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How Does Big Data Mining Affect Financial Reporting Quality in Saudi Banks? A Mediated and Moderated Model

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Abstract

High quality of financial reports is crucial to fostering transparency, boosting market reliability, and facilitating efficient decision-making in the banking industry, especially in growing markets like Saudi Arabia. Although reforms in regulation and the adoption of International Financial Reporting Standards (IFRS), financial reporting quality (FRQ) still an ongoing challenge due to data complexity, risk management techniques, and regulatory capability. The present research investigates the mediating role of Enterprise Risk Management (ERM) and the moderating role of IT readiness in the relationship between big data mining (BDM) and financial reporting quality in the Saudi banking sector. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), the findings demonstrate that mining of big data has a significant effect on FRQ and significantly improves ERM practices. Furthermore, Enterprise Risk Management has been shown to strongly moderate the association between BDM and financial reporting quality, emphasizing its importance in turning data-driven insights into better reporting outcomes. Yet, IT readiness has insignificant impact in BDM–FRQ nexus, implying that technology alone is not a sufficient condition for improving financial reporting quality. This article suggests that banks should integrate big data analytics into complete enterprise risk management frameworks rather than relying exclusively on technological investments. By emphasizing the necessity of integrating big data analytics within enterprise risk management to boost financial reporting quality and further the goals of Saudi Vision 2030, these outcomes have significant implications for bank managers and policymakers.

Keywords: Big Data Mining, Financial Reporting Quality, Enterprise Risk Management, IT Readiness, Saudi Arabia

Introduction

High quality of financial reporting is essential for the efficiency, transparency, and stability of financial systems. The quality of financial reporting reflects how accurately financial data represents a company's economic performance and risk exposure, enabling investors, regulators, and other stakeholders to make informed decisions (Herath & Albarqi, 2017; Dechow et al., 2010). In the banking system, inadequacies in financial reporting can disguise the true magnitude of risk, erode market discipline, and aggravate systemic vulnerabilities, raising the possibility of financial instability (Alsaadi et al., 2021; Bushman, 2014). Notwithstanding the broad adoption of the IFRS, literature indicates that enhanced reporting quality is not granted, especially in emerging countries, and depends extensively on institutional quality, governance, enforcement strength, and internal corporate information processing capabilities (Ball et al., 2015; Tang et al., 2016).

The International Monetary Fund (2022) identifies information inconsistencies and weak disclosure as key weaknesses in the Gulf Cooperation Council (GCC) countries, particularly during economic crises. The Kingdom of Saudi Arabia is a particularly significant case study, being one of the region's largest economies and the only member of the G20. The Kingdom has implemented vital financial reforms, including the adoption of the IFRS for financial institutions in 2010 and for listed companies in 2017, enhancing transparency and investor confidence (Chen et al., 2010; Almansour, 2019). Though, evidence suggests that the quality of financial reporting particularly in the banking sector remains uneven (Almoqren & Altayar, 2016; Boreik et al., 2023). Saudi banks possess more than 70% of the financial sector's total assets (Saudi Central Bank, 2024); thus, poor financial reporting is still a significant risk to financial stability, capital market growth, and the aims of Saudi Vision 2030.

The fast growth of digital banking and financial technology has resulted in vast amounts of both organized and unstructured data. worldwide, the banking sector generates around 2.5 quintillion bytes of data everyday, surpassing the capacity of conventional accounting and reporting systems and raising the risk of reporting delays, inaccuracies, and inadequate disclosures (McKinsey Global Institute, 2021). As a result, big data mining has become a crucial capability of organizations which allows banks process complicated datasets in real time, strengthen risk assessment, improve fraud detection, increase audit effectiveness, and support more accurate managerial decision-making, which are essential components of high-quality of financial reporting (Jan, 2018; Sharma & Panigrahi, 2013; Saleh et al., 2023).

Empirical research illustrates that banks using advanced analytics of data enhance the quality of their financial reporting by improving earnings predictability, strengthening internal controls, and making timely financial disclosures (Metair & Emary, 2022; Sihombing et al., 2023). Benefits of big data mining are still not evenly distributed throughout the Saudi banking industry, despite significant investment. Even though the industry spent more than USD 6.8 billion on technology in 2023 (Statista, 2024), the efficient application of advanced analytics is still constrained by enduring issues with data governance, system integration, legacy platforms, and organizational readiness (Alzaidi, 2018; Almoqren & Altayar, 2016). As a result, using BDM technologies alone does not guarantee better financial reporting. This emphasizes the necessity of looking at the organizational frameworks that allow BDM to be successfully used to improve the caliber of financial reporting in the Saudi banking industry.

