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Big Data Analytics and Operational Risk Management in Financial Institutions: A Systematic Review of Evidence, Methods, and Research Gaps

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Abstract

The increasing complexity of operational risks in financial institutions has challenged the effectiveness of traditional risk management approaches. This study conducts a systematic literature review to examine how big data analytics and advanced analytical techniques enhance operational risk management (ORM) practices. Following a structured Systematic Literature Review (SLR) methodology based on the PRISMA framework, peer-reviewed articles indexed in Scopus were identified, screened, and synthesized to ensure methodological rigor and transparency. The review analyzes how descriptive, diagnostic, predictive, and prescriptive analytics are applied across the ORM cycle, including risk identification, measurement, monitoring, and mitigation. The findings indicate that big data analytics, supported by artificial intelligence and machine learning, significantly improve early risk detection, predictive accuracy, and real-time monitoring capabilities. Moreover, these technologies strengthen operational resilience and data-driven decision-making in financial institutions. This study contributes to the literature by providing an integrated overview of analytical approaches in ORM and identifying key research gaps, while offering practical insights for financial institutions seeking to adapt their risk management frameworks to an increasingly data-intensive environment.

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1. Introduction

Operational risk in financial institutions has expanded beyond traditional sources such as human error and internal fraud to encompass more complex and dynamic risks arising from rapid technological advancement, evolving regulatory frameworks, and external shocks, including pandemics and cyber threats (Malik et al., 2023; Milojević & Redzepagic, 2021). These developments have fundamentally altered the operational risk landscape, requiring financial institutions to strengthen their Operational Risk Management (ORM) frameworks not only as a loss-control mechanism but also as a strategic tool for enhancing organizational resilience. Contemporary ORM plays an increasingly critical role in proactively identifying, measuring, and controlling a broad range of internal and external risks through

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adaptive and integrated approaches (Ivascu et al., 2023). Empirical evidence suggests that effective ORM implementation contributes to improved competitiveness, business continuity, and investor confidence, particularly through the adoption of advanced control systems and digital technologies within the financial sector (Bastida et al., 2022). Consequently, ORM has become a fundamental pillar for maintaining stability and performance in financial institutions operating in uncertain and volatile environments (Khuna et al., 2025).

Despite its growing strategic importance, ORM faces substantial challenges in the digital era due to the increasing volume, velocity, and variety of data that financial institutions must process. Traditional risk management methods, which often rely on manual procedures and historical loss data, are becoming increasingly inadequate in addressing complex and rapidly evolving risks (Chen et al., 2021). In response, big data analytics has emerged as a critical enabler for early risk detection and more precise decision-making in dynamic operational contexts (Patel & Singh, 2022). At the same time, regulatory complexity, sophisticated cyber threats, and heightened market volatility further constrain the effectiveness of conventional ORM practices (Zhang & Wong, 2021). The limited adaptation of advanced technologies implies that traditional risk identification and mitigation processes struggle to keep pace with the scale and speed of contemporary data flows (Johnson & Lee, 2019). Accordingly, the adoption of artificial intelligence and real-time data analytics has become essential to ensure that ORM frameworks remain relevant and effective amid an increasingly complex risk environment (Dewi et al., 2024; Atestasi, 2025).

Against this backdrop, the purpose of this study is to conduct a Systematic Literature Review (SLR) to synthesize existing scholarly evidence on how big data and data analytics enhance the effectiveness and efficiency of Operational Risk Management in financial institutions. Specifically, this study examines the role of advanced technologies, including machine learning and artificial intelligence, in optimizing risk management through real-time and predictive analytical capabilities (Cahyadi et al., 2025). By adopting an SLR approach, this research systematically explores how the integration of big data transforms previously manual ORM processes—such as risk identification, assessment, and mitigation—into more automated, accurate, and timely practices (Shen et al., 2020). The primary focus is on understanding how digitalization and data-driven technologies contribute to greater transparency, responsiveness, and operational resilience in financial institutions when managing operational risks (Wu et al., 2022). The synthesis of findings is expected to provide strategic insights for developing adaptive ORM capabilities capable of addressing the challenges posed by big data and the growing complexity of modern risk profiles (Sarker et al., 2021).

