and NFP interrelate. Stakeholder theory, as proposed by [21], suggests that firms should pay attention to all stakeholders within the organization instead of prioritizing shareholders' interests above other parties. Organizations are established to create value for stakeholders, which include suppliers, customers, employees, and the broader community. As a result, there could be many stakeholders who would benefit from the knowledge of how AIS quality impacts NFI quality, DME, and NFP. When firms understand how CG quality is dependent on AIS quality, how AIS quality impacts NFIs, and how NFIs can impact DM and NFP, then firms will be better able to improve and take advantage of their AISs when making decisions for the betterment of all stakeholders.

Decision-usefulness theory is grounded in assumptions based on accounting and financial reporting principles. Specifically, it concerns the effects that accounting information has on the decisions made by users of that information. The theory is developed based on the contributions of several economists and accounting researchers who collaborated to establish the ideal framework for how financial information should be utilized by stakeholders. Decision usefulness aims to provide stakeholders and investors with sufficient information needed to make informed decisions [12]. [22] indicates that the primary objective of accounting is to deliver financial information that is useful for decision-making. From this perspective, the provision of information involves presenting data that is relevant to users. The usefulness of such information is evaluated based on its timeliness for decision-making. Additionally, the theory posits that accounting information serves as a vital tool for management and organizational control. Managers require relevant, timely, and accurate accounting data to facilitate effective decision-making [23].

2.2 Literature and Hypothesis Development

2.1.1 Corporate Governance Quality and Non-financial Information Quality

CG quality and NFI quality are interrelated since reliable accounting information contributes to the quality of non-financial reporting. Good CG practices ensure the credibility of financial reporting through effective internal controls, transparency, and accountability [2], [3]. CG quality means having effective structures, processes, and practices for governing entities, ensuring accountability, oversight, transparency, and integrity [24]. CG quality attributes include effective board oversight, independence, defined roles, internal controls and risk management processes, transparency in decision-making, stakeholder engagement, and adherence to standards [25], [26]. CG quality involves these attributes to determine the mechanisms companies use to govern themselves effectively. High-quality CG should, therefore, ensure the quality of NFI because companies with quality CG mechanisms have controls to prevent misstatements and promote the quality of accounting data in a timely manner. Reliable accounting data serves as the backbone for making other disclosures by the company trustworthy, including NFI [25]. ESG and other types of non-financial reporting draw information from a company's accounting information. Thus, quality CG fosters high-quality accounting information, supporting the integrity and usefulness of NFI and creating a cohesive reporting system [27], [28], [29].

Empirical evidence supports the link between CG mechanisms and non-financial reporting. Board effectiveness, including independence, expertise, diversity (gender), meeting frequency, activity, and size, significantly impacts the reporting of voluntary disclosure and CSR [27], [28], [29], [30], [25]. For instance, increased gender diversity and expertise within board governance are positively associated with improved NFI [25]. The existence of different board committees is also linked to improved sustainability reporting and performance [26]. Greater board independence and a larger board size are associated with a higher level of risk disclosure in sustainability reports [31]. Gender diversity has a positive influence on NFI provision [32], [28]. Studies also show a positive relationship between female directors and financial reporting quality [33]. Gender and cultural diversity positively affect CG performance, suggesting female directors enhance board monitoring [34]. Board committees, by delegating duties, have significant potential to influence NFI decision-making. Companies with ESG and CSR committees, and their specific composition, tend to achieve improved CSR outcomes [35].

Furthermore, effective internal control procedures improve the quality of disclosed information [36], [37]. Studies show a positive relationship between internal control quality and NFI quality [13]. Firms adapt internal control systems to manage environmental uncertainty and ensure effectiveness [38]. Successfully applied internal control promotes higher quality and accuracy in both financial and non-financial reporting [39], [40], [41], [42], [13]. Thus, strong internal control is expected to increase NFI credibility and transparency [41]. Collectively, these studies indicate that CG quality positively impacts NFI quality and, consequently, company success. In view of the above, the first research hypothesis is formulated:

H1. Corporate governance quality has a positive impact on non-financial information quality.

2.1.2 Accounting Information System Quality and Non-financial Information Quality

Traditional accounting typically considers financial statement data sufficient for evaluating business performance. However, there is a notable shift towards integrating NFI, which has garnered recognition among practitioners and scholars for its important role in enhancing decision-making [43]. Despite this growing interest, NFI's definition remains complex and ambiguous, with a lack of consensus within academia [44], [45]. Initially seen as supplementary data absent from traditional financial statements [46], [43], NFI now encompasses a company's social responsibility and addresses a broader range of stakeholders beyond just owners and investors [47].

NFI encompasses various metrics, including index ratios, counts, and scores [48], as well as environmental and social policies [49]. It also considers external factors such as economic conditions, technological changes, and competitor products [50], alongside sustainability and social responsibility aspects such as safety and health, climate change, gender equality, energy use, waste management, pollution, biodiversity, and greenhouse gas emissions [51], [49]. As interest in NFI grows, businesses are increasingly producing annual and dedicated reports that provide stakeholders with access to both financial and non-financial data related to their impacts.

The recognition of corporate NFI has stimulated research into its value relevance for investors and overall corporate performance [12], [43]. Value relevance refers to the extent to which information, both financial and non-financial, influences decision-making and performance outcomes [52]. According to [52], NFI becomes value-relevant when seen as useful for decision-making. [12] found that firms with strong sustainability practices often enjoy higher market valuations, indicating that investors value sustainability-related NFI. Similarly, studies by [52], [53] highlight NFI's importance in investment decisions and its complementarity with traditional financial metrics.

The increasing emphasis on NFI underscores its significance for informed decision-making. However, [54] points out that the absence of established qualitative characteristics for NFI can create difficulties for stakeholders who rely on this type of information and seek assurances of its quality and comparability. [55] classify NFI according to several primary characteristics and indicate that information should be accurate, complete, and timely to ensure decision usefulness. The intensified focus on NFI, particularly regarding social and environmental impacts, intersects with AIS, which facilitates the collection, recording, storage, and processing of data to generate actionable information. AIS encompasses various components, including personnel, protocols, software, and security measures [56]. Robust AISs are necessary to deliver high-quality NFI alongside traditional financial metrics.

Research shows that organizations with strong data governance frameworks enhance decision-making through improved data integrity and reliability [14], [57]. AIS integration into broader management information systems enables effective data flow, allowing managers to make informed decisions regarding strategic planning, performance assessment, and resource allocation. [58] have listed various dimensions of AIS quality. These factors include system quality, information quality, and service quality. Information quality pertains to the completeness, accuracy, consistency, and timeliness of the output from the information system. Accounting information that is of high quality allows stakeholders to assess performance and recognize areas of improvement.

[14] emphasize that the integration of high-quality financial and NFI is crucial for achieving a competitive advantage. Non-financial metrics—such as operational efficiency and customer satisfaction—enhance decision-making when effectively captured through robust AIS frameworks. The quality of AIS is vital for producing relevant and reliable data that informs management decisions related to both financial and non-financial aspects [59]. [60], [61] argues that AIS quality is intrinsically linked to the system's capacity to process financial data while generating useful NFI, which is essential for organizational success. Consequently, good decision support should be achieved through an AIS framework that improves user satisfaction, effectiveness, and efficiency, as well as the quality and usefulness of the produced information. [14] explain that the dimensions of data quality affect the trustworthiness of AIS output. Producing inaccurate conclusions and misguided strategies can ultimately harm an organization's performance if the data is of poor quality.

Recent studies emphasize the significant impact of AIS quality on NFI quality and DME [62], [63], [64], [1], [18]. [15] found that high-quality AIS outputs enhance the NFI of Jordanian Islamic banks. [65] suggest that fostering an innovative culture within an organization enhances AIS quality, leading to more reliable NFI. Utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM), [64] analyzed data from 72 respondents in Indonesia and demonstrated that AIS quality significantly influences the generation of high-quality NFI. Likewise, [62] conducted a survey of 168 accountants in Jordan and identified that the efficiency and effectiveness of electronic AIS significantly impact NFI quality. Supporting this perspective, researchers such as [66] and [67] argue that AIS quality significantly affects NFI, enhancing its usefulness in decision-making. [1] further confirm a strong positive relationship between AIS quality and NFI quality. Additionally, [4] asserts that enhancing the quality of internal control systems and AIS leads to improved NFI quality. Based on these findings, the first hypothesis is proposed:

H2. Accounting information system quality has a positive impact on non-financial information quality.

2.1.3 Quality of Non-financial Information and Decision-making Effectiveness

Effective decision-making processes are crucial for organizational success and strategic alignment. This involves selecting optimal business alternatives and leveraging information to achieve specific goals [4]. Typically carried out by authorized individuals, decision-making is a systematic process conducted in collaboration with specialized stakeholders to plan, implement, and manage decisions [68]. However, managing this process can be challenging; timely decision-making often carries risks, while delays can lead to missed opportunities [69]. [70] note that the information needs of managers can vary based on their roles. Decisions are influenced by the accuracy, complexity, and amount of the information available, along with the difficulties in acquiring it [71], [72]. Notably, necessary information, particularly regarding NFI, is not always readily accessible or timely.

While traditional financial metrics have long been the cornerstone of decision-making frameworks, recognition of the importance of NFI has grown in recent years [73]. An expanding body of literature shows that integrating quality NFI can significantly enhance DME. [7] argue that non-financial indicators are instrumental in supporting managerial decisions. However, users of financial reporting often face challenges due to a lack of access to reliable information necessary for informed decision-making [41]. Non-financial metrics provide insights that align operational activities with strategic objectives. [74] emphasize that organizations monitoring NFP indicators can better synchronize daily operations with long-term goals, resulting in more effective decision-making outcomes. Further, [75] asserts that non-financial indicators help bridge the gap in information essential for informed decision-making, contributing to a more accurate assessment of the organization's overall health. Consequently, the existing literature suggests that NFI plays a pivotal role in determining DME [54], [76]. Based on these insights, the second research hypothesis is formulated:

H3. Non-financial information quality has a positive impact on decision-making effectiveness.

2.1.4 Quality of Non-Financial Information and Non-Financial Performance

Studies have shown that performance is multidimensional, where financial indicators are considered together with NFP. The combination of financial and non-financial metrics allows companies to balance their decisions while positively affecting their performance. [77] state that integrated reporting can lead to improved stakeholder engagement, resulting in better decisions by addressing the needs of stakeholders while encouraging social disclosure and long-term success. NFP refers to an organization's achievements in various critical areas, including innovation, market share, product quality, productivity, customer satisfaction, employee satisfaction, employee retention, and social and environmental responsibility [4]. [78] points out several specific indicators that can reflect a company's NFP, such as improvements in customer service, enhancements in employee and customer retention rates, and practices related to social responsibility. These indicators are crucial as they provide a more holistic view of a firm’s operational success and its impact on stakeholders.

