The Role of Business Intelligence in Enhancing Enterprise Risk Management: (ERM) Conceptual Framework

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Abstract

This research aims to analyze the role of business intelligence (BI) in enhancing enterprise risk management (ERM) by building a conceptual framework that demonstrates how analytics and governance techniques can support the different stages of risk management. In light of digital transformation, increasing data volume, and the complexity of organizational environments, business intelligence systems have emerged as a pivotal tool for transforming big data into usable knowledge, contributing to improved decision accuracy and responsiveness. The literature confirms that data quality and governance represent Predictive analytics and artificial intelligence have proven their ability to detect risks early and enhance the accuracy of estimates in sectors such as banking, insurance, and supply chains, reducing operational losses and increasing organizational stability. Interactive dashboards and smart reports provide an effective way to view results in a simplified and transparent manner, supporting faster decision-making at the senior management level. Infrastructure and data systems integration are key to the successful integration of BI and ERM across data warehouses and ETL technologies to improve the efficiency of enterprise performance. Despite these positives, organizations face challenges of resistance to change, lack of analytical competencies, and privacy concerns, as well as research gaps related to the lack of longitudinal studies or expanded applications in SMEs. The research proposes an integrated conceptual framework that starts with data quality, through predictive analytics and dashboards, to integrate them into the ERM (Identification, Evaluation, Response, Monitoring) stages, enhancing the ability of organizations to predict risks and adapt to the complex business environment to achieve sustainability and competitive advantage.

Keywords: Business Intelligence (BI), Enterprise Risk Management (ERM), Data Governance, Predictive Analytics, Decision-Making

INTRODUCTION

In recent decades, the business environment has undergone fundamental transformations resulting from the rapid spread of digitalization, the explosion of data, and the complexity of stakeholder relationships. Within a corporation, the various risks cover a multitude of lines and intermingle the facets of financing, operations, law, and technology, all of which are within the confines of a singular terrain, for which a holistic administration (ERM) is required. In the updated version of the COSO framework, the concept of enterprise-wide risk management is upheld with the work fusion and strategy integration of the management of risks along with the performance of the enterprise, and the reporting circulation and follow-up of the use of credible information for the use of reporting and information systems. In contrast, BI and analytics systems have come to be classified as a new category of technology systems that facilitate automation of the transformation of raw data to real-time information and enable BI systems to be faster for decisions of automatic and intelligent systems. BI technologies include dashboards and other performance assessment technologies, OLAP systems, and other predictive analytics systems, which utilize statistical tools and machine learning to augment the reliability and accuracy of risk prediction. With the use of these tools, an organization is able to foresee and identify patterns that are indicative of the possible occurrence of events, passivity, and dormant prospects.

To answer it, this study aims to build a conceptual framework that illustrates the role of business intelligence in enhancing enterprise risk management (ERM), by analyzing recent literature and reviewing applied practices to determine how business intelligence tools and techniques, such as predictive analytics, dashboards, and data governance, contribute to supporting risk management processes at all stages. The study also seeks to highlight the areas of direct and indirect impact of business intelligence in improving the accuracy of risk forecasting and speed of response, in addition to enhancing the ability of organizations to monitor and report more efficiently. The crucial aspect is to develop a theoretical vision with practical tips that enable organizations to adopt business intelligence in enterprise risk management to increase sustainability and gain a competitive edge. We will also rely on a comprehensive review of the literature and applied works that assessed the influence of BI and data analytics on risk performance indicators. Its practical and theoretical importance is the following: Practically, the research offers a roadmap for organizations poised to integrate analytical processes with ERM to improve response times and reduce losses. From the theoretical perspective, the research resolves the scant literature that associates certain technological components (BI/Analytics) with the outcomes of enterprise risk management, which is a promising but underdeveloped area with regard to reliable conceptual and practical frameworks.

PREVIOUS STUDIES

Latest studies have given attention to the intersecting focus of the application of business intelligence (BI) systems to the practice of enterprise risk management (ERM) as an area of focus that is likely to burgeon as the organizational environment becomes more complex and enriched with data (Anton & Nucu, 2020). Additionally, the authors claim that the foundations of ERM have evolved from static frameworks to sophisticated dynamic models fueled by data and analytics, which underscores the need to utilize BI systems within the practice of ERM. Moreover, recent BI literatures also support the claim that BI is intended for proactive and resilient decision-making in risky contexts (Darwiesh et al., 2022). The efforts toward the fusion of BI and ERM systems tend to regard data quality and governance issues as the main obstacles to fusion. Otto (2022), Weber et al (2023), Hidayah et al (2024) describes how lack of maestria in data integrity and governance systems leads to wrong assumptions being drawn and overlooked on predictive model making and analytic dashboards, which in turn, leads to downgrades in decision making and unnecessary escalation of risk, why these predictive dashboards are used in the first place. Strong frameworks of data governance in organizations are directly correlated to the degree of Business Intelligence leveraged in risk management, according to the research (Khatri & Brown, 2021).