Furthermore, enterprise risk management plays a critical role in boosting internal controls, governance, and reporting discipline and offers a thorough framework for recognizing, evaluating, and managing risks throughout the business (Cohen et al., 2017). The fact that risk management procedures are still dispersed, reactive, and inadequately incorporated into financial reporting and strategic planning procedures is a significant problem for many banks, especially in emerging countries (Kao et al., 2015; Adesango and Mahaka, 2017). Financial data analysis insights may stay unused in the absence of an efficient ERM, leading to inadequate risk disclosure and little increase in reporting quality. From the standpoint of resources, ERM is a unique and valuable organizational skill that supports financial reporting integrity, accountability, and transparency (Barney, 1991). As a result, the ERM is critical in this study since it reflects the way by which a BDM affects financial reporting quality. An ERM system allows banks to convert analytical results into precise, dependable, and consistent financial reports by incorporating data-driven insights into organized risk governance frameworks (Novatiani et al., 2022). Investments in data analytics are unlikely to produce noticeable increases in the caliber of financial reports without a strong ERM system.

Even with advanced analytics of data and risk management frameworks, banks' ability to improve the quality of financial reporting depends largely on their readiness of information technology level. Information technology readiness (ITR) in Saudi Arabia remains uneven due to legacy systems, weak integration, and a lack of advanced IT capabilities (Al-Muqrin & Al-Tayyar, 2016; Al-Zaydi, 2018). Despite Saudi Arabia’s heavy investment in information and communication technologies (ICTs), the World Economic Forum’s 2023 report indicates that the digital maturity of the financial sector still lags behind that of advanced economies. Empirical studies show that strong IT readiness improves the accuracy, timeliness, and reliability of reporting by enabling effective data integration, verification, and automated controls, while weak IT readiness limits the effectiveness of big data mining, leading to reporting delays and inefficient analysis (Talha et al., 2022; Saleh et al., 2023). Therefore, this study defines IT readiness as a critical intermediate condition that determines the extent to which big data mining translates into higher-quality financial reporting. This study is motivated by limited evidence on how big data mining improves financial reporting quality in emerging banking sectors, especially in Saudi Arabia’s rapidly digitalizing banking environment.

The main objective of this study, thus, is to explore the affect of big data mining on the quality of financial reporting in Saudi banks by investigating the role of enterprise risk management and IT readiness as mediation and moderation variables, respectively.
Consequently, this article makes at least three distinct contributions to the existing literature. Firstly, this article broadens the scope of research on financial reporting quality through exploring beyond traditional determinants like corporate governance, accounting standards, and audit quality to provide empirical evidence on the role of big data mining, which is largely unexplored, particularly in emerging economies' banking sectors. Second, this study expands research by recognizing ERM as an essential procedure that acts as a mediation between BDM and improved financial reporting quality. Third, the present study investigates the moderation influence of IT readiness and BDM to figure out if IT readiness has a meaningful indirect effect on FRQ, which has not yet been researched. Finally, it focuses on the Saudi banking sector from a strategically important emerging market that is undergoing rapid

regulatory and digital transformation within the framework of Saudi Vision 2030, as well as policy visions for regulators and specialists in the banking sector.
The remainder of the paper is organized as follows. The second part discusses the relevant literature and theoretical basis. The third section explains the method and data. The fourth section outlines and analyzes the empirical results. The study's final section summarize the paper and present policy implications as well as research constraints.

Literature Review and Hypotheses Development

Big Data Mining and Enterprise Risk Management

Big data mining is an advanced organizational capability, which allows companies to collect, process, and analyze large magnitude of organised and unstructured data in real period. According to Resource Theory (RBV), valuable, scarce, and distinctive competences like data analytics improve organizational processes and performance (Barney, 1991). The BDM in banks improves risk identification, monitoring, and prediction by converting raw transaction data into actionable risk intelligence. Previous empirical research has shown that the BDM plays an important role in enhancing risk management. The study of Cao et al. (2015) and Gu (2022) found that sophisticated analytics improves enterprise-level risk identification and allows for proactive responses to emerging threats. Similarly, Wang et al. (2011) and Zhang (2022) illustrated that data-driven risk management systems enable banks to combine operational, financial, and regulatory concerns into a single framework. In the Saudi banking sector, where risks are exacerbated by rapid digital transformation and regulatory requirements, data creation aids enterprise risk management by improving early warning systems, internal controls, and audit efficiency.

Yet, effectiveness of the ERM is determined not just by data availability, but also by how analytical findings are integrated into formal organizational risk management frameworks. Banks that incorporate data development into their integrated the ERM frameworks are better positioned to improve risk governance and reporting discipline. Consequently, this article demonstrated that data generation improves the effectiveness of ERM.
H1. Big Data Mining has a positive effect on Enterprise Risk Management.