Research on the relationship between NFI quality and NFP has yielded mixed results. [8] emphasize that both financial information and NFI are crucial for organizational performance, enhancing ratios, funding, and accountability while reducing fraud. Supporting this, [29] claims that using non-financial metrics improves performance. In contrast, [4] finds that the quality of NFI has no significant influence on NFP. They argue that NFI quality does not directly impact NFP but influences it indirectly through decision-making. [20] reaches a similar finding and reaffirms the relevance of high-quality NFI in shaping managerial decisions and contributing indirectly to overall firm performance. A thorough analysis of previous research suggests the possibility of direct relationships between NFI quality and NFP, leading to the formulation of the third research hypothesis:

H4. Non-financial information quality has a positive impact on non-financial performance.

2.1.5 Decision-Making Effectiveness and Non-Financial Performance

The relationship between DME and NFP is synergistic in nature. Decision-making choices have a significant impact on the overall health and sustainability of an organization [79], [80]. Research shows that when decisions are made with the right amount of information and participation from those affected by the outcomes, a culture of agility and resilience is developed. This type of culture has been proven to aid in organizational success, especially in today's ever-changing market. In addition, there have been studies that show a correlation between certain decision-making practices and an increase in metrics that fall under the category of NFP. One study by [81] found that there was a positive relationship between the decision-making process and certain non-financial outcomes. This research showed that when decisions are made with positive attributes such as inclusivity and transparency, it can lead to higher levels of employee engagement and customer satisfaction. [82] went on to say that organizations with better decision-making practices are able to execute strategies that can lead to an enhancement in corporate social responsibility.

Effective decision-making also leads to better operational efficiency, social responsibility, reputation, and other non-financial performance indicators. Decision-making that takes into account big data and stakeholder input can help build an organizational culture that can better withstand market shifts and create better relationships with customers and employees. [20] notes that organizations that make good decisions will likely improve their NFP. [37] asserts that better decision-making allows organizations to make decisions faster and more logically, allowing them to reach their performance targets. Decision-making reinforces itself as an important strategic component of a firm because it allows a firm to meet its current business objectives and create an environment where it can continue to create value for its stakeholders in the future.

Taken together, these studies show how improved decision-making yields positive outcomes across organizations and demonstrate that high-quality decision-making can create a positive ripple effect throughout many facets of NFP. This supports the hypothesis of a positive correlation between DME and NFP. Drawing from the literature discussed, the author formulates the fourth hypothesis of this study as follows:

H5. Decision-making effectiveness has a positive impact on non-financial performance.

2.1.6 The Mediating Effect of Non-financial Information Quality

[20] study the mediating impact of NFI quality on the relationship between AIS quality, DMS, and NFP through a sample of 306 companies in Vietnam. The study finds that NFI is a mediator that connects AIS quality and NFP. [83] demonstrate that accounting information quality mediates the relationship between AIS quality and organizational performance in Bali's banks, emphasizing its role in boosting performance. AIS provides managers with critical information for strategic decision-making [84]. Similarly, [63] found that AIS significantly streamlines HR decisions and supports policy development, training, and performance evaluation in Yemeni banks. They also note that higher AIS and accounting information quality positively impact decision-making success.

Furthermore, non-financial reporting alongside financial reports offers deeper insights into organizational performance. Research suggests that non-financial information quality mediates the link between AIS quality and organizational success [85]. [1], [4] highlights the mediating role of information quality—including non-financial data—in enhancing AIS and business performance. [18] emphasize the growing importance of non-financial disclosures in governance and overall performance. Combined, these propositions highlight how AIS and information quality affect organizations and their outcomes.

On the other hand, good quality non-financial information can also lead to good corporate governance. Greater transparency and completeness of non-financial reporting demonstrate responsible corporate behavior and accountability that is characteristic of good corporate governance. Therefore, as good governance increases, the quality of non-financial information will also increase as companies are managing their business responsibly and providing stakeholders with quality information they can use in their decision-making processes. Alignment with corporate strategies also increases as governance improves. Therefore, there exists a virtuous cycle between governance quality and information quality. From the above discussion, the following hypotheses are formulated:

H6a. Non-financial information quality mediates the relationship between CG quality and DME.

H6b. Non-financial information quality mediates the relationship between CG quality and NFP.

H6c. Non-financial information quality mediates the relationship between AIS quality and DME.

H6d. Non-financial information quality mediates the relationship between AIS quality and NFP.

Finally, in this research, the researcher considers firm industry, age, structure, and size as control variables to manage potential factors that may impact company performance. These variables have frequently been used as controls in various prior studies in the realm of business and management [86], [87], [88], [79]. The proposed model of the study is depicted in Figure 1.

2.3 Non-financial Information Context in Saudi Arabia

Disclosure on NFI in Saudi Arabia is becoming more developed through growing attention on ESG concerns. Saudi Arabian companies are shifting to enhanced business transparency through increased disclosure on ESG concerns. Policies established through Vision 2030 encourage diversification of the Saudi economy and investment in sustainable growth. The Saudi Arabian government supports corporate use of CSR and places emphasis on NFI [89]. The government views these practices as improving company image and satisfying stakeholder demands. The Saudi government is working to improve laws to promote doing business responsibly; Saudi Arabia's National Center for Performance Measurement (known as Adaa) is working to implement the Saudi Arabia Sustainability Index that measures ESG performance of listed companies. Listed companies follow disclosure requirements by the Saudi Stock Exchange, commonly known as Tadawul, and the Parallel Market (Nomu).

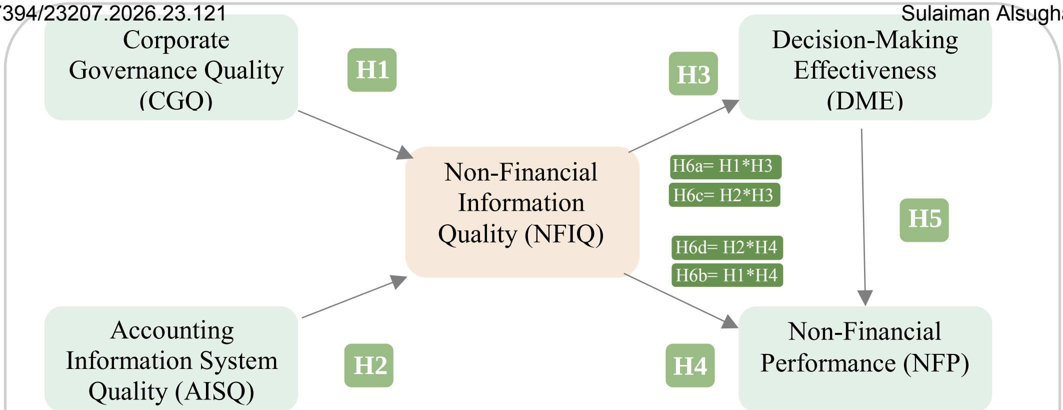


Fig. 1: Proposed model.

Source: created by the author.

Traditionally, disclosure has been centered around financial performance, but recently, attention has turned to how NFI can be included in annual and sustainability reports. For example, the Saudi Arabian Monetary Authority (SAMA) stresses the importance of transparency in the financial sector. In line with international practices, banks have been encouraged to disclose NFIs related to risk management activities and corporate governance. In addition, in order to support consistency and meet investors' demands for reliable and comparable NFI, many Saudi-listed companies are starting to align their disclosures with international standards, such as the Task Force on Climate-related Financial Disclosures (TCFD) and the Global Reporting Initiative (GRI).

Even with these improvements, there are still areas that need more work regarding non-financial reporting. Since these practices are voluntary, there is still limited information published by companies and inconsistency in the quality of disclosures, making it difficult for stakeholders to use this information to properly evaluate a company's sustainability and social responsibility initiatives. Larger companies with international ties provide more NFI, while small and medium-sized companies struggle to report NFI.

For this reason, improving AIS and NFI quality should not be just about compliance but should be considered crucial to establishing sustainable growth for businesses in Saudi Arabia.

3 Methodology

3.1 Population and Sample

This study used a quantitative research method to test the study hypotheses. A questionnaire survey was sent to sampled managers, chief accountants, department heads, and board members of listed companies in Saudi Arabia. They were selected because they are decision makers and performance evaluators. The proposed theoretical model is tested on Saudi-listed companies because they operate in a different regulatory environment, have different business diversity, focus on NFP criteria, cultural differences, and strategic transformation in vision that the country is going through. All these factors provided a good ground to study the relationship between AIS quality, NFI quality, DME, and NFI to add value to theory and practice. Moreover, this research was conducted on a country that plays a major role in political, economic, religious, and geopolitical levels. Saudi Arabia plays a major role economically because it's rich in oil and is in the process of diversifying its economy. It also has huge investment capacity and acts as a trading hub in the region, which shapes its economy and impacts other countries.

Due to the large size of the population (Saudi listed companies), a representative sample could not be drawn. Therefore, the researcher employed convenience sampling. Practical limitations such as time constraints, costs, and respondent accessibility influenced this choice. Given that this exploratory research aims to understand the impact of AIS quality on DME and NFP in the Saudi context, convenience sampling allows for efficient data collection within a short timeframe. This method is commonly used in business research, especially in developing countries with limited industry-wide databases. Additionally, it is a non-probability sampling technique frequently employed in studies involving large populations [68], [13].

[90] introduced the 10-times rule for determining minimum sample sizes, based on the greater of either ten times the maximum number of structural pathways to a specific latent construct or ten times the maximum number of formative indicators for a single construct. In this model, the latent variable NFP, which has two incoming paths, requires a minimum sample size of 20. According to [91], sample sizes can be classified as excellent (1,000), extremely good (500), good (201–300), adequate

(101–200), and weak (less than 50). [92] recommend 100 to 150 observations for reliable use of the maximum likelihood method, noting that larger samples further reduce sampling bias. Consequently, the researcher aims to collect 600 responses from 150 listed companies, which is considered an adequate size for robust statistical analysis. This study focuses on medium and large companies in the KSA that manage significant financial information, selected from the Saudi Tadawul Stock Exchange, which has more than 200 listed companies, and the Parallel Market "Nomu", which has 112 listed companies. These companies generate and manage a significant amount of financial information with audited accounts, different legal forms, and a minimum of 50 employees. In addition, data are sourced from companies active in key sectors in Saudi Arabia, which allows for an effective sample representation of the population and thus ensures a sufficiently robust statistical analysis.

