MEKATRONIKA: JOURNAL OF INTELLIGENT MANUFACTURING AND MECHATRONICS
E-ISSN: 2637-0883
VOLUME 8, ISSUE 1, 2026, In-Press
DOI: https://doi.org/10.15282/mekatronika.v8i2.14082

RESEARCH ARTICLE

Business intelligence and analytics for competitiveness and sustainability: Foundations, research gaps, and future pathways

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Abstract: Business Intelligence and Analytics (BIA) is now an emerging tool of importance for organisation's technological transformation. It helps grow organisations by enhancing their capability in decision-making and improves competitiveness. Although there are high levels of technological advancements, the research is still scattered, with little emphasis placed on cross-level integration, small and medium-sized enterprises (SMEs), and emerging economies. This study addresses these gaps by conducting a bibliometric and co-occurrence analysis of worldwide BIA research by using the Scopus database. VOSviewer was used to apply citation and keyword thresholds to analyze 45 influencing publications and 47 high-frequency keywords. This is to identify intellectual structures, thematic clusters, and research areas. Foundations and strategic value, performance drivers, organisational capabilities, sustainability, risk, human capital dimensions, and innovation pathways are the seven main clusters identified. Results indicate that BIA is multidimensional as a technological and socio-technical capacity that connects technical infrastructure and human, organizational, and contextual aspects. Challenges such as data quality, governance, adoption barriers, and skill gaps, particularly in SMEs as well as emerging economies are underscored in the results. Contributions by this study are integrating insights, extending theoretical perspectives and outlining a research agenda that emphasises inclusivity, sustainability, along with innovation. The implications can assist top level management in integrating BIA into strategic decision-making and provide scholars with a logical framework on which theory and practice can be applied.

Article History
Received :
Revised :
Accepted :
Published :

Keywords
Business intelligence and analytics
Digital transformation
Innovation
Small and medium enterprise
Bibliometric analysis
VOSviewer

1. Introduction

The transformations of Industry 4.0 to Industry 5.0 can be described in human-focused, sustainable and resilient systems of production. The combination of Industry 4.0 technologies, including blockchain, artificial intelligence, and big data with environmental, social, and governance (ESG) strategies improves the sustainability reporting, resource utilisation, and governance initiatives. That being said, obstacles such as high costs, low quality of data, and organisational resistance usually slow down adoption, so it is essential to source opportunities, overcome challenges, and create long-term roadmap towards sustainable innovation in this digital age [1]. Business Intelligence and Analytics (BIA) has become a significant asset in the last twenty years as organizations look to stay in a more dynamic and data-driven world [2]. Current studies have established that BIA improves decision-making, improves operational efficiency and creates strategic value across industries. Previous research demonstrated its role in process optimisation, organisational agility, competitive performance and sustainability, particularly when integrated with advanced technologies such as big data, artificial intelligence along with machine learning. Nevertheless, in spite of this accumulating body of knowledge, there are still major gaps to be filled. Current sources are disconnected across contexts, and most researchers focus on a particular element of the process, including adoption, benefits, or technical capabilities, ignoring cross-level interactions and frameworks. The SMEs are still under-researched especially about the leadership skills, cultural preparedness, and situational difficulties in implementing BIA. Besides, the research on developing economies is not evenly represented, it is still unknown how organisations in other markets implement BIA to create competitiveness and resilience [3]. The combination of the dimensions of foresight, governance, and sustainability also needs to be researched further to embrace the entire strategic potential of BIA.