Enterprise Risk Management and Financial Reporting Quality

Enterprise Risk Management offers a comprehensive framework for identifying, evaluating, and managing risks across corporate functions. ERM boosts governance systems, improves internal controls, and enforces accountability all of which are necessary for high quality of financial reporting. According to the theory of RBV, enterprise risk management is a strategic organizational capability that improves information integrity and transparency (Barney, 1991). Empirical literature consistently shows a significant association between ERM and the quality of financial reporting. The study of Cohen et al. (2017) indicated that organizations with mature ERM systems have better reporting discipline and a decreased probability of deception. Also, Novatiani et al. (2022) discovered that implementing ERM increases disclosure quality and reporting reliability in emerging markets. Similarly, Wadisango and Mahaka (2017) demonstrated that integrated ERM increases the effectiveness of internal audits while decreasing information discrepancies. In the banking industry, efficient enterprise risk management ensures that financial risks such as credit, liquidity, and operational risks are appropriately reflected in financial statements. The accuracy, timeliness, and dependability of disclosures are enhanced by this alignment between risk management

and FRQ. Therefore, it is anticipated that enterprise risk management will directly and favorably contribute to improving the quality of financial reports.
H2. Enterprise Risk Management has a positive effect on Financial Reporting Quality.

Big Data Mining and Financial Reporting Quality
Big data mining has arisen as a crucial technological factor impacting the accuracy of financial reporting, particularly in data-intensive segments like banking. By providing continuous monitoring, anomaly detection, and predictive analytics, big data mining improves the accuracy, completeness, and timeliness of financial data. From a resource and capability theory perspective, big data mining is a strategic analytical capability that enhances decision-making and reporting outcomes. Previous research provides empirical support for this relationship. The study by Jan (2018) and Sharma and Panigrahi (2013) confirmed that data mining techniques can significantly improve fraud detection and reduce reporting errors. As well, Metair and Emary (2022) found that banks using big data mining improve reporting accuracy and risk prediction. More recently, Saleh et al. (2023) and Sehombing et al. (2023) demonstrated how big data analytics improves audit quality and financial transparency. Due to organizational and infrastructural limitations, the direct impact of BDM on FRQ in Saudi Arabia is still unequal despite significant expenditures in digital technologies. However, banks that successfully implement BDM are better equipped to handle big datasets, enhance internal controls, and generate more trustworthy financial reporting. Consequently, it is anticipated that BDM will directly improve FRQ.
H3. Big Data Mining has a positive effect on Financial Reporting Quality.

Mediating Effect of Enterprise Risk Management
Although BDM improves analytical capabilities, it is unlikely to have an automatic effect on the quality of financial reporting. Instead, internal organizational procedures that convert data insights into better reporting are what determine its efficacy. By integrating analytics into organized risk governance and control systems, ERM offers this essential tool. ERM uses RBV and mediation theory (Baron & Kenny, 1986) to describe how BDM affects FRQ by transforming analytical results into risk-aware reporting procedures. This mechanism is supported by empirical evidence. Analytics-driven ERM increases reporting integrity by bolstering internal controls and compliance monitoring, as demonstrated by Cao et al. (2015) and Guo (2022). Additionally, Novatiani et al. (2022) affirm that ERM serves as a useful channel for improving reporting quality through technological capabilities. ERM is essential to ensuring that BDM insights are methodically applied to reporting procedures in the Saudi banking industry, where risk management standards are still developing. Therefore, the link between BDM and FRQ is anticipated to be mediated by ERM.
H4. Enterprise Risk Management mediates the relationship between Big Data Mining and Financial Reporting Quality.

The Moderating Role of IT Readiness
IT readiness refers to an organization's ability to provide the infrastructure, integration, security, and technical capabilities needed to support digital projects. According to Contingency Theory, the efficiency of organizational capacities is determined by contextual factors such as technological preparedness. Empirical studies found that IT readiness is an important enabler of big data initiatives. The work by Talha et al. (2022) and Saleh et al. (2023) demonstrated that a robust IT infrastructure improves data integration, automation, and

reporting accuracy. Conversely, poor IT readiness limits the benefits of analytics, resulting in reporting delays and data inconsistencies. According to evidence from Saudi Arabia, old systems, low cloud adoption, and talent shortages continue to impede digital efficiency (Alzaidi 2018). Consequently, readiness of IT is predicted to enhance BDM's favorable influence on FRQ by allowing for efficient data processing and system integration. Banks with stronger IT readiness can better use BDM capabilities to improve reporting quality.
H5. IT Readiness positively moderates the relationship between Big Data Mining and Financial Reporting Quality