This study contributes to the literature in several important ways. From a theoretical perspective, it addresses a gap in Operational Risk Management research by providing a systematic and integrated understanding of how big data and data analytics are incorporated into ORM frameworks, an area that has received limited structured attention in prior studies (Aisyah et al., 2024). From a practical standpoint, the findings offer guidance for financial institutions seeking to leverage digital technologies to improve the effectiveness and efficiency of ORM, particularly in managing large-scale and complex risks in real time (Dewi et al., 2024). Furthermore, this review highlights the strategic importance of advanced analytical tools, such as machine learning and artificial intelligence, in enhancing operational resilience and supporting data-driven decision-making (Yuwono & Vaddhano, 2024; Patel & Singh, 2022). By bridging theoretical insights and practical implications, this study aims to contribute meaningfully to both academic discourse and professional practice in the field of risk management within the modern financial industry (Mishra et al., 2020).

The remainder of this article is structured as follows. The next section outlines the research methodology, detailing the systematic literature search strategy and selection criteria. The subsequent section presents and discusses the synthesized findings, with particular emphasis on the application of big data and analytical technologies within ORM processes. The final section concludes the study by summarizing the main findings and offering recommendations for future research.

2. Literature Review

Operational Risk

Operational risk is commonly defined as the risk of loss resulting from inadequate or failed internal processes, people, systems, or from external events, including legal risk but excluding strategic and reputational risk (Malik et al., 2023). This definition, which is widely adopted in the financial industry, underscores the multifaceted nature of operational risk and its potential to disrupt institutional stability. Sources of operational risk include internal and external fraud, system failures, process inefficiencies, human error, and external shocks such as technological disruptions and cyber incidents (Milojević & Redzepagic, 2021). As financial institutions increasingly rely on complex digital infrastructures, the scope and intensity of operational risk exposure have expanded significantly.

In parallel with the growing complexity of operational risk, the emergence of big data has reshaped the way risks are identified and managed. Big data is commonly characterized by the "3Vs": volume, velocity, and variety, reflecting the massive scale, rapid generation, and diverse formats of data generated in modern organizations. This concept has been further extended to include veracity, which refers to data reliability, and value, which emphasizes the usefulness of data for decision-making purposes (Gartner IT Glossary, 2007; Elder Research, 2023). These characteristics highlight both the challenges and opportunities associated with leveraging big data for risk management. Compared to traditional data sources, big data enables financial institutions to capture a broader range of operational signals, allowing for deeper and more granular analysis of risk events (Patel & Singh, 2022).

The integration of big data into operational risk management represents a shift from reactive, loss-based approaches toward more proactive and predictive risk frameworks. By leveraging large-scale and heterogeneous datasets, financial institutions can move beyond historical loss data and gain insights into emerging risk patterns, supporting earlier intervention and more effective risk controls (Malik et al., 2023). As a result, operational risk management has evolved from a compliance-driven function into a strategic capability that supports organizational resilience and long-term performance.

Data Analytics in Operational Risk Management

Data analytics plays a central role in transforming operational risk management practices by enabling more informed and timely decision-making. In the context of ORM, data analytics is commonly classified into four categories: descriptive, diagnostic, predictive, and prescriptive analytics. Descriptive analytics focuses on summarizing historical data to explain what has occurred, while diagnostic analytics seeks to identify the underlying causes of observed risk events. Predictive analytics estimates the likelihood of future risk occurrences, and prescriptive analytics provides recommendations on optimal actions to mitigate or prevent potential losses (Dewi et al., 2024). Together, these analytical approaches support a comprehensive and data-driven ORM process (Atestasi, 2025).

Operational risk management itself is typically structured around four key stages: risk identification, risk measurement, risk monitoring, and risk mitigation (Ebnöther et al., 2001). This cyclical framework provides a systematic approach to managing operational risk and ensures continuous feedback and improvement. The integration of data analytics into each stage of this cycle enhances the effectiveness and efficiency of ORM activities. In the risk identification stage, big data analytics enables the detection of anomalies and emerging risk patterns by processing large and diverse datasets using machine learning algorithms (Sarker et al., 2021; Atestasi, 2025). These capabilities allow financial institutions to identify risks that may not be visible through traditional monitoring mechanisms.

During the risk measurement and monitoring stages, real-time data analytics supports dynamic assessment of risk exposure and enables institutions to adjust their risk profiles in response to changing conditions (Dewi et al., 2024). Continuous monitoring of transactional data, system logs, and external information sources improves the timeliness and accuracy of risk evaluation. In the risk mitigation stage, prescriptive analytics provides actionable insights that support faster and more effective responses to operational risk events, reducing potential losses and enhancing organizational resilience (Patel & Singh, 2022).