Predictive analytics enables risk detection much earlier than before, and such advancements are well-documented. For instance, Chen (2021) and Islam (2022) focused on machine learning and fraudulent transaction detection and its use for cost reduction. Predictive analytics, as noted by Johnson et al. (2023), when incorporated into ERM, enhances the accuracy of risk forecasts and eliminates risk reporting skewness. Mulamen and Rudin (2019) explained the form of opacity in AI models, which makes compliance and trust impossible. Jaradat et al. (2024) highlighted better than before management of operational and technical risks due to the integration of BI and ERM in different fields. The integration of data warehouses and data lakes eliminates the rigid time requirements, which assist in the integration of BI to ERM by increasing the speed of data integration and decision-making (Foshay & Kuziemsky, 2021; Seddon et al., 2022). Investments in analytics infrastructure, as noted by Elbashir, et al. (2020), is a prerequisite for success in enterprise project risk management. Later reviews, including those by Mekimah et al. (2024), have focused on operational and strategic data to illustrate the importance of predictive models and analytics in enhancing decision-making processes.

As far as the issue of the dashboards and reports is concerned, research by Popovič et al. (2020) and Troilo et al. (2021) shows that the use of interactive BI dashboards helps improve the quality of the decision to be made and speeds up the responsiveness of the boards of directors to emerging risks. A case Study in the energy sector found that risk dashboards improve transparency and activity in monitoring performance indicators (Mikalef et al., 2021). Patipan (2024) also demonstrated the positive influence of text analytics and BI tools in ERM systems on the ability to make more strategic decisions. From a more sectorial perspective, research in banking, insurance, and supply chains showed in different ways how BI helps ERM in banking by improving credit rating (Ain et al., 2019), insurance by monitoring transactions to identify suspicious ones for money laundering (Zhang & Lu, 2020), and in agriculture by managing climate risk in the stack of agricultural insurance (Kraus et al., 2022). All of these works have contributed towards minimizing losses and maximizing the stability of the organization, and thus, strengthens the case for the fusion of BI and risk management in improving the organization's resilience to risk (Nguyen et al., 2023).

Even with these encouraging findings, literature pointed out potential obstacles to the fusion of BI with ERM, which included, but were not limited to, organizational transformation, deficiency of privacy concerns, insufficient understanding of model results, and the scarcity of models that focus on BI and ERM (Arnott, 2020; Watson, 2022). These issues emphasize the need for actionable solutions in regards to insights on training, data stewardship, and capacity building (Hidayah et al, 2024). Recent literature reviews have pointed out the lack of in-depth research on the BI and ERM merger and the lack of focus on the issue in the context of small and medium-sized entities (Rikhardsson & Yigitbasioglu, 2021). These are the gaps that rationalize the need for conceptual research of this sort to elucidate and enhance the corpus of practical knowledge (AlMomani, 2025). Finally, the ISACA as well as COSO frameworks have suggested ERM's processes should integrate and strategically align analytics and organizational data to all levels within the organization (COSO, 2017, ISACA, 2024). These assertions justifies the importance of this research in contributing to the development of a conceptual model useful to institutions interested in implementing this ideal.

METHODOLOGY

This investigation seeks to understand the value of business intelligence at the intersection of risk management through the application and expansion of a practical conceptual framework that clarifies underlying relations between the elements of business intelligence and the stages of enterprise risk management (ERM) through BI." This study focuses on descriptive analytical research approaches to synthesize most of the backward literature and evaluation of past works, specifically to accelerate the identification of best practices and gaps in the literature and add a model that captures the essence of BI in the context of risk management."