The gaps in our work will be filled by performing a bibliometric and co-occurrence analysis that will map research trends in BIA globally. Being able to see the bigger picture and connect those BIA foundations, risks, drivers, capabilities, and challenges by the help of citation and keyword thresholds generation. This analysis reveals the most valuable contribution and thematic groups that provide a systematic summary of the development of BIA and its direction. In contrast to fragmented insights presented in the narrative reviews, this mapping presents a systematic synthesis reflecting the intellectual organisation, domains of knowledge and research frontiers of BIA. The uniqueness of this contribution lies in its comprehensiveness and general perspective. First, it contributes to the body of knowledge by integrating disjointed pieces of BIA research and building them into thematic clusters. Second, it moves the emphasis out of the technical aspects into the human, organisational, and contextual aspects, thus expanding the perspectives through which BIA effectiveness can be evaluated. Third, it raises the less explored settings, especially SMEs alongside emerging economies, creating the path to a more diverse and universal knowledge. Lastly, the paper is valuable in that it maps out

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a research agenda that can be used to utilise BIA to achieve sustainable growth, resilience, and innovation, creating a disruptive force that cuts across industries.

1.1 Objectives of the Study

i) To examine current trends in global research around Business Intelligence and Analytics (BIA) using bibliometric and co-occurrence strategies.
ii) To determine and categorise thematic groups that characterise the BIA research intellectual framework and changing landscapes.
iii) To discuss the research gaps and indicate future research directions, especially in the context of SMEs and developing economies.

2. Materials and Methods

Bibliometric analysis is a quantitative and systematic way of evaluating the scientific products of a research area with the help of visualisation tools which a researcher can track the intellectual changes, knowledge systems, and cooperation patterns of an academic field in the background [4]. It finds publication patterns, thematic discussions and contributions in tracing the developmental pattern of academic inquiry over the years. It is a methodology that emphasises central discussions, methodological orientations, and novel streams of thought that define the future of scholarship [5]. In this study, bibliometrics coupling was applied to investigate the international literature on Business Intelligence and analytics (BIA). The Scopus database was utilised as the source of data, which is known to have a wide coverage of peer-reviewed journals and conference proceedings. The original data composing 182 results were retrieved using the following search string:

((KEY (business intelligence) AND TITLE-ABS-KEY (analytics)) AND PUBYEAR > 2014 AND PUBYEAR < 2026) AND (SME OR SMES) AND (big data) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp") OR LIMIT-TO (DOCTYPE , "re")) AND (LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "DECI") OR LIMIT-TO (SUBJAREA , "SOCI")) AND (LIMIT-TO (LANGUAGE , "English"))

The search terms and criteria were selected to align with the specific aims of this study. The primary string “business intelligence” was searched in the keyword field (KEY) to ensure subject relevance. The term “analytics” was applied across titles, abstracts, and keywords (TITLE-ABS-KEY) to capture a broader body of work that addresses analytics as a core theme even when not using the exact BI label. The inclusion of “SME” or “SMEs” and “big data” directly reflects the study’s focus on the intersection of BIA with small and medium-sized enterprises and large-scale data environments. This criteria will filter out studies that treat BI in general or contexts that is not related the research area. The publication year range of 2015–2025 was chosen to capture the modern era of BIA. Document types included only journal article (ar), conference paper (cp), and review article (re), to guarantee the scholarly rigor. Subject areas were limited to Computer Science, Business, Decision Sciences, and Social Sciences due to their being the primary intellectual ground of BIA research. The English-language restriction was applied to maintain analytical consistency across the dataset, as keyword co-occurrence and bibliographic coupling analyses are sensitive to terminological differences between languages.

VOSviewer software was employed to visualise bibliometric maps, enabling the identification of citation links, keyword clusters, and thematic discussions. Based on the bibliometric data, two main analyses were conducted which are bibliographic coupling and co-occurrence analysis. Through this process, this study delivers an integrated understanding of key themes, contributors, and underexplored areas in BIA research.

Bibliographic Coupling: This analysis forms a conceptual proximity of documents depending on the level of shared references. When two publications cite common sources, they are considered coupled, and the strength of their linkage depends on the volume of overlapping citations [6]. These are the relationships through which thematic alignments and intellectual interactions can be seen among research papers. They can be used to investigate the works which were recently published but do not yet have citation counts. Beyond documents, bibliographic coupling can be extended to evaluate intellectual ties among authors, journals, countries, and institution [7].