Overall, the application of big data and data analytics across the operational risk management cycle represents a significant advancement compared to traditional, manually driven approaches. These technologies enhance the scalability, speed, and precision of risk management processes, enabling financial institutions to respond more effectively to increasingly complex and volatile risk environments (Bastida et al., 2022; Khan & Khan, 2023). Moreover, data-driven ORM supports greater transparency and accountability in risk governance, aligning risk management practices with the demands of modern financial systems and regulatory expectations (Yuwono & Vaddhano, 2024).

3. Methodology

Research Design

This study adopts a Systematic Literature Review (SLR) approach to identify, evaluate, and synthesize existing scholarly research on the application of big data and data analytics in Operational Risk Management (ORM) within financial institutions. The SLR method was selected due to its ability to provide a transparent, structured, and replicable process for reviewing prior studies, thereby minimizing researcher bias and ensuring comprehensive coverage of the relevant literature. This approach is particularly suitable for consolidating fragmented research findings and identifying dominant themes, methodological trends, and research gaps in an emerging field such as data-driven operational risk management.

Literature Search Strategy

The literature search was conducted using the Scopus database, given its broad coverage of high-quality, peer-reviewed academic journals. A structured search strategy was developed using specific keywords and Boolean operators to capture relevant studies. The primary search string applied was:

"Big Data" AND "Financial Institution"

The search was performed within the fields of article title, abstract, and keywords to ensure relevance. This initial search yielded 1,018 documents, including journal articles and conference proceedings. The search strategy was intentionally broad at this stage to avoid excluding potentially relevant studies during the identification phase.

Study Selection Process

To ensure transparency and methodological rigor, the study selection process followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework. The selection process was conducted through several sequential stages: identification, screening, eligibility, and inclusion.

During the screening stage, an accessibility filter was applied by limiting the results to open-access publications, reducing the number of documents from 1,018 to 62 articles. This step ensured that all selected studies could be fully accessed and systematically analyzed. Subsequently, subject area filters were applied to restrict the scope to disciplines directly relevant to the research topic, namely Business, Management, and Accounting as well as Economics, Econometrics, and Finance. This filtering process resulted in 19 articles deemed potentially relevant for further evaluation.

In the eligibility stage, the abstracts of the remaining articles were reviewed to assess their relevance to the intersection of big data, data analytics, and operational risk management. Articles that focused exclusively on other forms of risk, such as credit risk or market risk, or that did not explicitly address operational risk management were excluded. The full texts of the remaining studies were then examined to ensure compliance with the predefined inclusion and exclusion criteria.

The final inclusion stage resulted in a set of 19 peer-reviewed articles, which formed the basis for the qualitative synthesis presented in the results and discussion sections. The entire selection process is summarized using a PRISMA flow diagram, as described in the original study, to provide a clear overview of the document filtering stages and outcomes.

Data Extraction and Synthesis

Data extraction was conducted systematically to ensure consistency across the selected studies. Key information extracted from each article included the research objectives, methodological approach, analytical techniques employed, and principal findings related to the use of big data and data analytics in operational risk management. The extracted data were then synthesized using a narrative synthesis approach, which enabled the identification of recurring patterns, dominant analytical methods, and thematic relationships across studies.

Rather than aggregating results quantitatively, this study emphasizes qualitative synthesis to capture conceptual insights into how big data analytics supports different stages of the ORM cycle, including risk identification, measurement, monitoring, and mitigation. This approach allows for a deeper understanding of methodological diversity and practical implications within the reviewed literature.

Validity and Reliability

To enhance the validity and reliability of the review, several measures were implemented. First, the use of a single, well-established academic database ensured consistency in publication quality. Second, clearly defined inclusion and exclusion criteria were applied throughout the selection process to reduce subjectivity. Third, adherence to the PRISMA framework strengthened the transparency and replicability of the review process. These methodological safeguards collectively ensure that the findings of this SLR provide a robust and credible synthesis of existing research on big data–driven operational risk management in financial institutions.

4. Results

This section presents the results of the Systematic Literature Review based on the final set of 19 peer-reviewed articles selected through the PRISMA-guided screening process. The findings synthesize how big data, data analytics, machine learning, and artificial intelligence have been applied across different domains, with particular emphasis on their implications for operational risk management in financial institutions. The results are organized thematically to highlight dominant research focuses, methodological approaches, and key outcomes identified in the reviewed literature.