Methodology
The present study adopts a quantitative research design with a deductive approach, focusing on the banking sector in Saudi Arabia as the population of interest. This sector was selected due to its strategic role in the national economy and its relevance to financial reporting practices. Data were collected through a structured questionnaire based on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The instrument has been widely used in prior academic research (e.g., Al-Hazaima et al., 2025; Alhasnawi et al., 2024). To ensure content validity, the questionnaire was reviewed by academic experts, and a pilot test was conducted with a small group of respondents. Reliability was later confirmed using Cronbach’s alpha during the analysis stage. Sampling technique: A purposive sampling method was applied to target professionals working in accounting, finance, and auditing departments within Saudi banks, as they are directly engaged with financial reporting practices. Ethical considerations were strictly observed: informed consent was obtained from each participant, and anonymity and confidentiality were ensured throughout the process (Khoa, 2023). To determine the minimum sample size, G*Power software was used (Hair et al., 2017), which indicated that at least 129 respondents were required to achieve a power of 0.80 for the proposed framework. The final number of valid responses retained for analysis was 505, which comfortably exceeds the minimum requirement and thus enhances the generalizability and robustness of the findings. Data collection process: The researcher personally distributed 610 questionnaires between January and May 2023. Of these, 534 were returned, representing a response rate of 87.5%. After excluding incomplete responses and statistical outliers, 505 valid and complete questionnaires (85.5%) were included in the final dataset.

Measures
The independent variable of this study is BDM, which comprises four dimensions: external environment, internal environment, operational management, and strategic decision-making. These four dimensions of BDM were adapted from Chahadah et al. (2018). The mediating variable is ERM, which includes eight dimensions: internal environment, objective setting, event identification, risk assessment, risk responses, control activities, information and communication, and monitoring. These eight dimensions of ERM were adapted from Saeidi et al. (2019). The moderating variable is ITR, which consists of four dimensions: optimism, innovation, discomfort, and insecurity. These dimensions were adapted from Berndt et al. (2010). Finally, FRQ was measured based on the qualitative characteristics of financial statements, namely relevance, faithful representation, understandability, and comparability. This construct was measured using a four-item scale adopted from Abed et al. (2022). See Appendix A for full questionnaire items and parts.

Sample Descriptive

The survey gathered data from 505 participants, providing an overview of their demographic characteristics across gender, age, education, job position, and work duration. As shown in Table 1, 287 males (56.8%) and 218 females (43.2%) completed the survey, indicating a predominantly male response with notable female participation. Regarding age, 152 participants (30.1%) were aged below 30, 100 (19.8%) were between 30 and 39, 160 (31.7%) were between 40 and 49, and 93 (18.4%) were above 49, reflecting both younger and experienced respondents. In terms of education, the majority held a Bachelor's degree (421, 83.4%), followed by Diploma (32, 6.3%), Master's (32, 6.3%), and PhD holders (20, 4%), indicating a largely undergraduate but overall well-educated sample. Concerning job position, 175 (34.7%) were in Accounting & Auditing, 162 (32.1%) in Finance, 65 (12.9%) in IT, 59 (11.7%) in Computer Science, and 44 (8.7%) in Economics, highlighting the interdisciplinary nature of the respondents. Regarding work experience, 213 participants (42.2%) had between 5 and 10 years, 190 (37.6%) had 10–15 years, 34 (6.7%) had less than 5 years, and 68 (13.5%) had more than 15 years of experience, indicating a balanced distribution across career stages. This demographic breakdown offers insights into the qualifications, experience, and professional diversity of participants in the study of financial reporting quality in the banking sector.

Table 1.
Demographic Characteristics of Participants

n = 505	Demographic characteristics	Frequency	Percentage (%)
Gender	Male	287	56.8%
	Female	218	43.2%
Age	less than 30	152	30.10%
	30 to 39	100	19.80%
	40 to 49	160	31.68%
	more than 49	93	18.42%
Education	Bachelor	421	83.37%
	Diploma	32	6.34%
	Master	52	10.3%
	PhD	32	6.34%
Field of specialization	Accounting & Auditing	175	34.65%
	Finance	162	32.08%
	Information Technology	65	12.87%
	Computer Science	59	11.68%
	Economics	44	8.71%
Experiences	Less than 5 years	34	6.73%
	5 to 10	213	42.18%
	10 to 15	190	37.62%
	More than 15	68	13.47%

Common Method Bias

Since the same instrument was used to determine both intrinsic and extrinsic data, there is a risk of common method bias (CMB). There are two methods to address the variability of this bias as suggested by (Podsakoff et al., 2012): a procedural treatment and a statistical treatment. The latter uses a preventative strategy, which involves the provision of data confidentiality among respondents and is done by standing data sources apart between independent and dependent variables. In line with that, respondents were assured that they will remain anonymous, and that the questionnaire had no right or wrong answers (Leong et al., 2020). The latter plan is statistical adjustments. To exercise statistical control, the researcher used the single-factor test by (Fuller et al., 2016). The unrotated exploratory factor analysis performed in SPSS showed that the maximum covariance attributed to a single factor was 37.45, which is less than the traditional 50 per cent threshold. As a result, the presence of common method bias in the study does not have any substantive reason to be worrying.