In order to relate the conceptual aspects of the study with observable evidence from real organizations, the study analyzes survey data using well-established statistical procedures designed to infer population-wide relationships from a large sample of publicly listed corporations. Data are gathered from individuals who hold positions (senior executive managers, financial managers, board of directors, and primary accountants) which are given official capacity to represent their organizations views and procedures. Questionnaires were distributed to these individuals through official means (company email and corporate communication departments) to help validate the authenticity of the information.

In addition, participants were asked in the questionnaires cover letter to respond based on what they know to be the position of the company and not based on their opinion or perceived position of the company. Follow-up emails were sent to participants asking them to ensure their responses would reflect the official position of the company. All data provided by participants was triangulated with data found on company websites. Public data used to triangulate responses included: annual financial reports, annual non-financial reports, information posted on the company website, voluntary disclosure, regulatory filings, and official press releases if available. By using this triangulation with public data and gaining official contact from key decision makers within the organizations, the study can assure greater reliability of the data and ensure responses capture the impacts of CGQ, AISQ, and NFI on DME and NFP from the perspective of the organization.

3.2. Data Collection

The researcher implements a web questionnaire created by Google Forms that has been prepared in both English and Arabic in order to gather quantitative data quickly from a large sample size of geographically dispersed participants. This questionnaire consists of two parts: the first includes questions about the company, and the second assesses the dimensions of the model using adapted or validated scales from previous literature. The questionnaire used a five-point Likert scale with answers ranging from strongly agree to strongly disagree. The researcher implemented a pretest on two business managers and two academics. Based on their feedback, some survey statements were reworded for clarity and completeness.

Targeted participants were emailed a link to the online questionnaire together with an explanation of the study's purpose in November 2024. Two follow-up emails were sent as part of optimizing response rates and acquiring adequate information. For key participants, additional attempts were made to confirm receipt of their responses. Informed consent was obtained from all participants in writing. After the survey, data were prepared for analysis using SPSS, where procedures for data cleaning—including handling missing data, examining central tendencies, identifying outliers, and assessing normality—were conducted. The preliminary analysis resulted in the elimination of five responses, yielding 344 valid responses and a usable response rate of 55.3%, deemed appropriate for this survey method [93].

3.3. Measurement of Items

The survey instrument used in this study is derived from existing research. CG quality is evaluated using a six-item scale sourced from [25], [2], [94]. AIS quality is evaluated using a seven-item scale sourced from [4], [78]. NFI quality is measured with a five-item scale from [4]. The six-item scale for DME is derived from [4], [94]. The six-item scale for NFP is sourced from [78]. Appendix A outlines the measurement scales utilized in this study.

3.4. Analysis Techniques

Reflective indicators are used to measure all constructs, and PLS-SEM is used to analyze the data and test the hypotheses of this study. PLS-SEM was selected because it is flexible and performs well when sample sizes are small. Furthermore, PLS-SEM can estimate complex models with many constructs and allows for the assessment of both direct and indirect effects, which makes it beneficial when there are restrictions on sample size. Additionally, it allows researchers to analyze data with non-normal distributions. Its high capacity to handle complex models, maximize the variance explained by endogenous constructs, and estimate parameters efficiently allows for a comprehensive analysis of relationships from the latent construct level to the indicator level. Additionally, given that this research is exploratory in nature, aiming to test theories and models, PLS-SEM performs better than traditional regression methods.

As depicted in Table 1, there are two major steps involved in PLS-SEM analysis: measurement model assessment and structural model assessment. There are two types of measurement models: reflective and formative. In the current study, the author used a formative measurement model, which entails assessment of convergent validity and discriminant validity [95]. Convergent validity implies how well the items that constitute a construct measure that construct (ensuring internal reliability). Discriminant validity, also known as differential validity, refers to the extent to which items distinguish between constructs.

Following this, the structural model is evaluated to determine model fit and predictivity. This assessment involves five parts: (a) collinearity, (b) significance and relevance of relationships, (c) coefficient of determination (R²), (d) effect size (f²) and (e) predictive relevance (Q²). An overview of the criteria and accepted values for each test can be found in Table 1.

3.5. Software Environment

Analyses were performed using SmartPLS version 3.3.9. Internal reliability, validity, and robustness tests were completed using SmartPLS built-in tests, which included Cronbach's alpha, composite reliability, AVE, HTMT ratio, and effect sizes.

3.6. Bias Assessment

Before proceeding with the measurement and structural model assessment, the recommended diagnostic tests to control for common method bias (CMB) and non-response bias (NRB) are executed. This step helps to validate the data by identifying and accounting for any biases that may skew results.

Table 1. Partial Least Squares Path Modeling Method

Steps	Criteria	Accepted value	
Step 1. Evaluation of the Measurement Model (Outer model)			
Convergent validity	Individual item reliability	Cronbach's $\alpha > 0.7$	
	Composite reliability	$CR > 0.7$	
	Factor Loadings	Loadings > 0.7	
	Average Variance Extracted	$AVE > 0.5$	
Discriminant validity	Variable correlation (Root square of AVE)	The Fornell and Larcker (1981) criteria- the AVE of each latent construct should higher than the construct's highest squared correlation with any other latent construct.	
	Construct distinctiveness	HTMT ratio <0.85	
Step 2. Evaluation of the Structural Model (Inner model)			
Variance Inflation Factor (VIF)	.	VIF < 3.3 (or sometimes < 5 in different contexts) is generally considered acceptable, indicating no significant collinearity issues.	
Coefficient of determination of the endogenous constructs (R2)		$R^2 < 0.19$	Unacceptable
		$0.19 \leq R^2 < 0.33$	Weak
		$0.33 \leq R^2 < 0.67$	Moderate
		$R^2 \geq 0.67$	Substantial
Effect size (f2)		$f^2 < 0.02$	No effect size
		$0.02 \leq f^2 < 0.15$	Small effect size
		$0.15 \leq f^2 < 0.35$	Medium effect size
Predictive relevance (Q2)		$Q2 > 0$	Acceptable validity
		$Q2 < 0$	No validity
Hypotheses Testing (Path Coefficient & t-value)		t-value = 1.96 → Significant at p-value < 0.05;*	
		t-value = 2.58 → Significant at p-value < 0.01;**	
		t-value = 3.29 → Significant at p-value < 0.001***	

Source: created by the author.

3.6.1 Common method bias (CMB) assessment

According to [96], common method variance (CMV) could be a major problem and a threat to the validity of the results. While CMV refers to the variance attributable to the measurement method, CMB is the distortion or bias in the results caused by that variance and is often considered a causal factor that causes the observed relationships to be biased, threatening the validity of the findings. CMB typically emerges from influences such as social desirability and the consistency motif. Researchers tackle CMB in survey-based studies by using multiple informants for each observable item [97]. To mitigate CMB in self-reported data, the researcher employs both procedural and statistical strategies. Procedurally, the author uses three methods: a clear introduction to concepts like CG quality, AIS quality, and NFI quality, randomization of measurement items to obscure relationships, and assurance of respondent anonymity. Statistically, the author applies variance inflation factors (VIFs) after data collection, finding that all indicators had a VIF below 5.0, indicating no multicollinearity among indicators and no concerns regarding CMB. Further, to ascertain whether CMV threat is present in the dataset, the Harman's single factor test was executed. All items from all constructs under study were entered for analysis and constrained to a single factor and the results showed that the single factor explained only 28.7% of the total variance. The results suggest that the collected data is free from the threats of CMV.

3.6.2 Non-response bias test

To test for NRB, the author followed the steps in previous research [96] by looking at the level of statistical significance of the difference between initial survey responses (response from 30% of initial respondents) and later surveys (response from the last 30% of respondents), based on the assumption that the opinions of late respondents represent the opinions of non-respondents. To do this, the study utilized the Lavene test (One-Way ANOVA) using SPSS ver. 26 software and found no significant differences between the two groups in any of the constructs examined in this study at the 5% significance level.

Table 2. Demographic information

	Answers	**Freq.**	**Percent**		**Answers**	**Freq.**	**Percent**
Gender	Male	253	73.5	**Experience**	0-5 years	62	18.0
	Female	91	26.5		6-10 years	216	62.8
	Total	**344**	**100**		11-15 years	42	12.2
Entity size	Medium nterprises	143	41.6		Above 15 years	24	7.0
	Large	201	58.4		**Total**	**344**	**100**
	Total	**344**	**100**				
Sector	Financial	69	20.1	**Age**	24-32	206	59.9
	Industrial	114	33.1		33-44	77	22.4
	Commercial	139	40.4		45-54	41	11.9
	Other	22	6.4		Above 54	20	5.8
	Total	**344**	**100**		**Total**	**344**	**100**
Education	Diploma	37	10.8	**Position**	Mangers	213	61.9
	Bachelor	189	54.9		Chief accountants	91	26.5
	Master	92	26.7		Department heads	26	7.6
	PhD	26	7.6		Board members	14	4.0
	Total	**344**	**100**		**Total**	**344**	**100**

Source: created by the author.

4 Results

4.1. Demographic Information

Following the preliminary analysis section, the study provides information about the sample characteristics. As shown in Table 2, from the total of 344 respondents, 253 are males (73.5%), and 81 are females (26.5%). This difference between male and female leaders who participated in the study can affect decision-making, as a team with an even distribution of women and men can bring different perspectives. Concerning age groups, 24- to 32-year-olds represent 59.9% of the sample, 33- to 44-year-olds represent 22.4%, and respondents aged 45 years and above constitute 17.7%. Most of the participants are relatively young professionals who can be more open to technology and new AIS solutions. The new generation of accountants and managers cares about reporting and analyzing information on time. They tend to implement new technologies for non-financial reporting.

Regarding educational level, over half of the sample holds a bachelor's degree (54.9%), followed by 34.3% with postgraduate degrees, and 10.8% with other degrees. Overall, the participants who completed the survey can be considered to be fairly educated. This level of education may enhance understanding of AIS integration with NFI. In terms of positions, most participants are managers (61.9%), followed by chief accountants (26.5%), department heads (7.6%), and board members (4.0%). As managers, these individuals play a key role in implementing AIS. Regarding experience, 18.0% have less than five years, 62.8% have at least five years, and 15.2% have over ten years. The distribution suggests a strong majority with at least five years of experience, which likely fosters an appreciation for the role of CG and AIS's tracking both financial and NFP indicators.

The distribution of company size shows that 201 (32.1%) are large and 143 (41.6%) are medium-sized. Medium-sized enterprises face unique challenges and opportunities that may influence their adoption and use of AIS. Medium-sized businesses range from having 50–249 employees and annual turnovers between USD 10.6 million and USD 53.3 million. From a sectorial standpoint, 139 (40.4%) are classified as commercial, 114 (33.1%) as manufacturing, 69 (20.1%) as financial services, and the remaining 22 (6.4%) fall under others. This difference in industry may affect what types of NFI's are valued most in decision-making.