Overview of the Reviewed Studies

The 19 articles included in this review cover a broad range of applications of big data analytics across financial services, banking, and related sectors. As summarized in Table 1, the reviewed studies employ diverse methodological approaches, including qualitative literature reviews, quantitative empirical analyses, econometric modeling, and advanced machine learning techniques. The primary research focus of these studies revolves around financial risk management, predictive modeling, fraud detection, decision-making optimization, and the processing of large-scale financial data.

Across the literature, big data analytics is consistently identified as a critical enabler of improved forecasting accuracy and enhanced risk assessment capabilities (Dicuonzo et al., 2019; Diebold et al., 2019). Several studies emphasize the role of big data in strengthening financial institutions' ability to anticipate and manage uncertainties, particularly through improved modeling techniques and real-time data processing (Shen et al., 2020; Wu et al., 2022). The findings indicate that the adoption of big data technologies supports more proactive and forward-looking approaches to risk management compared to traditional, retrospective methods.

Tabel 1. Main Findings from Various Articles

Aspects of Analysis	Main Findings from Various Articles
Objectives & Scope	Identifying and evaluating how Big Data, Machine Learning, and AI affect various aspects in the financial industry such as risk management, credit assessment, fraud detection, and decision-making.
Methodology	Most studies use qualitative (literature reviews), quantitative (data analysis), or a combination of both methodologies. Common algorithms analyzed include XGBoost, Random Forest, and Neural Networks for credit risk prediction and ranking.
Technology Implementation	Credit Risk Management: AI models are used to predict creditworthiness by analyzing financial and demographic data. Deep Learning models are more accurate than traditional models, especially with large datasets. Fraud Detection: Deep Learning models like LSTM and GRU are used to detect anomalies in sequential financial transactions. Financial Management: Big Data and AI technologies are applied to process large volumes of data, helping financial institutions balance risk and income. Market & Investment Analysis: Probabilistic models assess investment portfolio risks (Value at Risk or VaR) and predict corporate compliance with Environmental, Social, and Governance (ESG) standards using heterogeneous information networks.
Results & Advantages	Improved Accuracy: The use of AI and Machine Learning significantly enhances the accuracy of risk prediction and credit assessment. Operational Efficiency: Automation of processes like credit assessment and fraud detection reduces costs and time. Decision-Making: The integration of Business Intelligence (BI) and AI allows for deeper data analysis, leading to more efficient reports and better strategic decisions.
Challenges & Implications	Cybersecurity: Increased use of digital technologies also increases vulnerability to cyber threats, requiring further research. Data Quality: Model accuracy depends heavily on the quality of input data, presenting challenges in data collection and management of heterogeneous data. Workforce Needs: Financial institutions need to develop a workforce with combined expertise in finance and technology to implement and manage AI solutions effectively.
Conclusion	The application of AI and Big Data in the financial sector is inevitable. These technologies not only offer powerful tools for risk management and optimization, but also demand evolution in infrastructure, data governance, and human resource development.

Analytical Methods and Technological Approaches

The reviewed literature demonstrates extensive use of advanced analytical techniques, including machine learning algorithms and artificial intelligence models, to process large and complex datasets. As shown in Table 2, commonly analyzed algorithms include Random Forest, XGBoost, Neural Networks, and deep learning architectures for credit risk assessment, fraud detection, and financial prediction. These methods are frequently applied to enhance the accuracy and reliability of risk-related decision-making processes.

In the context of operational risk management, predictive and prescriptive analytics are highlighted as particularly valuable. Predictive models enable financial institutions to estimate the likelihood of adverse operational events, while prescriptive analytics supports decision-makers by recommending optimal mitigation strategies (Dewi et al., 2024). The results suggest that these analytical capabilities contribute to faster response times and more efficient allocation of organizational resources, thereby strengthening operational resilience.

Key Findings Related to Risk Management Outcomes

A recurring finding across the reviewed studies is the positive impact of big data analytics on risk prediction accuracy and operational efficiency. Several articles report that data-driven models outperform traditional risk assessment techniques, particularly when dealing with large and heterogeneous datasets (Hasan et al., 2020; Mishra et al., 2020). In fraud detection, deep learning models such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) are shown to be effective in identifying anomalies in sequential transaction data, enabling earlier detection of fraudulent activities and reducing potential losses.