This research looks for the multidisciplinary dimensions of the literature and works that were published within the time frame of 2019 to 2025, as well as peer-reviewed articles and reference literature from the COSO and ISACA bodies, together with works regarding the banking, insurance, and commercial and industrial case studies, along with other pertinent instructions. Core studies regarding the research reports sought to position themselves on the intersection of the constituents of policy and governance master frameworks, data governance, predictive analytics, governance, quality infrastructure, interactive dashboards, and analytics, and focused on the examination of their impact on various stages of enterprise risk management (ERM).

Relevant population and professionally BI reports from different organizations and previously published scholarly articles, as well as externally available BI and RM frameworks, focus on the intersection and impact of Business Intelligence (BI) and Risk Management (RM) and their associated analytical frameworks. This research focuses on assembling recent work on BI and Enterprise Risk Management (ERM) to carry out structured literature reviews, resulting in classification and analysis. Conclusions on the impact of BI on various stages of ERM are formulated, from which a conceptual framework is derived to elucidate and define the relationships and impacts, accompanied by recommendations for their practical application in business.

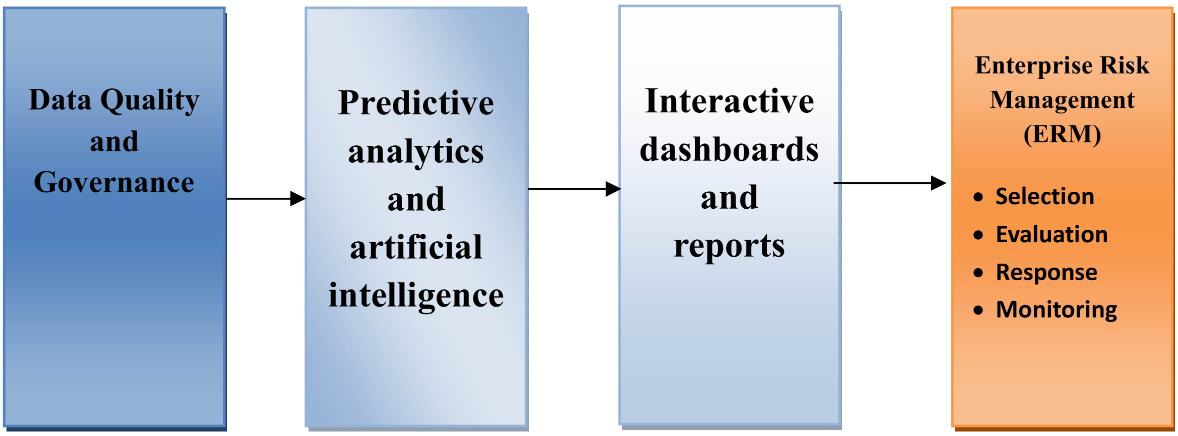

Figure1. Conceptual framework

The proposed conceptual framework relies on four fundamental components, which are chronologically interlinked. The first element, ‘data quality and data governance,’ is the starting point for the trait of every business intelligence tool, which is an unerring analysis and accurate risk prediction. The second element, ‘predictive analytics and artificial intelligence, hinges on structured and unstructured data to identify prospective risks and enable proactive decision-making, which reduces Fin-Op losses. ‘” interactive dashboards and reports’ are the subsequent element, and communicate the findings. The real-time follow-up on analyzed performance indicators and risk metrics reinforces the speed and efficacy of decisions in its powerful and intuitive design, which is appreciated by users and executives. The latter culminates in the incorporation of the components into ‘Enterprise Risk Management (ERM). The ERM encompasses identification, assessment, response, and monitoring, in which BI enhances the efficacy and augments the organization’s capacity to address operational and strategic risks.

Thus, this framework shows the relationship between BI and ERM, and sets the groundwork for an actionable approach that entities can use to enhance effectiveness and mitigate operational and financial risks. The inertia and lack of analytical capabilities inherent to almost any organization help to balance policy-centered and practitioner-centered strategies. This gives rise to contextually relevant and actionable ERM business intelligence policy.

RESULTS AND DISCUSSION

Reviewing over thirty studies between 2019 and 2025 confirms that the use of business intelligence (BI) technologies within enterprise risk management (ERM) systems adds value to how organizations mitigate identified risks. Researchers emphasize that data quality and data governance are the cornerstone of their BI success because deficient and incomplete data result in unreliable analytics and ineffective risk forecasting (Otto, 2022; Weber et al., 2023; Hidayah et al., 2024). Scholars argue that organizations that enforce data governance frameworks tend to use BI systems during risk evaluation and strategy formulation (Khatri & Brown, 2021).