Co-occurrence Analysis: This method investigates the co-occurrence of keywords across the literature to uncover the thematic composition of the field [8], specifically BIA. Through the analysis of the repetitive terms on the use of words, one can also identify the main focus of research as well as the new issues of potential interest. This method does not only emphasize the conceptual framework of BIA research, but also reflects its evolution to shifting technological, managerial, and societal priorities [9]. Co-occurrence analysis as an overall, helps to determine the clusters of related concepts that demonstrate the growing interest in the scholarly world from classic and basic themes to a more specialised area.

3. Results and Discussion

3.1 Bibliographic Analysis

In the bibliometric analysis, a threshold was applied to select the minimum number of citations per document to ensure the quality and relevance of the dataset. A minimum citation threshold of 7 was applied to 182 documents retrieved. This threshold was determined using VOSviewer’s built-in threshold optimisation function, which identifies the minimum citation count that yields the largest connected network of documents. A threshold of 7 produced a network of 45

documents that were mutually interconnected, representing approximately 25% of the original collection. Lower thresholds (e.g., 5 or 6) introduced a large number of isolated nodes with minimal connectivity which reduces the analytical coherence of the bibliographic coupling map. Higher thresholds (e.g., 10 or above) resulted to too few documents which is hard to produce a meaningful cluster structure. This filtering process has identified 45 documents which are interconnected and fit the criteria of inclusion into the mapping process. This process of filtering contributes to the strength of analysis since it assumes that only the most significant elements in the collection of data are included.

Table 1. List of publications according to rank based on TLS for each publication

Ranks	Author (Year)	Title	Citation	TLS
1	Di Vaio et al. (2022)	Data intelligence and analytics: A bibliometric analysis of human–Artificial intelligence in public sector decision-making effectiveness	166	21
2	Božič & Dimovski (2019)	Business intelligence and analytics use, innovation ambidexterity, and firm performance: A dynamic capabilities perspective	178	20
3	Rana et al. (2022)	Understanding dark side of artificial intelligence (AI) integrated business analytics: assessing firm's operational inefficiency and competitiveness	303	19
4	Oesterreich et al. (2022)	What translates big data into business value? A meta-analysis of the impacts of business analytics on firm performance	68	17
5	Egwuonwu (2024)	Drivers of Big Data Analytics' Adoption and Implications of Management Decision-Making on Big Data Adoption and Firms' Financial and Nonfinancial Performance: Evidence From Nigeria's Manufacturing and Service Industries	16	16
6	Cheng et al. (2023)	The impact of business intelligence, big data analytics capability, and green knowledge management on sustainability performance	60	12
7	Liu et al. (2023)	Examining how and when digital platform capabilities drive technological innovation: a strategic information perspective	38	12
8	Al-Edenat & Alhawamdeh (2022)	Reconsidering individuals' competencies in business intelligence and business analytics toward process effectiveness: mediation-moderation model	8	10
9	Bordeleau et al (2020)	Business intelligence and analytics value creation in Industry 4.0: a multiple case study in manufacturing medium enterprises	125	10
10	Belhadi et al., (2019)	Understanding Big Data Analytics for Manufacturing Processes: Insights from Literature Review and Multiple Case Studies	174	9