4.2. Measurement model assessment

In order to tackle outliers effectively, recent literature [98] pointed out that robust estimation procedures needed to be integrated into the analysis. Therefore, the measurement model should be evaluated based on the reliability and validity of each latent variable included in the model. Validity was determined through convergent validity, which describes the degree of confidence when measuring the goodness of each indicator. In addition, the measurement model should be evaluated using discriminant validity, which demonstrates the variance between indicators in latent variables.

Convergent validity was assessed using four criteria: factor loading (should be ≥0.7), Cronbach's alpha (α should be ≥0.7), AVE (should be ≥0.50) and CR (should be ≥0.70) (see Table 2) [99]. Table 3 displays the results of the convergent validity assessment of the measurement model. As shown in Table 3, all criteria are met. Therefore, convergent validity can be assumed.

Table 3. Convergent validity

Constructs	Items	Outer loadings	VIF	α	CR	AVE
Corporate Governance Quality (CGQ)	CGQ1	0.823	3,654	0.912	0.942	0.620
	CGQ2	0.779	2,883			
	CGQ3	0.902	3,765			
	CGQ4	0.796	2,977			
	CGQ5	0.875	3,470			
	CGQ6	0.843	3,328			
Accounting Information System Quality (AISQ)	AISQ1	0.734	2,839	0.866	0.896	0.520
	AISQ2	0.711	2,838			
	AISQ3	0.856	3,932			
	AISQ4	0.795	3,741			
	AISQ5	0.747	3,527			
	AISQ6	0.719	3,216			
	AISQ7	0.733	2,968			
Non-financial Information Quality (NFIQ)	NFIQ1	0.864	2,989	0.937	0.965	0.789
	NFIQ2	0.919	3,661			
	NFIQ3	0.845	2,956			
	NFIQ4	0.823	2,855			
	NFIQ5	0.899	3,644			
Decision-Making Effectiveness (DME)	DME1	0.845	2,879	0.923	0.956	0.690
	DME2	0.895	3,466			
	DME3	0.748	2,663			
	DME4	0.870	3,918			
	DME5	0.798	2,796			
	DME6	0.792	2,667			
Non-Financial Performance (NFP)	NFP1	0.862	3,642	0.945	0.936	0.783
	NFP2	0.931	3,992			
	NFP3	0.774	2,887			
	NFP4	0.868	3,119			
	NFP5	0.897	3,465			
	NFP6	0.833	3,212			

Source: created by the author.

Table 3 indicates that all constructs have adequate reliability, as all outer loadings are strong (ranging from 0.711 to 0.931) across items. Further, all constructs, with respect to Cronbach's Alpha, have values greater than the widely accepted threshold of 0.7, representing good internal consistency [100], [92]. Composite reliability scores ranged from 0.896 to 0.965, which is higher than the minimum threshold of 0.7, suggesting that the constructs used are reliable to measure latent behavior. Evidence of Convergent validity was established since AVE scores ranged from 0.520 to 0.789, which are above the minimum threshold of 0.5 [101]. These thresholds align with consensus in the literature for maintaining a robust and reliable measurement model. Collectively, these findings affirm the adequacy of the measurement model, confirming the reliability and validity of the constructs in effectively capturing their intended dimensions within publicly listed companies in Saudi Arabia.

After the convergent validity evaluation, discriminant validity was evaluated by implementing the Fornell and Larcker criteria as well as the Heterotrait-Monotrait (HTMT) ratio [99]. To test discriminant validity, Fornell and Larcker's test compared the square root of AVE for each construct with the correlations between the respective constructs. As displayed in Table 4, the results evidently indicate that this criterion has been met, and therefore, discriminant validity of the model can be assumed.

To further support discriminant validity, the HTMT ratio was used as a recommended tool to compare the strength of the relationships within the same construct (monotrait) with the strength of the relationships between other constructs (heterotrait). Threshold values for HTMT are <0.85 (conservative) and <0.90 (less conservative) [92]. The ratio matrix of HTMT shown in Table 5 reports values from 0.226 to 0.288 in the off-diagonal elements, while all the diagonal elements (monotrait comparisons) are equal to 1. All the off-diagonal values are well below the recommended threshold of <0.85, which demonstrates evidence of good discriminant validity [92], [100].

Table 4. Discriminant validity (Fornell-Larcker criterion).

Constructs	CGQ	AISQ	NFIQ	DME	NFP
CGQ	0.787	0.000			
AISQ	0.000	0.721			
NFIQ	0.331*	0.297*	0.888		
DME	0.248*	0.255*	0.141*	0.831	
NFP	0.229*	0.228*	0.252*	0.312*	0.885

Source: created by the author.

Table 5. Heterotrait-monotrait ratio of correlations

Constructs	CGQ	AISQ	DME	NFP
CGQ				
AISQ				
NIQ	0.248	0.267		
DME	0.265	0.255	0.312	
NFP	0.273	0.288	0.226	0.246

Source: created by the author.

These low HTMT values further confirm that the latent constructs—CGQ, AISQ, NFIQ, DME, and NFP—are clearly distinguishable, ensuring that the measurement model effectively isolates unique variances for each construct without significant overlap. This reinforces the reliability of the measurement model and emphasizes the distinctiveness of the constructs examined within publicly listed companies in Saudi Arabia

3.3. Structural Model Assessment

Following the measurement evaluation, the structural model was evaluated based on collinearity (VIF), coefficient of determination (R^2), predictive relevance (Q^2), significance of path coefficients and effect size f^2. VIF shows how much the variance (and subsequently the standard error) of a regression coefficient is increased because of linear dependency with other predictor variables in the model. Table 1 shows that VIF < 3.3 (sometimes this value is <5 in other studies) indicates an acceptable tolerance value and no collinearity problem. Table 3 presents the VIF value of the structural model, which ranges from 2.663 to 3.992 for all constructs, falling between the acceptable range of multicollinearity as proposed by [82], [102]. Table 3 reveals that none of the values exceed 5.0; therefore, there is no collinearity problem in the structural model.

The coefficient R^2 shows the amount of variation caused by exogenous latent variables for the endogenous latent variables. Accordingly, high values of R^2 are desired. There is no formal benchmark value for R^2; however, based on literature, thresholds of <0.19 are considered unacceptable, values between 0.19 and 0.33 are considered weak, values between 0.33 and 0.67 are considered moderate, and values >0.67 are considered substantial. R^2 values of 0.10 are commonly accepted as satisfactory [103]. Figure 3 displays the output for the structural model with R^2 values ranging from 19% to 22%. All values for R^2 are above the accepted level of 10%, which shows that the exogenous latent variables are able to explain the variance of their assigned endogenous latent variables, supporting the model's predictive capacity.

Q^2 assesses the degree to which the model can predict data points of the endogenous constructs through the blindfolding technique [104]. If the value of $Q^2 > 0$, then the model shows predictive relevance [104]. As shown in Figure 3, values of Q2 are 0.281, 0.327, 0.421, which are greater than zero (0). Therefore, it can be concluded that the model is predictive and the findings imply that the prediction of constructions is relevant (Figure 3; [103]).

Path coefficients are unstandardized estimates that indicate the strength and direction of relationships between constructs in the model. The significance levels of these path coefficients were assessed using t-statistics and p-values generated through bootstrapping. As shown in the criteria in Table 2, a path is considered significant if its t-value exceeds the critical value (typically 1.96 at 5% significance), and the associated p-value is below .05. Table 6 reveals that all the key path coefficients included in the research model are statistically significant, confirming the hypothesized relationships between constructs and supporting the validity of the proposed theoretical model that captures the structural relationships.

Effect Size (f^2) measures how much the squared path coefficients reduce if an exogenous construct is dropped from the model. Hence, it shows whether the deleted construct has a small, medium, or large impact on the endogenous latent variables. f^2 value less than 0.02 means no effect, while a value ranging from 0.02 to 0.15 shows a small effect size. Lastly, a value higher than 0.15 and less than 0.35 can be referred to as a medium effect size [103]. Table 6 reveals that the f^2 values range from 0.118 to 0.197, hence indicating that exogenous variables have a greater impact on the endogenous variables and therefore have good explanatory power.

Additional tests were conducted to assess the predictive accuracy of the model. The fit indices mentioned above evaluate relationships, paths, and multicollinearity within the model; however, the Chi-square test assesses the overall fit of the model to the data. For the assumption to be met, the p-value should be greater than 0.05. Most scholars prefer models having non-significant chi-square because this represents a good fit. This study's chi-square is 286.435 (p>0.05), which is satisfactory. This result indicates the model has predictive relevance and that the data fit well, supporting the proposed theory.

5.3. Hypothesis testing

The research hypotheses were tested using path analyses in which t-tests were conducted. The path coefficient estimate shows the strength and direction of the relationship between exogenous and endogenous constructs. Statistical significance of path relationships is based on t-values and associated p-values. Therefore, a t-value >1.96 is significant at the 5% level (p-value < 0.05). More stringent significant levels are represented by higher t-values (e.g., 2.58 represents p-value < 0.01; 3.29 represents p-value < 0.001). Values presented outside of brackets in Figure 2 output are the path coefficients; values in brackets are the associated p-values. Results of the hypothesis tests are summarized in Table 6.

4.4.1. Direct relationship results

Path coefficients were examined to specify the direction and strength of the relation between latent variables. Hypothesis testing was conducted to determine whether or not the relationship between latent variables is statistically significant, to accept or reject the hypothesized paths. Table 6 shows path coefficients, while Figure 3 illustrates their t-values. A summary of the hypothesis testing results can be found in Table 6. The results show relations and mediating effects among constructs of the structural model.

H1 and H2 show that AISQ and CGQ had a positive influence on NFIQ. Hypotheses H1, which indicates the relationship between CGQ and NFIQ, and H2, which represents the relationship between AISQ and NFIQ, were found to be positive and significant (0.295 and 0.332 path coefficients, respectively). Both have t-values greater than 1.96 (6.062 and 6.568, respectively) and p-values less than 0.05 (0.000 and 0.000, respectively). This means that improvement in accounting information systems and corporate governance has a direct positive effect on NFIQ

Further, NFIQ has a positive effect on DME (H3), as evident from the positive coefficient of 0.244 and the t-statistic of 4.793 (<1.96) and a p-value of 0.008 (<0.05). This highlights the contribution of better quality of NFI, facilitating a better decision-making process. Moreover, NFIQ also has a significant positive impact on NFP (H4), as indicated by the positive coefficient of 0.239 and t-statistic of 4.687 (<1.96), along with a p-value of 0.009 (<0.05), suggesting that quality NFI helps in better non-financial performance. Lastly, DME shows a positive relationship with NFP (H5) with a coefficient of 0.287 and t-statistic of 5.561 (<1.96) and a p-value of 0.000 (<0.05), implying effective decision-making results in better NFP among publicly listed companies.