The use of ML for better ERM predictive analytics in capturing data pertaining to business silos, as well as the use of predictive ERM analytics for enhancing the performance of the other attributes of ERM, indicates the growing reliance of almost every domain on ERM's foresight and risk detection capabilities. ML, supervised and unsupervised, enhances the ERM for administrative and technical functions, thus optimizing administrative cost controls while streamlining expense ratio controls. In Jaradat et al. (2024), their research found that augmented BI concerning ERM fundamentally improved organizational agility towards operational and technological risks, fostering proactive decision-making based on analyzed data. Furthermore, interactive reports and dashboards enable decision-makers to easily translate analyzed data into actionable information, improving responsiveness and decision quality in real-time tracking of ERM frameworks (Popovič et al., 2020). The active authoring of Mikalef et al. (2021) showed that interactive dashboards improve strategic decision-making through increased system transparency. It was complemented by Patipan (2024), who found that deploying text analytics alongside BI techniques helped improve ERM decision-making efficiency within complex environments.

The building blocks and connections between various data systems and information sources play a crucial role in operationalizing BI in ERM. Data silos and BI integration were shown to be streamlined through the use of data warehouses and ETL technologies, lowering lag time and thereby the ability to use forecasting tools in a more robust manner (Foshay & Kuziemsky, 2021; Seddon et al., 2022). Other research found that the greatest hurdle to which enterprise efforts in mitigating risks fail is in determining the analytics infrastructure to be employed (Elbashir et al., 2020; Mekimah et al., 2024). From a BI perspective, its practical utility in supporting ERM has been acknowledged across various sectors. It enables more accurate credit evaluation and assists in the detection of ML in the banking sector, whereas in insurance and supply chains, it addresses climate and operational risks, thereby lowering losses and improving institutional resilience (Ain et al., 2019; Zhang & Lu, 2020; Kraus et al., 2022; Nguyen et al., 2022).

The research provides ample evidence on BI and ERM integration barriers, including a reluctance to change, a lack of analytical and problem-solving skills, and vast comprehension issues regarding the results of certain analytical frameworks (Arnott, 2020; Watson, 2022). Besides these barriers, there is a shocking deficit of BI and ERM integration research, especially considering the absence of evidence in

SMEs, which testifies to the urgent necessity to develop a formalized integration framework of BI and risk management Rikhardsson & Yigitbasioglu, 2021; AlMomani, 2025). This is the gap this research attempts to bridge, outlining a conceptual framework for integration of BI risk management. This framework provides a conceptual view depicting the sequence of integration of different components of BI to the stages of ERM. The integration begins with the data governance and quality that set the conditions for dependable risk estimation and analytics. This is followed by the application of AI and Predictive Analytics that enable loss mitigation and preemption of new threats through swift, decisive action.

These outcomes are integrated in interactive reports and dashboards, which form part of the decision support systems and are used for the ongoing tracking of performance and risk measurements, as well as providing high-level operational decision support. The value added is that the elements applied improve the efficiency of the steps of the risk management process in identification, assessment, response, monitoring, and control, which in turn improves the operational and financial efficiency of the organization while decreasing the associated risks. The differential conclusion highlights that the addition of BI to ERM is not the simple enhancement of the tool set, but rather an all-encompassing strategy that is built around data, analytics, interactive reports and reporting systems, trained people systems, and structured infrastructure. This provides an answer to the research problem in the form of a practical and simplified conceptual model that can be used by an organization for improving its ERM system in addition to making a rigid structural arrangement to the entire organization in response to severe risks.

CONCLUSIONS AND RECOMMENDATIONS

The survey results indicate that the adoption of business intelligence (BI) tools and techniques with enterprise risk management (ERM) is vital for improving the operational and financial risk management of organizations. As data governance and quality control are the cornerstones of all BI processes, the ability to analyze and forecast risk with any degree of certainty enhances the capability of the organizations to visualize and make real-time decisions (Otto, Weber et al, 2023; Hidayah et al, 2024) Predictive analytics and artificial intelligence are, to the same degree, indispensable in risk anticipation and identification, thus improving the outcomes of the organization and minimizing losses. Johnson et al, 2023.