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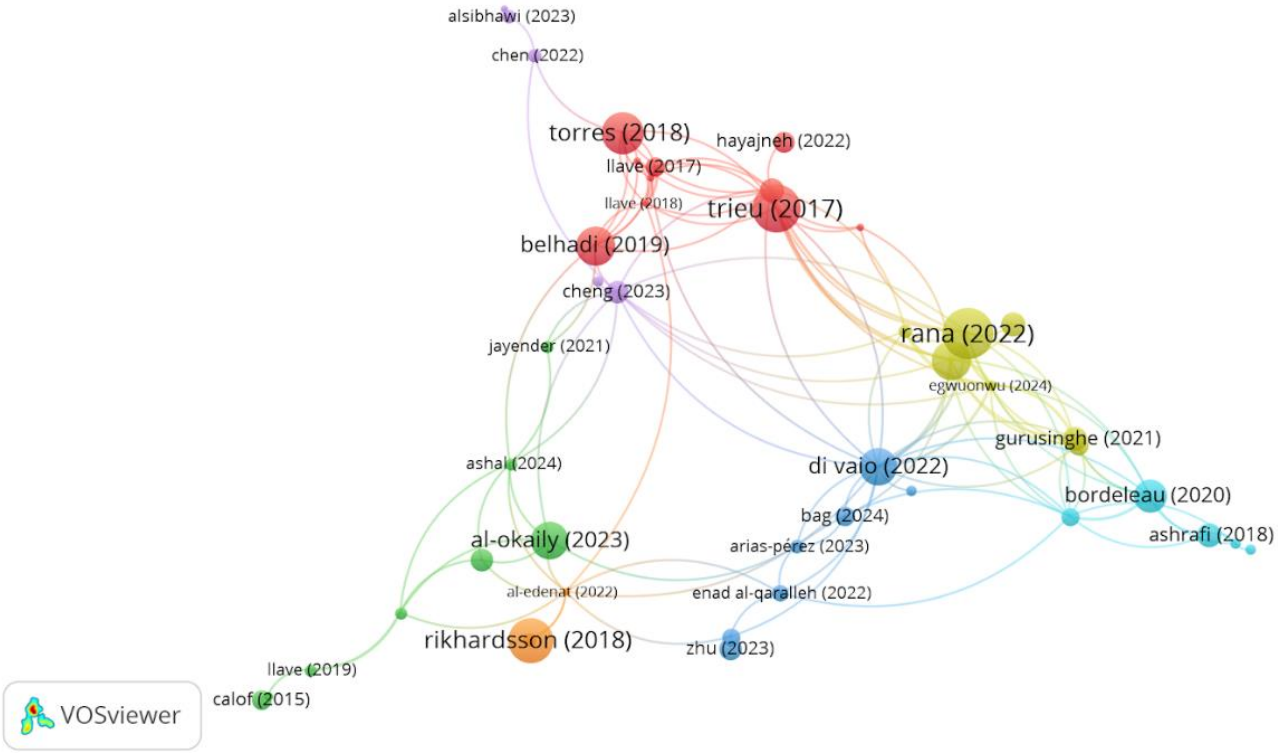


Figure 1. VOSviewer-generated bibliographic coupling network of the 45 selected publications

The network reveals several influential studies that occupy central positions within the field. Among these, Di Vaio et al. [10] recorded the highest Total Link Strength (TLS = 21), followed by Božič and Dimovski [11] (TLS = 20) and Rana et al. [12] (TLS = 19). Their central placement suggests that these studies have played an important role in shaping the development of Business Intelligence Analytics (BIA) research. Seven distinct clusters were identified, reflecting different areas of scholarly focus. Cluster 1 (Red) and Cluster 4 (Yellow) display particularly strong internal connections, indicating a high degree of similarity among the studies within these groups. By comparison, Clusters 6 (Sky Blue) and 7 (Orange) are located towards the edge of the network, suggesting that they represent more specialised or emerging topics that have yet to develop stronger links with the broader literature.