Empirical Results and Discussions

The empirical findings of the study are divided into two main parts. First, the measurement model is assessed to evaluate the reliability and validity of the constructs. Second, the structural model is examined to test the proposed hypotheses and to explore the relationships among the study variables.

Measurement Model

The two-stage method, as proposed by Hair et al. (2017), was employed to analyse the Hierarchical Component Model (HCM), which consists of two layers of constructs. In the initial stage of the measurement model analysis, the first-order reflective constructs are assessed using PLS-SEM, whereas in the second stage, the higher-order formative constructs are evaluated. The SMART PLS 4 software was utilized for the analysis of both the measurement and structural models. According to the recommendation of Hair et al., (2017), factor loadings (FL), average variance extracted (AVE), and composite reliability (CR) were tested in this research to measure convergent validity. The results retrieved are summarised in Table 2. The FL ranged between 0.708 and 0.941, all of which exceeded the threshold value of 0.70, indicating strong to very strong associations. The AVE values, which ranged from 0.640 to 0.891, were above the recommended minimum of 0.50 suggested by (Henseler et al., 2015). This confirms that each construct achieved satisfactory convergent validity. In addition, CR values were between 0.876 and 0.937, surpassing the minimum acceptable value of 0.70, thereby indicating high internal consistency reliability of the constructs.

Table 2
Measurement Model on Loading, CR and AVE

Construct	Items	Factor Loading	CR	AVE
CA	7	0.819 - 0.873	0.930	0.891
COM	7	0.793 - 0.859	0.908	0.712
DIS	7	0.783 - 0.865	0.913	0.725
EE	7	0.856 - 0.887	0.929	0.719
EID	4	0.819 - 0.849	0.907	0.709
FR	4	0.781 - 0.876	0.876	0.640
IC	4	0.804 - 0.902	0.932	0.872
IE	4	0.749 - 0.805	0.930	0.689
IERA	4	0.884 - 0.889	0.928	0.763
INN	4	0.941 - 0.928	0.895	0.682
INS	4	0.930 - 0.938	0.901	0.696
MO	4	0.899 - 0.905	0.914	0.809
OM	4	0.805 - 0.840	0.931	0.693

OP	4	0.719 - 0.815	0.890	0.670
OS	4	0.739 - 0.849	0.900	0.693
RA	4	0.708 - 0.892	0.927	0.762
RE	5	0.812 - 0.883	0.899	0.691
RR	5	0.741 - 0.830	0.937	0.787
SDM	5	0.769 - 0.915	0.928	0.764
UND	5	0.760 - 0.882	0.897	0.685

AVE = Average variance extracted, EE = External Environment, IE= Internal Environment, OM= Operational Management, SDM = Strategic Decision Making, IERA = Internal Environment (Resk Management), OS = Objective Setting, EID = Event Identification, RA = Risk Assessment, RR = Risk Response, CA = Control Activities, IC = Information and Communication, MO = Monitoring, OP = Optimism, INN = Innovativeness, DIS = Discomfort, INS = Insecurity, RE = Relevance, FR = Faithful Representation, UND = Understandability, COM = Comparability

Regarding to the discriminant validity, Henseler et al. (2015) highlighted the limitations of traditional approaches such as cross-loadings and the Fornell-Larcker criterion in assessing discriminant validity. Accordingly, this study employed the Heterotrait-Monotrait (HTMT) criterion, which considers discriminant validity satisfactory when HTMT values are below 0.85. As shown in Table 3, all values met this threshold, confirming that each construct is conceptually distinct and free from multicollinearity concerns.

In the second stage of the measurement model analysis using PLS-SEM, a new path model was developed to examine higher-order constructs, namely big data mining, enterprise risk management, financial reporting quality, and IT readiness. As recommended by Sarstedt et al. (2019), these constructs were assessed in terms of multicollinearity, indicator weights, and their statistical significance. Table 4 presents the outer weights and loadings, indicating that all values were significant and within acceptable VIF thresholds. This confirms that the indicators meaningfully contribute to their respective higher-order constructs and validates the adequacy of the second-stage measurement model.