The interactive analysis or reports highlight the importance which converting data and analytics into actionable insights for the users. This importance also underlines the importance for the decision-makers for the need to possess data on the ongoing surveillance of performance and risk parameters to improve the timeliness and the effectiveness of their decisions (Popovič et al., 2020; Troilo et al., 2021; Patipan, 2024). On the other hand, the technological infrastructure and the interconnectivity among the data systems have been described as essential facilitators for organizations to systematically embed business intelligence within the Enterprise Risk Management. This follows the availability of data warehouses integrated with ETL technologies, which enhance the response time and precision of analytics (Foshay & Kuziemsky, 2021; Mekimah et al., 2024).

With BI governance captured in workflows and tracked in registers, the architecture is beyond merely technical in the BI remarked-within-by-ERM (business intelligence and enterprise risk management) fusion, as it correlates with a managerial paradigm, including but not limited to Responsible Data Management, ETL (Extraction, Transformation, Loading) technology procurements, systems, trained personnel, governance of organizational analytics, and framing the analytics to attain decision-centric outcomes (Arnott, 2020; Watson, 2022). The current work is also the BI-ERM (business intelligence and enterprise risk management) fusion with a productive pole-advocating for impact longitudinal studies to gauge outcomes on the financial position and a more cross-sectional eye-level on SMEs and BI (Rikhardsson & Yigitbasioglu, 2021).

Organizations looking to improve their risk management in BI would benefit from these recommendations. First, focus on data governance to enhance reliability and value analytics, then monitor, assess, and invest in artificial intelligence and predictive analytics for early risk detection and scenario anticipation. Second, develop and deploy reporting frameworks and dashboards that monitor risk and performance in near-real-time, and develop appropriate technology infrastructure, institutional continuous education, and training programs, so that BI outputs are managed and used to the fullest capability.

As for the rest of the recommendations, the author would like to see the proposed conceptual framework used as a guide for organizations, since it illustrates the interdependence of various BI components (data quality, predictive analytics, dashboards, and infrastructure) in improving all tiers of ERM from identification and evaluation, through response, to monitoring and reporting. Adopting this framework will enhance the accuracy of risk forecasting, responsiveness, decision-making, and overall agility in a dynamic and complex business environment.

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References

1. Ain, N., Vaia, G., DeLone, W. H., & Waheed, M. (2019). Two decades of research on business intelligence system adoption, utilization, and success – A systematic literature review. *Decision Support Systems, 125*, 113113. https://doi.org/10.1016/j.dss.2019.113113
2. Al-Momani, M. M. (2025). *The impact of business intelligence factors on risk management: A study of technical and human-administrative risks*. Salud, Ciencia y Tecnología - Serie de Conferencias, 4, 1527. https://doi.org/10.56294/sctconf20251527
3. Anton, S. G., & Nucu, A. E. (2020). Enterprise risk management: A literature review and agenda for future research. *Journal of Risk and Financial Management, 13*(11), 281. https://doi.org/10.3390/jrfm13110281
4. Arnott, D. (2020). Editorial: Decision support systems evolution: The makers’ knowledge perspective. *Decision Support Systems, 130*, 113233. https://doi.org/10.1016/j.dss.2019.113233
5. Chen, Y., Hu, W., & Xu, X. (2021). Predictive analytics in risk management: Applications in the banking sector. *Journal of Banking Regulation, 22*(3), 205–221. https://doi.org/10.1057/s41261-020-00146-0
6. Committee of Sponsoring Organizations of the Treadway Commission (COSO). (2017). *Enterprise risk management—Integrating with strategy and performance.* COSO. https://www.coso.org