4.4.1. Indirect relationship results

Hypotheses H6a and H6b examined whether the quality of corporate governance (CGQ) impacts

DMS and NFP through NFIQ's mediating effect. Concerning mediating effects, it is revealed that the indirect effect of CGQ on DME through NFIQ (H6a) is significant (coefficient = 0.114, t-statistic = 2.286 (>1.96), and p-value = 0.003 (<0.05)). This suggests that NFIQ could be a mediating variable in this relationship. Similarly, NFIQ exerts a significant mediating effect between CGQ and NFP (H6b, coefficient = 0.137, t-statistic = 2.110 (>1.96), and p-value = 0.006 (<0.05)). Hypotheses H6c and H6d tested whether accounting information system quality (AISQ) influences DMS and NFP through NFIQ's mediating effect. The mediation effect of NFIQ between AISQ and DME (H6c, coefficient = 0.182, t-statistic = 2.263 (>1.96), and p-value = 0.001 (<0.05)) is significant. This means that NFIQ can indicate the positive impact of AISQ on DME. NFIQ also shows a significant mediation effect between AISQ and NFP (H6d, coefficient = 0.109, T-statistics = 2.101(>1.96), and p-value = 0.004 (<0.05)). Hence, NFIQ mediates and significantly affects the relationship between AISQ-NFP.

5.4 Robustness tests

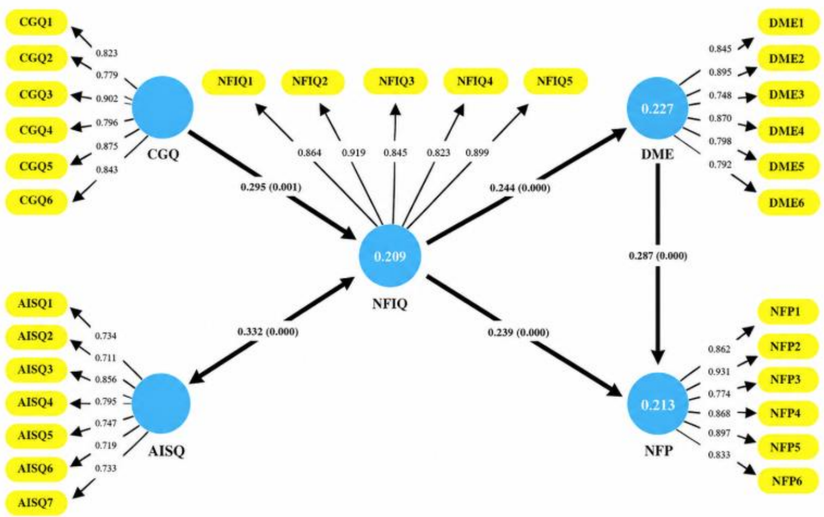
Supplementary analyses were performed to increase confidence in the results and obtain PLS-SEM estimates that are numerically stable. In a first step, bootstrapping (5,000 subsamples with replacement) was conducted to determine the significance of the path coefficients. Confidence intervals were specified at 95%. Initial values of the latent variables were set to 1 (equal weights), and all analyses were conducted with default settings of the software. Confidence intervals did not overlap, and path coefficients and significance levels were very similar to those presented above. In a second step, alternative specifications of the model were estimated. By dropping the mediating paths and indicators with low loadings from the model, the main relations remained statistically significant and of similar size. Third, the stability of the path coefficients and predictive power was tested using 10-fold cross-validation, and no differences were found in any of the folds. Finally, predictive relevance of the final model was assessed using out-of-sample prediction (blindfolding with an omission distance of 7), which produced Q^2 values >0 for key endogenous constructs (e.g., NFIQ, DME, NFP).

Table 6. Hypothesis testing results.

Hypo.	Latent Constructs Relationship	Path Coefficient	SD	T-statistics	P Value	Inference	Hypo. Testing	f^2
H1	CGQ ➔ NFIQ	0.295	0.087	6.062	0.000***	+ Significant	supported	0.154
H2	AISQ ➔ NFIQ	0.332	0.092	6.568	0.000***	+ Significant	supported	0.179
H3	NFIQ ➔ DME	0.244	0.098	4.793	0.008***	+ Significant	supported	0.181
H4	NFIQ ➔ NFP	0.239	0.091	4.687	0.009***	+ Significant	supported	0.178
H5	DME ➔ NFP	0.287	0.070	5.561	0.000***	+ Significant	supported	0.197
Mediating Effects of NFIQ								
H6a	CGQ ➔ NFIQ➔DME	0.114	0.093	2.286	0.003*	+ Significant	supported	0.129
H6b	CGQ ➔ NFIQ➔NFP	0.137	0.089	2.110	0.006*	+ Significant	supported	0.171
H6c	AISQ ➔ NFIQ➔DME	0.182	0.091	2.263	0.001*	+ Significant	supported	0.118
H6d	AISQ ➔ NFIQ➔NFP	0.109	0.087	2.101	0.004*	+ Significant	supported	0.173

Note: ***Significant on p < 0,01, **Significant p < 0,05, *Significant p < 0,1
f2 < 0.02 No effect size, 0.02 ≤ f2 < 0.15 Small effect size, 0.15 ≤ f2 < 0.35 Medium effect size

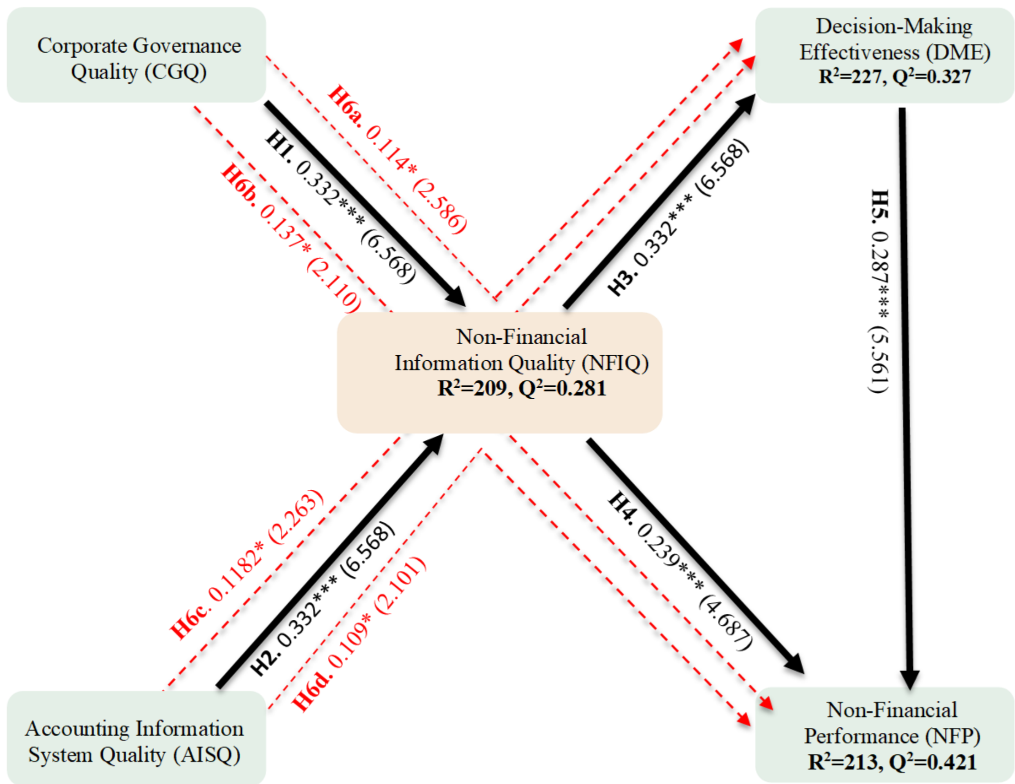
Source: created by the author



Note: Path coefficient, p-value, factor loading

Fig. 2: Structural model result

Source: created by the author



***Significant on p < 0.01, **Significant p < 0.05, *Significant p < 0.1
R^2 value represent the variance explained by the exogenous variables.
Q^2 value greater than 0 is indicative of predictive relevance of the research model

Source : created by the author

Fig. 3: Structural equation model analysis

6 Discussion

The results show that CG quality positively influences the NFI quality, supporting H1. Attributes of CG, such as diverse and independent boards, supervise the production of high-quality nonfinancial reports. This result is consistent with prior research and theoretical underpinnings ([2], [3], [24], [32], [34]. The results also indicate a strong positive correlation between AIS quality and NFI quality, supporting (Hypothesis H2). Organizations with robust AIS systems tend to produce better NFI. This study's results are similar to those of other studies ([1], [4], [59]). Additionally, these results align with [62], highlighting that quality AIS enhances both accounting information and overall financial performance. The correlation between AIS quality and NFI quality relates to decision-usefulness theory because stakeholders need information that helps them understand their decision-related needs. Quality AIS contributes to more accurate, dependable, and timely information. As a result, organizations that invest in their AIS create better NFI for stakeholders to use when making decisions. This helps improve financial reporting but takes it a step further by allowing an organization to craft an overall picture of information that stakeholders can feel confident about. Stakeholder theory explains how NFI strives to meet the needs of everyone with a vested interest in the company. These needs can range from ethical to social and environmental. By concentrating on improving AIS quality, an organization can improve the quality of NFI and ensure it relates to as many stakeholders as possible. Organizations can invest in better AIS technology and work with outside consultants to help improve what they currently have while maintaining the quality of data. Regular audits of AIS are essential for maintaining the integrity and reliability of financial information.

The results of this research practically suggest that higher CGQ has positive effects on NFIQ, as better governed organizations may have characteristics like an independent and diverse board of directors, which impacts quality disclosures related to environmental, social, and governance (ESG). As such, firms can increase their board of directors' diversity and independence to improve the quality of disclosures about sustainability or social responsibility matters in their annual reports. Likewise, organizations can increase their AIS sophistication by investing in technology with features like integrated reporting, which can help firms provide their stakeholders with more accurate and up-to-date information about non-financial items in a real-time manner. Higher levels of NFIQ can improve non-financial performances such as employee satisfaction, environmental impacts, and social responsibility.