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Technology Implementation	Credit Risk Management: AI models are used to predict creditworthiness by analyzing financial and demographic data. Deep Learning models are more accurate than traditional models, especially with large datasets. Fraud Detection: Deep Learning models like LSTM and GRU are used to detect anomalies in sequential financial transactions. Financial Management: Big Data and AI technologies are applied to process large volumes of data, helping financial institutions balance risk and income. Market & Investment Analysis: Probabilistic models assess investment portfolio risks (Value at Risk or VaR) and predict corporate compliance with Environmental, Social, and Governance (ESG) standards using heterogeneous information networks.
Results & Advantages	Improved Accuracy: The use of AI and Machine Learning significantly enhances the accuracy of risk prediction and credit assessment. Operational Efficiency: Automation of processes like credit assessment and fraud detection reduces costs and time. Decision-Making: The integration of Business Intelligence (BI) and AI allows for deeper data analysis, leading to more efficient reports and better strategic decisions.
Challenges & Implications	Cybersecurity: Increased use of digital technologies also increases vulnerability to cyber threats, requiring further research. Data Quality: Model accuracy depends heavily on the quality of input data, presenting challenges in data collection and management of heterogeneous data. Workforce Needs: Financial institutions need to develop a workforce with combined expertise in finance and technology to implement and manage AI solutions effectively.
Conclusion	The application of AI and Big Data in the financial sector is inevitable. These technologies not only offer powerful tools for risk management and optimization, but also demand evolution in infrastructure, data governance, and human resource development.

Moreover, the integration of big data analytics into financial management processes supports more informed strategic decision-making. By leveraging real-time and non-traditional data sources, financial institutions can better balance risk and profitability while adapting to rapidly changing market conditions (Shen et al., 2020; Wu et al., 2022). These findings indicate that big data analytics plays a crucial role in enhancing both the effectiveness and efficiency of operational risk management practices.

Organizational and Implementation Challenges

Despite the demonstrated benefits, the reviewed studies also highlight several challenges associated with the implementation of big data and advanced analytics. Data quality emerges as a critical concern, as the accuracy and reliability of analytical models depend heavily on the availability of high-quality and well-governed data (Prescott et al., 2020). In addition, cybersecurity risks are identified as a significant issue, as increased reliance on digital infrastructures exposes financial institutions to potential data breaches and cyber threats.

Another important finding relates to organizational readiness. Several studies emphasize the need for managerial support and skilled human capital to successfully implement and sustain big data analytics initiatives (Kenton, 2021; Kim & Jang, 2025). The results suggest that financial institutions must invest not only in technological infrastructure but also in workforce development to fully realize the benefits of data-driven operational risk management.

5. Discussion

The findings of this Systematic Literature Review demonstrate that the integration of big data analytics, machine learning, and artificial intelligence has fundamentally transformed operational risk management (ORM) practices in financial institutions. Consistent with prior studies, the results indicate a shift from traditional, reactive risk management approaches toward more proactive, predictive, and data-driven ORM frameworks (Shen et al., 2020; Wu et al., 2022). This transformation reflects the growing complexity of operational risks and the limitations of conventional methods that rely heavily on historical loss data and manual processes (Chen et al., 2021; Johnson & Lee, 2019).

One of the most prominent insights from the reviewed literature is the role of predictive and prescriptive analytics in enhancing risk identification and measurement. By leveraging large and heterogeneous datasets, financial institutions are increasingly able to detect emerging risk patterns at an earlier stage, particularly those related to cyber threats, system failures, and process inefficiencies (Dewi et al., 2024; Patel & Singh, 2022). These findings support the argument that big data analytics strengthens the risk identification phase of the ORM cycle by enabling continuous monitoring and anomaly detection, which were previously difficult to achieve using traditional tools (Sarker et al., 2021).

The results also highlight the importance of real-time analytics in improving risk monitoring and mitigation. Several studies emphasize that the ability to process and analyze data in real time allows institutions to dynamically adjust their risk profiles and respond more rapidly to operational disruptions (Wu et al., 2022). This capability enhances operational resilience by reducing response times and minimizing the potential impact of adverse events. In this regard, the findings extend existing ORM frameworks by demonstrating how digital technologies complement established risk management processes, rather than replacing them entirely (Bastida et al., 2022; Khan & Khan, 2023).