Table 3

Discriminant Validity Based on HTMT Method

	CA	COM	DIS	EE	EID	FR	IC	IE	IERA	INN	INS	MO	OM	OP	OS	RA	RE	RR	SDM	UND
CA																				
COM	0.035																			
DIS	0.062	0.064																		
EE	0.250	0.037	0.045																	
EID	0.081	0.046	0.155	0.141																
FR	0.052	0.795	0.045	0.039	0.054															
IC	0.071	0.030	0.165	0.119	0.801	0.045														
IE	0.062	0.053	0.184	0.134	0.807	0.053	0.109													
IERA	0.344	0.037	0.104	0.662	0.075	0.068	0.107	0.125												
INN	0.019	0.108	0.785	0.049	0.048	0.054	0.072	0.082	0.098											
INS	0.086	0.041	0.113	0.047	0.130	0.082	0.154	0.195	0.052	0.764										
MO	0.322	0.061	0.077	0.656	0.121	0.109	0.116	0.093	0.719	0.088	0.041									
OM	0.026	0.080	0.089	0.113	0.710	0.098	0.650	0.712	0.074	0.059	0.107	0.045								
OP	0.045	0.109	0.475	0.055	0.036	0.069	0.043	0.041	0.045	0.813	0.655	0.030	0.031							
OS	0.103	0.056	0.171	0.109	0.475	0.076	0.704	0.679	0.060	0.069	0.132	0.131	0.617	0.064						
RA	0.135	0.055	0.204	0.071	0.745	0.060	0.543	0.521	0.053	0.123	0.193	0.082	0.429	0.036	0.821					
RE	0.054	0.732	0.050	0.132	0.043	0.513	0.045	0.059	0.112	0.058	0.028	0.174	0.044	0.048	0.039	0.045				
RR	0.349	0.041	0.085	0.670	0.127	0.045	0.190	0.184	0.672	0.091	0.068	0.649	0.135	0.040	0.105	0.063	0.061			
SDM	0.345	0.039	0.106	0.662	0.074	0.068	0.106	0.125	0.345	0.099	0.053	0.719	0.074	0.045	0.059	0.053	0.110	0.672		
UND	0.052	0.778	0.059	0.053	0.043	0.345	0.036	0.047	0.063	0.058	0.046	0.103	0.115	0.066	0.063	0.053	0.705	0.071	0.063	

EE = External Environment, IE= Internal Environment, OM= Operational Management, SDM = Strategic Decision Making, IERA = Internal Environment (Resk Management), OS = Objective Setting, EID = Event Identification, RA = Risk Assessment, RR = Risk Response, CA = Control Activities, IC = Information and Communication, MO = Monitoring, OP = Optimism, INN = Innovativeness, DIS = Discomfort, INS = Insecurity, RE = Relevance, FR = Faithful Representation, UND = Understandability, COM = Comparability

Table 4

Assessment of outer weights and loading

HOFC	First order construct Efficient	Weights	t-value	Results	VIF
Big Data Mining	External Environment	0.520	22.88	Significant	1.585
	Internal Environment				1.741
	Operational Management				1.728
	Strategic Decision Making				1.580
Enterprise Risk Management	Internal Environment (Resk Management)	0.710	15.95	Significant	2.786
	Objective Setting				3.545
	Event Identification				3.974
	Risk Assessment				2.176

	Risk Response				1.970
	Control Activities				1.186
	Information And Communication				2.64
	Monitoring				2.001
Financial Reporting Quality	Relevance	0.522	11.70	Significant	1.992
	Faithful Representation				3.180
	Understandability				3.548
	Comparability				2.596
IT Readiness	Optimism	0.780	24.11	Significant	2.220
	Innovativeness				2.973
	Discomfort				3.006
	Insecurity				3.933

Structural Model and Hypotheses Testing

The structural model was employed to examine the relationships among BDM, ERM, FRQ, and ITR. Following the confirmation of reliability and validity, the analysis proceeded according to Hair et al. (2017), which includes assessing collinearity, the significance of relationships, R^2, f^2, and Q^2. Using the bootstrapping method with 5,000 resamples, the results demonstrated that BDM had a significant positive relationship with FRQ (β = 0.246, t = 2.250, $p < 0.05$) and a strong effect on ERM (β = 0.834, t = 59.112, $p < 0.001$), while ERM significantly influenced FRQ (β = 0.788, t = 6.782, $p < 0.01$). Moreover, ERM mediated the link between BDM and FRQ (β = 0.657, t = 6.626, $p < 0.001$), providing robust evidence of its intermediary role. However, ITR did not moderate the relationship between BDM and FRQ (β = 0.030, t = 0.539, p = 0.590), leading to the rejection of this hypothesis. Overall, the model explained 36.1% of the variance in FRQ ($R^2 = 0.361$), with predictive relevance ($Q^2 = 0.145$), confirming both the explanatory and predictive validity of the proposed framework (see table 5).