The findings also demonstrate a significant positive relationship between NFI quality and DME. This finding indicates that high-quality NFI allows better decisions to be made, resulting in improved NFP. Hypotheses H3 and H4 are therefore supported. These findings are consistent with previous research that established high-quality NFI contributes towards effective decision-making ([4], [66], [68]) and improved performance ([4], [8], [20], [18]). The link between NFI quality and DME supports decision-usefulness theory's contention that providing decision-makers with reliable and relevant information will allow them to better assess their choices. Gaining an understanding of how the business will be affected by their decisions will help decision-makers make well-informed choices. The stakeholder theory also confirms that decisions that meet the needs of stakeholders are more likely to be sustainable. Businesses prioritizing NFI quality are likely to adopt a balanced decision-making approach, enhancing DME.

Additionally, a strong positive correlation between DME and NFP was established. This provides support to Hypothesis H5 and is consistent with previous research on corporate performance [4], [20], [37], [79]. Meaningful decisions based on quality information allow organizations to act and create plans that will enable them to meet stakeholder expectations and perform well on non-financial outcomes such as corporate social responsibility and stakeholder management. DME that is based on quality information will allow an organization to act on insights in ways that create value and meet stakeholder expectations. When decisions are made based on quality information, an organization can decide what actions will help it focus on creating non-financial outcomes that are favorable to the company. By combining decision usefulness theory with stakeholder theory, it can be concluded that making quality decisions (ones based on quality financial and non-financial information) will lead to better performance, as it allows a business to act in ways that will satisfy its stakeholders and show what the company values. Managerial training could help improve DME by allowing managers to better understand how to react to non-financial measurements. The use of decision support technology could allow businesses to better analyze data and create quality insights through AI and machine learning. These tools can simulate the impact of decisions on NFP indicators.

This study supports hypotheses H6a, H6b, H6c, and H6d. Confirming these hypotheses reveals that NFI quality is a critical mediator in how CG and AIS quality influence both DME and NFP. Multiple studies aligned with these results have empirically examined and confirmed similar findings regarding the mediating role of NFI between CGQ and DME and NFP ([20], [63], [84]), as well as between AISQ and DME and NFP ([4], [20], [83]). This suggests that while good governance structures and robust information systems are important, their positive effects on improving decisions and non-financial outcomes are primarily achieved by enabling the generation and use of high-quality non-financial data. Essentially, the study indicates that CG and AIS quality facilitate the production of reliable, relevant, and transparent NFI. This high-quality information then empowers better decision-making processes, leading to more effective outcomes (i.e., DME), and also allows for clearer communication and management of non-financial aspects, thereby improving NFP. Therefore, the focus for companies should not only be on governance and systems but also on ensuring the integrity and utility of the NFIs they produce.

The empirical findings of this research provide evidence for the decision-usefulness theory because they prove that when relevant, reliable, and timely information exists within organizations, then individuals are able to make better decisions that help organizations function more effectively. Since CGQ and AISQ were found to positively influence NFI quality, and NFI quality was found to positively impact DME and NFP, this suggests that high-quality information acts as an asset for the organizations that possess it. This strengthens decision-usefulness theory by showing that NFI plays a mediating role between CGQ/AISQ and performance outcomes. Additionally, the significant relationships found throughout this research also help to uphold stakeholder theory. Stakeholder theory elaborates on how organizations can establish trust with stakeholders by communicating and making stakeholders a priority. Because this study shows that when governance and system quality are high, information quality will also be high, it can be inferred that creating quality NFI for stakeholders to review helps organizations meet stakeholder demands and thus gain legitimacy and social capital.

This research contributes valuable insights to the academic literature by exposing a gap concerning the determinants of NFI quality and its influence on DME and NFP. It develops and tests a model that emphasizes the mediating role of NFI quality between CG, AIS, DME, and NFP. By highlighting this aspect, the study offers fresh insights into how high-quality NFI can be influenced by CG and AIS, thereby impacting DME and NFP. Furthermore, the study provides confirmation of Western theories in relation to emerging markets, specifically in the Middle East, and the need for further research to be carried out in Saudi Arabia as disclosure of NFI continues to develop.

The study has important ramifications for regulators, legislators, standard-setters, and managers. It emphasizes, first and foremost, the need for regulators to encourage AIS and NFI integration within current regulatory frameworks. Regulatory bodies can improve the quality of information available and the DME of organizations by establishing clear standards for NFI reporting. Second, creating supportive policies that motivate businesses to strengthen CG and invest in AIS and NFI of the highest caliber should be a top priority for policymakers. Offering incentives for implementing cutting-edge procedures and technologies that improve data relevance and accuracy could be one way to achieve this. Third, the increasing need for transparency in non-financial reporting also requires standard-setters to concentrate on bringing accounting standards into line with this demand. They can improve organizational performance and decision-making processes by developing guidelines that address the quality and applicability of NFI.

In order to improve DME, training should be utilized to develop managerial capabilities. Training could help managers better understand non-financial measures, perform environmental scans, and qualitatively analyze data. This training will create a connection between technical systems and decision-making. The training can cover both rational analysis and intuitive decision-making. Decision support technologies should also be embedded in the organization. Artificial intelligence and machine learning can analyze big data to identify patterns and provide decision-makers with insights. Technology can create models that show the consequences of decisions on certain NFPs, like employee morale or environmental impacts.

7 Conclusion

This study significantly extends the literature on the impacts of CG quality, AIS quality, and NFI quality on DME and NFP in Saudi Arabian organizations. Using PLS-SEM, it empirically validates the strong linkages between these constructs, illustrating how high-quality CG, AIS, and structured NFI contribute to decision-making practices and organizational performance. The findings emphasize that improved CG quality and AIS quality are essential for presenting relevant and accurate information to decision-makers, ultimately enhancing NFP.

Even though this study provides further addition to existing literature, there are still limitations in this study that should be addressed. First, because the sample only consists of organizations that operate within Saudi Arabia, the generalizability of this study may be limited to other countries with different cultures and/or economic developments. Also, since the research sample may not represent Saudi Arabia as a whole in terms of industry, generalizability to other industries may be limited and may not account for industry-specific factors. Second, since a cross-sectional research design was employed, this study only observes one point in time and the relationships between CG quality, AIS quality, NFI quality, DME, and NFP. For this reason, no causal relationship can be drawn, and no trends can be observed. Third, common method bias might be present since data were self-reported by participants. As individuals can have different opinions regarding the quality of their CG and AIS as well as the quality of their decisions, there might be a difference between what is reported and what is being practiced, which might overstate relationships. Lastly, this study did not consider external forces that impact CG quality and AIS quality. Organizational culture, regulation, and market conditions are external forces that influence CG and AIS quality and practices.

To overcome limitations with potential observed relationships being inflated, future research can utilize multiple sources of data or a longitudinal approach. This would also allow researchers to better understand how construct relationships may vary over time. Qualitative analysis could be used to uncover organizational idiosyncrasies and contextual factors that influence CG and AIS effectiveness and decision-making. Research can further broaden generalizability by increasing the sample size or sourcing participants from different types of industries. External validity can also be strengthened by studying external influences that affect AIS usage and implementation, such as governmental regulations, cultural norms, and technology. As technology continues to be adopted by firms, future researchers can study how emerging technologies like cloud accounting, AI, and Big Data can be leveraged to improve AIS quality and decision-making.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author used ChatGPT in order to improve the readability and language of the manuscript. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

References:

[1] Monteiro, A., Vale, J., Leite, E., & Lis, M. (2024). Linking quality of accounting information system and financial reporting to non-financial performance: The role women managers. *International Journal of Accounting Information Systems*, 54, 100692. https://doi.org/10.1016/J.ACCINF.2024.100692

[2] Dragomir, V. D., & Dumitru, M. (2023). Does corporate governance improve integrated reporting quality? A meta-analytical investigation. *Meditari Accountancy Research*, 31(6), 1846–1885. https://doi.org/10.1108/MEDAR-03-2022-1618

[3] Gerwing, T., Kajüter, P., & Wirth, M. (2022). The role of sustainable corporate governance in mandatory sustainability reporting quality. *Journal of Business Economics*, 92, 1–39. https://doi.org/10.1007/s11573-022-01092-x

[4] Monteiro, A., Vale, J., Leite, E., Lis, M., & Pysz, J. (2022). The impact of information systems and non-financial information on company success. *International Journal of Accounting Information Systems*, 45, 100557. https://doi.org/10.1016/j.accinf.2022.100557

[5] Abu Hussain, M., Alsayegh, M. F., & Boshnak, H. A. (2024). The impact of environmental, social, and governance disclosure on the performance of Saudi Arabian companies: Evidence from the top 100 non-financial companies listed on Tadawul. *Sustainability*, 16(17), 7660. https://doi.org/10.3390/SU16177660

[6] Sharawi, H. (2024). The impact of ESG disclosure on financial reporting quality: Evidence from KSA. *SSRN Electronic Journal*, 11(4), 98-108. https://doi.org/10.2139/SSRN.5092540

[7] Sievers, S., Mokwa, C., & Keienburg, G. (2012). The relevance of financial versus non-financial information for the valuation of venture capital-backed firms. *European Accounting Review*, 22(3), 467-511. https://doi.org/10.1080/09638180.2012.741051

[8] Abdullah Hadi, H., Bakar, A. N., Mohd Noor, N. H., & Ashfahany, A. El. (2022). The value of financial and non-financial information

towards non-profit organisations. *Environment-Behaviour Proceedings Journal*, 7(21), 349–355. https://doi.org/10.21834/EBPJ.V7I21.3693

[9] Paridhi, P.; Ritika, R. (2024). Sustainability reporting for boosting national commitment and overcoming challenges: A hierarchical model. *Business Strategy Development*, 7(1), 1-19. https://doi.org/10.1002/bsd2.334

[10] Ahmed, A. H., Elmaghrabi, M. E., Dunne, T., & Hussainey, K. (2021). Gaining momentum: Towards integrated reporting practices in Gulf Cooperation Council countries. *Business Strategy & Development*, 4(2), 78–93. https://doi.org/10.1002/BSD2.130

[11] Alatawi, M. S., Mat Daud, Z., & Johari, J. (2025). Integrated reporting and firm value: moderating role of CEO integrity in the context of GCC countries. *Cogent Business & Management*, 12(1), 2462273. https://doi.org/10.1080/23311975.2025.2462273

[12] Chehade, S., & Procházka, D. (2024). Value relevance of accounting information in an emerging market: the case of IFRS adoption by non-financial listed firms in Saudi Arabia. *Journal of Accounting in Emerging Economies*, 14(1), 220–246. https://doi.org/10.1108/JAEE-06-2022-0165

[13] Eccles, R. G., Ioannou, I., & Serafeim, G. (2014). The impact of corporate sustainability on organizational processes and performance. *SSRN Electronic Journal*, 60(11), 2835-2857 https://doi.org/10.2139/SSRN.1964011

[14] Monteiro, A. M., Vale, J. M., Cepêda, C. M., & de Almeida Leite, E. M. (2021). Internal control system quality and decision-making success: The role of the financial information quality. *Universal Journal of Accounting and Finance*, 9(3), 285-294. http://doi.org/10.13189/ujaf.2021.090302

[15] Ali, B., & Oudat, M. (2020). Information quality and data quality in accounting information system: Implications on the organization performance. *International Journal of Psychosocial Rehabilitation*, 24(5), 3258–3269.