Despite these advantages, the reviewed literature consistently identifies several challenges that may limit the effectiveness of data-driven ORM. Data quality remains a critical concern, as inaccurate, incomplete, or inconsistent data can undermine the reliability of analytical models and lead to misleading risk assessments (Prescott et al., 2020). In addition, increased reliance on digital infrastructures exposes financial institutions to heightened cybersecurity risks, which may themselves become a significant source of operational risk (Malik et al., 2023). These challenges suggest that technological adoption alone is insufficient and must be accompanied by robust data governance frameworks and security controls.

Organizational factors also play a crucial role in determining the success of big data–driven ORM initiatives. The literature emphasizes the need for strong managerial support, cross-functional collaboration, and the development of human capital with combined expertise in finance and data analytics (Kenton, 2021; Kim & Jang, 2025). Without adequate organizational readiness, financial institutions may struggle to fully exploit the potential benefits of advanced analytical tools. This finding aligns with previous research highlighting that technological innovation in risk management must be supported by institutional capabilities and cultural change (Mishra et al., 2020).

Overall, the discussion underscores that big data analytics does not merely improve the efficiency of existing ORM practices but also reshapes the strategic role of operational risk management within financial institutions. By enabling more accurate forecasting, timely monitoring, and informed decision-making, data-driven ORM contributes to enhanced organizational resilience and long-term stability in increasingly uncertain operating environments (Yuwono & Vaddhano, 2024).

Policy Implications and Recommendations

The findings of this review carry several important policy implications for regulators and policymakers in the financial sector. First, regulatory frameworks should recognize the growing role of big data analytics and artificial intelligence in operational risk management and provide clear guidance on their responsible and effective use. This includes establishing standards for data quality, model transparency, and accountability to ensure that analytical tools support, rather than undermine, sound risk governance (Patel & Singh, 2022).

Second, regulators may need to encourage financial institutions to strengthen data governance and cybersecurity policies as integral components of operational risk management. Given the increased exposure to cyber threats associated with digitalization, supervisory authorities should emphasize the integration of cybersecurity risk within existing ORM frameworks (Malik et al., 2023; Zhang & Wong, 2021).

Third, policymakers should support capacity-building initiatives aimed at developing human capital with expertise in both financial risk management and data analytics. Investment in education and professional training can enhance institutions' ability to implement advanced ORM technologies effectively and sustainably (Mishra et al., 2020; Kim & Jang, 2025). By aligning regulatory expectations with technological and organizational capabilities, policymakers can foster a more resilient and data-driven financial system.

6. Conclusion

This study provides a systematic synthesis of the existing literature on the role of big data analytics, machine learning, and artificial intelligence in enhancing operational risk management (ORM) within financial institutions. The findings of this Systematic Literature Review indicate that the increasing complexity of operational risks—driven by digitalization, regulatory pressures, and external shocks—has rendered traditional, manual risk management approaches increasingly insufficient (Chen et al., 2021; Johnson & Lee, 2019). In response, big data analytics has emerged as a critical enabler of more proactive, predictive, and resilient ORM practices.

The review demonstrates that the application of descriptive, diagnostic, predictive, and prescriptive analytics across the ORM cycle significantly improves risk identification, measurement, monitoring, and mitigation processes (Dewi et al., 2024; Patel & Singh, 2022). By leveraging large-scale and heterogeneous data sources, financial institutions are better equipped to detect emerging risk patterns, enhance forecasting accuracy, and support real-time decision-making (Shen et al., 2020; Wu et al., 2022). These capabilities contribute to stronger operational resilience and more transparent risk governance frameworks (Yuwono & Vaddhano, 2024).

Despite these benefits, the findings also highlight persistent challenges related to data quality, cybersecurity risks, and organizational readiness, which may limit the effectiveness of data-driven ORM if not adequately addressed (Prescott et al., 2020; Malik et al., 2023). Furthermore, the successful integration of advanced analytics requires not only technological investment but also managerial support and the development of human capital with interdisciplinary expertise in finance and data analytics (Mishra et al., 2020; Kim & Jang, 2025).

Overall, this study contributes to the literature by providing an integrated overview of how big data analytics reshapes operational risk management in financial institutions and by identifying key methodological trends and research gaps. Future research is encouraged to explore empirical validations of data-driven ORM frameworks, assess the long-term impacts of artificial intelligence adoption on risk governance, and examine regulatory responses to emerging analytical technologies. By addressing these areas, subsequent studies can further advance both theoretical understanding and practical implementation of operational risk management in an increasingly data-intensive financial environment.

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