Table 5

Path Coefficient Assessment

Path coefficient	St. Beta	S. D	T-t	P-v	Confidence Interval LB	Confidence Interval UB	f^2	Result
H1: BDM-> FRQ	0.246	0.110	2.250	0.024	0.214	0.329	0.029	Accepted
H2: BDM-> ERM	0.834	0.014	59.112	0.000	0.179	0.872	0.125	Accepted
H3: ERM-> FRQ	0.788	0.116	6.782	0.000	0.320	0.863	0.296	Accepted
H4: BDM-> ERM-> FRQ	0.657	0.099	6.626	0.000	0.103	0.710		Accepted
H5: ITR x BDM-> FRQ	0.030	0.056	0.539	0.590	0.253	-0.420		Rejected
$R^2 = 0.361$	$Q^2 = 0.145$							

BDM = Big Data Mining; FRQ = Financial Reporting Quality; ERM = Enterprise Risk Management; ITR = Information Technology Readiness

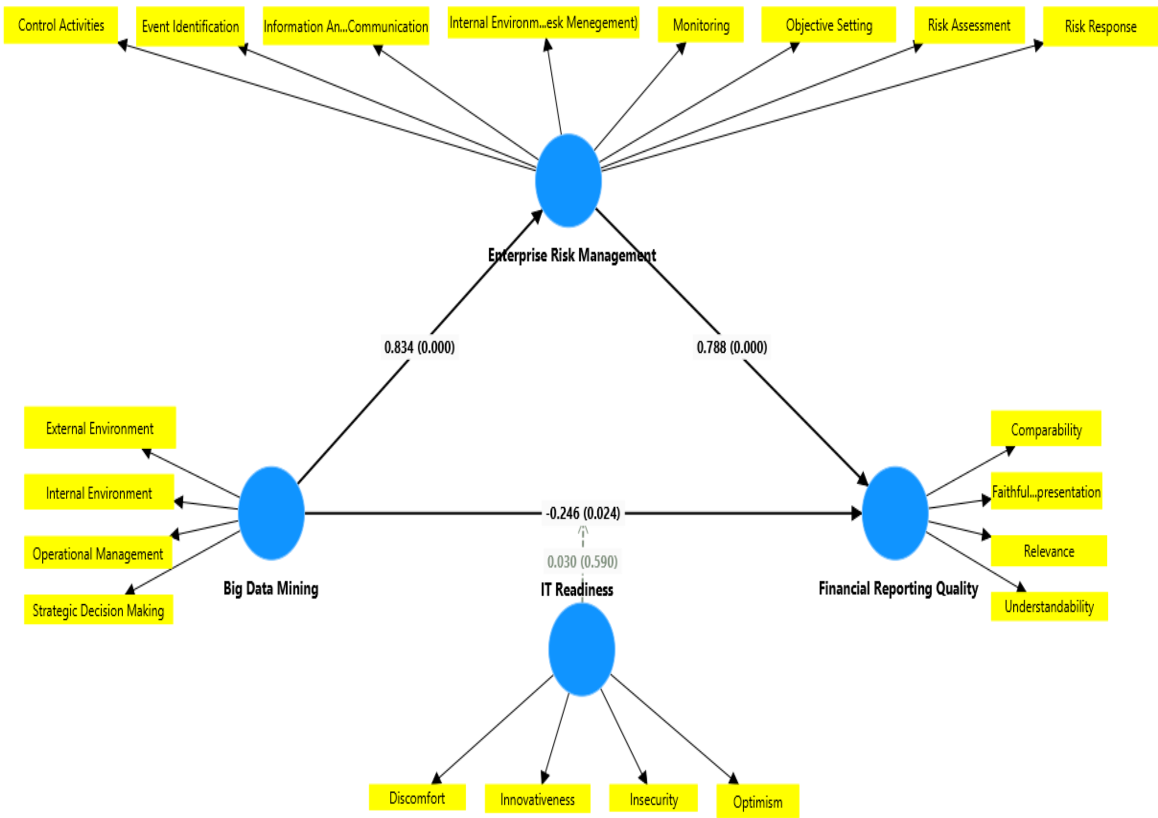

Figure 1. Structural Model Assessment

Discussion

This paper observes how big data mining can be used to improve the quality of financial reporting in the Saudi banking industry with special reference to the mediating and moderating effects of enterprise risk management and the readiness of information technology respectively. The results have a number of significant implications that can be added to the existing body of research on digital transformation, risk management, and the quality of financial reporting in the emergent financial market.

The findings reveal that big data mining has a positive impact on the quality of the financial reporting, where the banks with the ability of extracting and processing the big amount of data are in a better position to generate quality and accurate, timely, and transparent financial reports. In the Saudi banking environment with growing regulatory requirements and sophisticated financial activities, data empowering analytical functions seem to be the way to advance the credibility of financial data and minimize information asymmetry between parties involved. This observation reinforces previous studies that identify advanced analytics as having a reinforcement effect on the quality of accounting information and is consistent with the resource-based perspective, which thinks of analytical capabilities as strategic organizational resources that produce value when integrated into key reporting procedures.
The results also show that big data mining is very important to enhance the practice of enterprise risk management. The data mining tools facilitate improved ERM structures by allowing the identification of more risks and monitoring them and forecasting risks in the future. This finding underscores the fact that big data analytics are not only tools of operational efficiency, but also are major facilitators of organizational risk intelligence. The

banking industry, where financial, operational, and compliance risks are significant, seems to require the introduction of big data analytical tools into the ERM systems to ensure that the uncertainty is managed and the sound financial reporting practices are promoted.