[16] Qatawneh, A. (2020). Quality of accounting information systems and their impact on improving the non-financial performance of Jordanian Islamic banks. *Academy of Accounting and Financial Studies Journal*, 24(6), 1–19.

[17] Trabulsi, R. U. (2018). The impact of accounting information systems on organizational performance: The context of Saudi's SMEs. *International Review of Management and Marketing*, 8(2), 69–73.

[18] Abdelraheem, A., & Mubarak, A. (2022). The effect of application of non-financial dimensions of balanced scorecard on performance evaluation: An empirical study from Saudi Arabia. *The Journal of Asian Finance, Economics and Business*, 9(4), 63–72. https://doi.org/10.13106/JAFEB.2022.VOL9.NO4.0063

[19] Ortiz-Martínez, E., Marín-Hernández, S., & Santos-Jaén, J. M. (2023). Sustainability, corporate social responsibility, non-financial reporting and company performance: Relationships and mediating effects in Spanish small and medium sized enterprises. *Sustainable Production and Consumption*, 35, 349–364. https://doi.org/10.1016/J.SPC.2022.11.015

[20] Mondal, M. S. A., Akter, N., & Ibrahim, A. M. (2024). Nexus of environmental accounting, sustainable production and financial performance: An integrated analysis using PLS-SEM, fsQCA, and NCA. *Environmental Challenges*, 15, 100878. https://doi.org/10.1016/J.ENVC.2024.100878

[21] Tran Thanh Thuy, N. (2025). Effect of accounting information system quality on decision-making success and non-financial performance: does non-financial information quality matter? *Cogent Business & Management*, 12(1), 2447913. https://doi.org/10.1080/23311975.2024.2447913

[22] Freeman, R. Edward. (1984). Strategic management: a sakeholder approach. Boston, MA: Pitman.

[23] Staubus, G. J. (1999). *The decision-usefulness theory of accounting: A limited history*.Garland Publishing, New York.

[24] Turpin, S. M., & Marais, M. A. (2004). Decision-making: Theory and practice. *ORiON*, 20(2), 143–160. https://doi.org/10.5784/20-2-12

[25] Bui, H., & Krajcsák, Z. (2024). The impacts of corporate governance on firms' performance: from theories and approaches to empirical findings. *Journal of Financial Regulation and Compliance*, 32(1), 18–46. https://doi.org/10.1108/JFRC-01-2023-0012

[26] Velte, P. (2022). Does sustainable board governance drive corporate social responsibility? A structured literature review on European archival research. *Journal of Global Responsibility*, 14(1), 46-88. https://doi.org/10.1108/JGR-05-2022-0044

[27] Velte, P., & Stawinoga, M. (2020). Do chief sustainability officers and CSR committees influence CSR-related outcomes? A structured literature review based on empirical-quantitative research findings. *Journal of Management Control*, 31(4), 333–377. https://doi.org/10.1007/s00187-020-00308-x

[28] E-Vahdati, S., Zulkifli, N., & Zakaria, Z. (2018). Corporate Governance: The International Journal of Business in Society Corporate governance integration with sustainability: a systematic literature review. *Corporate Governance International Journal of Business in Society*, 19(2), 255–269. https://doi.org/10.1108/CG-03-2018-0111

[29] Lagasio, V., & Cucari, N. (2019). Corporate governance and environmental social governance disclosure: A meta- analytical review. *Corporate Social Responsibility and Environmental Management*, 26(4), 701–711. https://doi.org/10.1002/csr.1716

[30] Said, A. A., HassabElnaby, H. R., & Wier, B. (2003). An empirical investigation of the performance consequences of nonfinancial measures. *Journal of Management Accounting Research*, 15(1), 193–223. https://doi.org/10.2308/JMAR.2003.15.1.193

[31] Ntim, C., Soobaroyen, T., & Broad, M. (2015). Governance structures, voluntary disclosures and public accountability: The case of UK higher education institutions. *Accounting, Auditing & Accountability Journal*, 30(1), 65-118. https://doi.org/10.1108/AAAJ-10-2014-1842

[32] Vitolla, F., Raimo, N., Campobasso, F., & Giakoumelou, A. (2023). Risk disclosure in sustainability reports: Empirical evidence from the energy sector. *Utilities Policy*, 82, 101587 https://doi.org/10.1016/J.JUP.2023.101587,

[33] Cooray, T., Gunarathne, N., & Senaratne, S. (2020). Does Corporate Governance Affect the Quality of Integrated Reporting? *Sustainability*, 12(10), 4262. https://doi.org/10.3390/su12104262

[34] Donkor, A., Djajadikerta, H. G., & Mat Roni, S. (2021). Board gender diversity and integrated reporting quality: evidence from South Africa. *Accountancy Business and the Public Interest*, 20, 248–265.

[35] Yilmaz, M. K., Hacioglu, U., Tatoglu, E., Aksoy, M., & Duran, S. (2023). Measuring the impact of board gender and cultural diversity on corporate governance and social performance: evidence from emerging markets. *Economic Research-Ekonomska Istraživanja*, 36(2), 2106503 https://doi.org/10.1080/1331677X.2022.2106503

[36] Eberhardt-Toth, E. (2017). Who should be on a board corporate social responsibility committee? *Journal of Cleaner Production*, 140, 1926–1935. https://doi.org/10.5465/ambpp.2014.16709abstract

[37] Baugh, M., Ege, M. S., & Yust, C. G. (2021). Internal control quality and bank risk-taking and performance. *Auditing: A Journal of Practice & Theory*, 40(2), 49–84. https://doi.org/10.2308/AJPT-19-037

[38] Phornlaphatrachakorn, K. (2019). Internal control quality, accounting information usefulness, regulation compliance, and decision-making success: Evidence from canned and processed foods businesses in Thailand. *International Journal of Business*, 24(2), 199–215.

[39] Jokipii, A. (2010). Determinants and consequences of internal control in firms: a contingency theory based analysis. Journal of Management & Governance, 14, 115–144.

[40] Bauer, A., Henderson, D., & Lynch, D. (2017). Supplier Internal Control Quality and the Duration of Customer-Supplier Relationships. *The Accounting Review*, 93(3), 59-82. https://doi.org/10.2308/accr-51889

[41] Bozzolan, S., & Miihkinen, A. (2019). The Quality of Mandatory Non-Financial (Risk) Disclosures: The Moderating Role of Audit Firm and Partner Characteristics. *The International Journal of Accounting (TIJA)*, 56(02), 1-55. *https://doi.org/10.1142/S1094406021500086*

[42] Frazer, L. (2020). Does internal control improve the attestation function and by extension assurance services? A practical approach. *Journal of Accounting and Finance*, 20(1), 28-38. https://doi.org/10.33423/JAF.V20I1.2739

[43] Gal, G., & Akisik, O. (2020). The impact of internal control, external assurance, and integrated reports on market value. *Corporate Social Responsibility and Environmental Management*, 27(3), 1227–1240. https://doi.org/10.1002/CSR.1878,

[44] Orens, R., & Lybaert, N. (2010). Determinants of sell- side financial analysts' use of non-financial information. *Accounting and Business Research*, 40(1), 39–53. https://doi.org/10.1080/00014788.2010.9663383

[45] Haller, A., Link, M., & Groß, T. (2017). The term 'non-financial information' – A semantic analysis of a key feature of current and future corporate reporting. *Accounting in Europe*, 14(3), 407–429. https://doi.org/10.1080/17449480.2017.1374548

[46] Tarquinio, L., & Posadas, S. C. (2020). Exploring the term "non-financial information": an academics' view. *Meditari Accountancy Research*, 28(5), 727–749. https://doi.org/10.1108/MEDAR-11-2019-0602

[47] Banker, R., Potter, G., & Srinivasan, D. (2000). An empirical investigation of an incentive plan that includes nonfinancial performance. *International Conference on Contemporary Accounting Issues*, 75(1), 65–92. https://doi.org/10.2308/accr.2000.75.1.65

[48] Meek, G. K., Roberts, C. B., & Gray, S. J. (1995). Factors influencing voluntary annual report disclosures By U.S., U.K. and continental European multinational corporations. *Journal of International Business Studies*, 26(3), 555–572.

[49] Upton, W. (2001). *Special Report From FASB: Business and Financial Reporting, Challenges from the New Economy. Financial Accounting Standards Board*, Norwalk, Connecticut, MA.

[50] Manes-Rossi, F., Tiron-Tudor, A., Nicolò, G., & Zanellato, G. (2018). Ensuring more sustainable reporting in Europe using non-financial disclosure—De facto and de jure evidence. *Sustainability*, 10(4), 1162. https://doi.org/10.3390/SU10041162

[51] Cohen, J. R., Holder-Webb, L. L., Nath, L., & Wood, D. (2012). Corporate reporting of nonfinancial leading indicators of economic performance and sustainability. *Accounting Horizons*, 26(1), 65–90. https://doi.org/10.2308/ACCH-50073

[52] Barbosa, F., Monteiro, A. P., & Pereira, C. (2021). Determinants of environmental responsibility disclosure on mandatory and voluntary reporting of Portuguese listed firms. *Journal of Environmental Accounting and Management*, 9(3), 219–233. https://doi.org/10.5890/JEAM.2021.09.003

[53] Flöstrand, P., & Ström, N. (2006). The valuation relevance of non-financial information. *Management Research News*, 29(9), 580–597. https://doi.org/10.1108/01409170610709014

[54] Callen, J. L., Gavious, I., & Segal, D. (2010). The complementary relationship between financial and non-financial information in the biotechnology industry and the degree of investor sophistication. *Journal of Contemporary Accounting & Economics*, 6(2), 61–76. https://doi.org/10.1016/J.JCAE.2010.09.001

[55] Barker, R., & Eccles, R. G. (2018). Should FASB and IASB be responsible for setting standards for nonfinancial information? *SSRN Electronic Journal*, 1-43. https://doi.org/10.2139/SSRN.3272250

[56] Rezaee, Z., & Tuo, L. (2019). Are the quantity and quality of sustainability disclosures associated with the innate and discretionary earnings quality? *Journal of Business Ethics*, 155(3), 763–786. https://doi.org/10.1007/S10551-017-3546-Y

[57] Romney, M., Steinbart, P., Summers, S., & Wood, D. (2017). *Accounting information systems*. Pearson Education Limited. Jakarta: Salemba Empat.