7. Darwiesh, A., El-Baz, A., & Elhoseny, M. (2022). Business intelligence for risk management: A systematic review. *International Journal of Information Management Data Insights, 2*(2), 100073. https://doi.org/10.1016/j.jjimei.2022.100073
8. Elbashir, M. Z., Collier, P. A., & Sutton, S. G. (2020). The role of business analytics in strategic performance measurement systems. *International Journal of Accounting Information Systems, 36*, 100446. https://doi.org/10.1016/j.accinf.2019.100446
9. Foshay, N., & Kuziemsky, C. (2021). Towards an implementation framework for business intelligence in healthcare. *Information Systems Frontiers, 23*, 411–426. https://doi.org/10.1007/s10796-019-09985-2
10. Hidayah, N., Azhar, Z., Setiany, E., Utami, W., & Tarmidi, D. (2024). Determinants of ERM quality and its impact on company value. *Business: Theory and Practice, 25*(1), 11–23. https://doi.org/10.3846/btp.2024.19302
11. ISACA. (2024). *State of enterprise risk management and governance report.* ISACA. https://www.isaca.org
12. Islam, N., Nguyen, P., & Sarker, S. (2022). Artificial intelligence in banking: Applications, challenges, and research directions. *Journal of Business Research, 145*, 336–348. https://doi.org/10.1016/j.jbusres.2022.03.056
13. Jaradat, Z., Al-Hawamleh, A., & Hamdan, A. (2024). Examining the integration of ERP and BI in the industrial sector and its impact on decision-making processes in KSA. *Digital Policy, Regulation and Governance*. Advance online publication. https://doi.org/10.1108/DPRG-04-2024-0077
14. Johnson, M., Patel, R., & Adams, T. (2023). Leveraging predictive analytics in enterprise risk management: Evidence from financial institutions. *Risk Management, 25*(1), 45–63. https://doi.org/10.1057/s41283-022-00099-2
15. Khatri, V., & Brown, C. V. (2021). Designing data governance. *Communications of the ACM, 64*(12), 112–120. https://doi.org/10.1145/3487571
16. Kraus, S., Kanbach, D., Krysta, P., Steinhoff, M., & Tomini, N. (2022). Digital transformation and environmental sustainability: A review and research agenda. *Technological Forecasting and Social Change, 176*, 121441. https://doi.org/10.1016/j.techfore.2021.121441
17. Mekimah, S., Zighed, R., Mili, K., & et al. (2024). Business intelligence in organizational decision-making: A bibliometric analysis of research trends and gaps (2014–2024). *Discover Sustainability, 5*, 532. https://doi.org/10.1007/s43621-024-00692-7
18. Mikalef, P., Pappas, I. O., Krogstie, J., & Giannakos, M. (2021). Big data and business analytics: A research agenda for realizing business value. *Information & Management, 58*(3), 103385. https://doi.org/10.1016/j.im.2021.103385
19. Molnar, C. (2022). *Interpretable machine learning.* 2nd ed. Leanpub. https://christophm.github.io/interpretable-ml-book/
20. Nguyen, T. H., Ngo, L. V., & Ruël, H. (2023). Digital transformation and small and medium-sized enterprises: A systematic review. *Journal of Small Business Management, 61*(4), 1001–1023. https://doi.org/10.1080/00472778.2022.2050073
21. Otto, B. (2022). Data governance. In R. von Ammon, G. Schwabe, & R. Winter (Eds.), *Handbook of digital transformation* (pp. 455–478). Springer. https://doi.org/10.1007/978-3-030-80041-8_21
22. Patipan, S.-L. (2024). Modeling enterprise risk management ecosystems using text analytics. *Foundations of Management, 16*(1), 391-406. https://doi.org/10.2478/fman-2024-0024

23. Popovič, A., Hackney, R., Tassabehji, R., & Castelli, M. (2020). The impact of big data analytics on firms' high-value business performance. *Information Systems Frontiers, 22*, 1351–1367. https://doi.org/10.1007/s10796-019-09979-0
24. Rikhardsson, P., & Yigitbasioglu, O. (2021). Business intelligence & analytics for management accountants. *International Journal of Accounting Information Systems, 40*, 100501. https://doi.org/10.1016/j.accinf.2020.100501
25. Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence, 1*(5), 206–215. https://doi.org/10.1038/s42256-019-0048-x
26. Seddon, P. B., Constantinidis, D., & Dod, H. (2022). Business analytics and organizational performance: A review and research agenda. *Journal of Business Analytics, 5*(1), 1–19. https://doi.org/10.1080/2573234X.2021.2013255
27. Troilo, G., De Luca, L. M., & Guenzi, P. (2021). Linking data-rich environments with service innovation in incumbent firms: A conceptual framework and research propositions. *Journal of Service Research, 24*(1), 3–19. https://doi.org/10.1177/1094670520927086
28. Watson, H. J. (2022). Business intelligence: Past, present, and future. *Communications of the Association for Information Systems, 51*(1), 102–116. https://doi.org/10.17705/1CAIS.05119
29. Weber, K., Otto, B., & Österle, H. (2023). One size does not fit all: A contingency approach to data governance. *Journal of Information Technology, 38*(2), 129–146. https://doi.org/10.1177/02683962221075661
30. Zhang, Y., & Lu, X. (2020). Big data analytics for detecting money laundering in financial institutions. *Journal of Money Laundering Control, 23*(2), 387–401. https://doi.org/10.1108/JMLC-04-2019-0036