Besides, the paper ascertains that enterprise risk management has a pronounced effect on the quality of financial reporting which highlights the importance of the type of governance as a focus tool in banks. The good ERM systems will help improve internal controls, foster consistency in risk assessment and financial disclosures, as well as improve adherence to regulatory and reporting standards. This observation supports the current body of governance and accounting literature according to which ERM is an important tool in increasing transparency and credibility in financial reporting, especially in regulated financial contexts.

Notably, the findings indicate that enterprise risk management is one of the most important transmission pathways with the help of which big data mining can enhance the quality of financial reporting. Such mediating effect suggests that the utility of big data analytics does not become automatic due to the presence of data data, but to the capacity of organizations to transform the analytical insights into systematized risk management activities. Dynamically speaking, this implies that banks have to incorporate analytical capabilities in their risk governance processes to translate data-driven insights to sustainable enhancements in the quality of reporting.

Conversely, the results reveal that the information technology readiness does not substantially modify the connection between the big data mining and the financial reporting quality. This finding indicates that technological infrastructure, although being a prerequisite, is not an adequate requirement of improving the quality of reporting. Within the setting of the Saudi banking industry, i.e., the comparatively high present level of the IT infrastructure, the changes in IT readiness might have posed a relatively low explanatory power. In its place, it seems that organizational forces like the quality of governance, the commitment of the managers or the inclusion of analytics in the ERM procedures are even more decisive. This observation is consistent with recent literature that warns of excessive focus on technological investments without the parallel enhancement of the processes in the organization, as well as the governance of risk. The results suggest that enhancing the financial reporting quality at banks has to be achieved comprehensively and encompass more than compliance with regulation and the use of technology. The integration of big data analytics into the overall enterprise risk management strategies will help banks become more transparent, increase their governance, and more credible in the preparation of financial reporting. These findings are especially applicable due to the Saudi Vision 2030, which focuses on digital transformation, financial sector resilience, and increased transparency. As a result, this research adds to the literature by showing that enterprise risk management is the key organizational process that can help big data analytics to be translated into significant changes in the quality of financial reporting.

Conclusion

Financial reporting quality is vital for transparency, market faith, and financial stability, especially in highly leveraged and systemically significant banking industries. This paper investigated the effect of big data mining on the quality of financial reporting in the Saudi banking sector, using ERM as a mediator and IT readiness as a moderator. Using questionnaire responses gathered data from 505 participants and partial least squares structural equation modeling (PLS-SEM), the author discovered that big data mining considerably improves ERM and quality of financial reporting. Furthermore, enterprise risk management has a significant influence on the connection amongst mining of big data and financial reporting quality, suggesting that analytical skills lead to improved reporting results, particularly through organized risk governance processes. Conversely, IT readiness has no significant influence on the association between BDM and quality of financial reporting, implying that technology infrastructure alone is insufficient to surge FRQ in the absence of strong organizational integration.

These results have vital theoretical and practical implications. The present research broadens the Resource-Based View (RBV) theory by examining the quality of financial reporting as a result of risk and data management capabilities. It also expands on the contingency theory by demonstrating that the efficiency of technology is determined by internal regulatory mechanisms rather than investment levels alone. In reality, the findings indicate that Saudi banks should emphasize integrating big data analytics into comprehensive corporate risk management frameworks over pursuing separate digital initiatives. For policymakers and regulators, the study emphasizes the importance of strengthening risk and data governance requirements alongside digital transformation activities to ensure financial stability and accomplish Saudi Vision 2030 goals. This study contributes to the literature by integrating big data mining, enterprise risk management, and IT readiness into a unified framework for explaining financial reporting quality. It also provides practical guidance for enhancing reporting reliability in emerging banking sectors undergoing rapid digital transformation.

Future research directions

The current research has several limitations, such as its cross-sectional design restricts the ability to infer causal relationships; therefore, future research should utilize panel data to examine dynamic effects over time. The study also employs cognitive assessments, which may be effected by respondent bias, and the analysis is limited to the Saudi banking sector, potentially limiting the generalizability of the findings. Future studies could therefore broaden this scope to include other GCC countries, compare islamic and conventional banks, or investigate additional regulatory mechanisms such as corporate governance or audit committee performance. Furthermore, future research should explore why IT readiness does not have a substantial impact on the relationship between business management and performance indicators, in addition to other contextual aspects.

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