[58] Malmi, T., & Granlund, M. (2009). In search of management accounting theory. *European Accounting Review*, 18(3), 597–620. https://doi.org/10.1080/09638180902863779

[59] DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems*, 19(4), 9–30. https://doi.org/10.1080/07421222.2003.11045748

[60] Fitriati, A., & Mulyani, S. (2015). The influence of leadership style on accounting information system success and its impact on accounting information quality. *Research Journal of Finance and Accounting*, 6(11), 167-173.

[61] Binha, V. T. T., Tranb, N. M., Thanhc, D. M., & Phamd, H. H. (2020). Firm size, business sector and quality of accounting information systems: Evidence from Vietnam. Accounting, 6(3), 327–334. https://doi.org/10.5267/J.AC.2020.2.002

[62] Fitrios, R., Suharman, H., Susanto, A., & Soemantri, R. (2018). The influence of environmental uncertainty on the accounting

information system quality and its impact on the accounting information quality. *Journal of Theoretical and Applied Information Technology*, 96(21), 7164–7175.

[63] Al Tarawneh, E. M., Alqaraleh, M. H., Ali, B. J. A., & Atta, A. A. B. (2023). The impact of the efficiency and effectiveness of electronic accounting information systems on the quality of accounting Information. *Information Sciences Letters*, 12(3), 1685–1692. https://doi.org/10.18576/ISL/120352

[64] Al-Hattami, H. M., & Kabra, Jawahar. D. (2019). The role of accounting information system (AIS) in rationalizing human resource related decisions: A case study of selected commercial banks in Yemen. *International Journal of Management Studies*, VI (2), 84-91.

[65] Anggraeni, A. F., & Winarningsih, S. (2021). The effects of accounting information system quality on financial performance. Economic Annals-XXI, 193(9–10), 128–133. https://doi.org/10.21003/EA.V193-16

[66] Binh, V. T., Tran, N. M., & Vu, M. C. (2022). The effect of organizational culture on the quality of accounting information systems: Evidence from Vietnam. *SAGE Open*, 12(3), 215824402211215. https://doi.org/10.1177/21582440221121599

[67] Monteiro, A., Cepêda, C., Silva, A., Leite, E., & Camacho, É. (2021). The role of accounting information in decision-making and companies' sustainability development: the Portuguese accountants' perspective. *Entrepreneurship and Sustainability Issues*, 9(1), 486–501. https://doi.org/10.9770/JESI.2021.9.1(30)

[68] Fitriati, A., & Susanto, A. (2017). The accounting information system quality improvement through internal control and top management support effectiveness. *Journal of Theoretical and Applied Information Technology*, 95(19), 5003–5011.

[69] Cepeda, C., & Monteiro, A. (2020). The Accountant's Perception of the Usefulness of Financial Information in Decision Making – A Study in Portugal. *Review of Business Management*, 22, 363–380. https://doi.org/10.7819/rbgn.v22i2.4050

[70] Shahsavarani, A., Azad, E., & Abadi, M. (2015). The bases, principles, and methods of decision-making: A review of literature. *International Journal of Medical Reviews*, 2(1), 214–225.

[71] Buljubašić, E., & Ilgùn, E. (2015). Impact of accounting information systems on decision making case of Bosnia and Herzegovina. *European Researcher*, 96(7), 460–469. https://doi.org/10.13187/ER.2015.96.460

[72] Athanasou, J. A., & Perera, H. N. (2020). *International handbook of career guidance (second edition)*. Springer.

[73] Gati, I., & Kulcsár, V. (2021). Making better career decisions: From challenges to opportunities. *Journal of Vocational Behavior*, 126, 103545. https://doi.org/10.1016/J.JVB.2021.103545

[74] Ahmad, K., & Zabri, S. M. (2016). The application of non-financial performance measurement in Malaysian manufacturing firms. *Procedia Economics and Finance*, 35, 476–484. https://doi.org/10.1016/S2212-5671(16)00059-9

[75] Bititci, U., Garengo, P., Dörfler, V., & Nudurupati, S. (2012). Performance Measurement: Challenges for Tomorrow. *International Journal of Management Reviews*, 14(3), 305–327. https://doi.org/10.1111/J.1468-2370.2011.00318.X

[76] Laskin, A. V. (2016). Nonfinancial Information in Investor Communications. *International Journal of Business Communication*, 53(4), 375–397. https://doi.org/10.1177/2329488414525458

[77] Boulianne, E. (2007). Revisiting fit between AIS design and performance with the analyzer strategic-type. *International Journal of Accounting Information Systems*, 8(1), 1–16. https://doi.org/10.1016/J.ACCINF.2006.12.001

[78] Farneti, F., Guthrie, J., & Canetto, M. (2019). Social reports of an Italian provincial government: a longitudinal analysis. *Meditari Accountancy Research*, 27(4), 580–612. https://doi.org/10.1108/MEDAR-11-2018-0397

[79] Soudani, S. N. (2012). The usefulness of an accounting information system for effective organizational performance. *International Journal of Economics and Finance*, 4(5), 136–145. https://doi.org/10.5539/IJEF.V4N5P136

[80] Hung, B. Q., Hoa, T. A., Hoai, T. T., & Nguyen, N. P. (2023). Advancement of cloud-based accounting effectiveness, decision-making quality, and firm performance through digital transformation and digital leadership: Empirical evidence from Vietnam. *Heliyon*,

9(6), e16929. https://doi.org/10.1016/J.HELIYON.2023.E16929

[81] Patel, S. B. (2015). Effects of accounting information system on Organizational Profitability. *International Journal of Research and Analytical Reviews*, 2(1), 72–76.

[82] Goll, I., & Rasheed, A. A. (2005). The Relationships between top management demographic characteristics, rational decision making, environmental munificence, and firm performance. *Organization Studies*, 26(7), 999–1023. https://doi.org/10.1177/0170840605053538

[83] Lussier, R. N., & Kimball, D. C. (2004). *Applied sport management skills (2nd ed).* Champaign, IL: Human Kinetics.

[84] Sunarta, I. N., & Partiwi Dwi, A. (2023). The influence quality accounting information systems, quality accounting information, and decision-making success. *Journal of Economics, Finance and Management Studies*, 6(1), 358–366. https://doi.org/10.47191/jefms/v6-i1-40

[85] Lilis, P., & Sri Dewi, A. (2019). The influence of the quality accounting information system to the quality of accounting information—Evidence in Indonesia. Majalah Ilmiah UNIKOM, 17(1), 3–12. https://doi.org/10.34010/MIU.V17I1.2228

[86] Omran, M., Khallaf, A., Gleason, K., & Tahat, Y. (2019). Non-financial performance measures disclosure, quality strategy, and organizational financial performance: A mediating model. *Total Quality Management & Business Excellence*,32(5-6), 652–675. https://doi.org/10.1080/14783363.2019.1625708

[87] Achi, A., Adeola, O., & Achi, F. C. (2022). CSR and green process innovation as antecedents of micro, small, and medium enterprise performance: Moderating role of perceived environmental volatility. *Journal of Business Research*, 139, 771–781. https://doi.org/10.1016/j.jbusres.2021.10.016

[88] Gerged, A. M., Zahoor, N., & Cowton, C. J. (2024). Understanding the relationship between environmental management accounting and firm performance: The role of environmental innovation and stakeholder integration – Evidence from a developing country. *Management Accounting Research*, 62, 1-14. https://doi.org/10.1016/J.MAR.2023.100865

[89] Hoai, T. T., & Nguyen, N. P. (2022). Internal control systems and performance of emerging market firms: The moderating roles of leadership consistency and quality. *SAGE Open*, 12(3), 1-14. https://doi.org/10.1177/21582440221123509

[90] Alsulami, F. (2023). Non-financial risk disclosure practice: Evidence from Saudi Arabian listed companies. *Corporate & Business Strategy Review*, 4(4), 121–143. https://doi.org/10.22495/cbsrv4i4art12

[91] Barclay, D., Higgins, C., & Thompson, R. (1995). The partial least squares (PLS) approach to causal modelling personal computer adoption and use as an illustration. *Technology Studies*, 2(2), 285–309.

[92] Comrey, A. Laurence., & Lee, H. B. (1992). *A first course in factor analysis (2nd ed.).* Lawrence Erlbaum Associates.

[93] Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate Data Analysis (7th Edition).* Pearson Education, Upper Saddle River, NJ.

[94] Zikmund, W. G., Babin, B. J., Carr, J. C., & Griffin, M. (2013). *Business Research Methods*, 9th Edition, International Edition. South-Western: Australia.

[95] Phornlaphatrachakorn, K. (2020). Accounting control system, accounting information quality, value creation, and firm success: An empirical investigation of auto parts businesses in Thailand. *International Journal of Business*, 25(2), 159–177.

[96] Kock, N. (2015). Common Method Bias in PLS-SEM: A Full Collinearity Assessment Approach. International *Journal of e-Collaboration*, 11(4), 1-10. https://doi.org/10.4018/ijec.2015100101

[97] Karim, K. S., Islam, M., Pan, S.-H., & Ibrahim, A. (2024). Online marketing trends and purchasing intent: Advances in customer satisfaction through PLS-SEM and ANN approach. *Advances in Decision Sciences*, 27(4), 24–54. https://doi.org/10.47654/v27y2023i4p24-54

[98] Fakhreddin, F. (2023). *Nonresponse bias and common method bias in survey research. In Researching and analysing business (pp. 275–282). Routledge*. https://doi.org/10.4324/9781003107774-21

[99] Rocha, M., Miranda, C., and De Miranda, M. (2024). Handling Outliers in Panel Data Models. *WSEAS Transactions on Systems*, 23, 306-313. https://doi.org/10.37394/23202.2024.23.34

[100] Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18(1), 39-50. https://doi.org/10.2307/3151312

[101] Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. Technological Forecasting and Social Change, 173, 1-11. https://doi.org/10.1016/J.TECHFORE.2021.121092

[102] Hair, J. F., Tomas, G., Hult, M., Ringle, C. M., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) (Third edition)*. Thousand Oaks, CA: Sage.

[103] Sarstedt, M., Ringle, C. M., Cheah, J. H., Ting, H., Moisescu, O. I., & Radomir, L. (2020). Structural model robustness checks in PLS-SEM. *Tourism Economics*, 26(4), 531–554. https://doi.org/10.1177/1354816618823921

[104] Falk, R. F., & Miller, N. B. (1992). *A primer for soft modeling*. University of Akron Press, Akron , OH.

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