3.1.1 Cluster 1 (Red): Foundations and strategic value of business intelligence and analytics

Organisations are becoming reliant on data-driven decision-making to enhance performance. Although the role of BI has reached common awareness, studies on the subject of this phenomenon show major gaps. The existing research lacks comprehensive explanation of the processes that link investment in BIA and organisational performance, as well as does not provide sufficient coverage of the effects of BIA on different organisational levels [13]. The situation gets even more complicated as smaller organisations are analysed. The research on SME establishes significant gaps in knowledge. Recent research studies largely focus on each of these aspects separately, such as system functionality, implementation methods, or quantifiable outcomes. Another significant gap in the academic literature notes the lack of integrated models targeted at the enterprises with limited sources [14]. Comparative research from multiple nations reveals an important finding which is organisational success with analytics depends more on people and systems than on technology alone. Human resource quality, leadership competence, and organisational culture have stronger associations with analytics value than infrastructure or algorithm [15]. Several manufacturing reports support this conclusion. This is evidenced by a number of manufacturing reports. There are recorded instances in the manufacturing environment that demonstrate how analytics which are applied systematically can support the operational processes and build resilient systems [16]. Together, these results show the growing importance of analytics in businesses. They simultaneously underscore an essential scholarly gap which is the need for research frameworks that cover multiple sectors to comprehend BIA's complete organisational impact.

3.1.2 Cluster 2 (Green): Business intelligence and analytics as drivers of performance and strategic development

Competencies in business intelligence and analytics enhance process effectiveness through multiple mechanisms. Research claims that individuals with strong BIA technical skills in data analysis, managerial capabilities to implement insights and cultural understanding of data-driven decision making can enhance organizational effectiveness and strategic decision making [17]. System quality, information quality, and training quality influence user satisfaction, while data quality strongly predicts both perceived benefits and satisfaction, and together these factors drive organisational benefits from business intelligence technologies [18]. Combining foresight, intelligence, and business analytics reduces uncertainty in industrial programs by detecting external signals, using scenarios and dashboards to guide long-term policy, and identifying industry opportunities such as in the nutraceutical sector [19]. SMEs demand BIA skills in data management and analytics, business processes, cultural change, and investment decisions and a developmental pattern in which this can be adopted progressively and lead to sustainable organisational growth [20]. Collectively these examples demonstrate that business intelligence and analytics are not simply technical tools but can be used to influence organisational effectiveness, industrial foresight and the practices of leadership. The combination of competencies, quality and strategic foresight make organizations more resilient and competitive in rapidly changing environments. The broader picture highlights the idea of BIA being a revolutionary facilitator of innovation, sustainable development and value generation in the long-term in sectors.

3.1.3 Cluster 3 (Blue): Analytics, organizational capabilities, and sustainability in decision-making

Reflections on the study of data intelligence indicate that it is increasingly acquiring an important role in improving decision-making in the sector of the public where focus has not been much on the human-AI interface but rather on technological capabilities like AI and big data [21].Research on the supply chain explains that political and analytics competencies applied by executives, along with the culture that is AI-driven by the use of big data, can greatly enhance an environmental orientation, regenerative practices, and long-term viability of supply chains on a long-term basis in accordance with sustainability objectives [22]. Digital transformation studies conceptualise ambidextrous digital transformation, showing how data-driven insights drive efficiency and value creation, mediated by resource orchestration and supported by organisational agility and strategic decision-making [23]. The findings of the hospitality industry show that knowledge based HRM practices, analytics capabilities, and agility contribute to innovative performance, and agility is an essential prerequisite to reach high performance of innovation [24]. These views taken collectively are of strategic convergence between analytics, organizational capabilities, and the sustainability practices in development of decision-making, competitiveness and innovations across industries.

3.1.4 Cluster 4 (Yellow): Risks, ambidexterity, and human capital dimensions of BIA

Literature shows that incorporating AI in business analytics is not necessarily the way to acquire competitive advantage since an opaque environment caused by bad governance, poor data quality, and inadequate training leads to suboptimal decisions, perceived risk, and inefficient operations that eventually decline sales growth and employee satisfaction [12]. Analytics is also essential in driving innovation ambidexterity where companies strike a balance between explorative and

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exploitative activities, reinforce absorptive capacity and enhance performance by enhancing experimentation and predictability in new products and services provided [11]. In human capital management, predictive HR analytics potential, which is technologically, organisational, and environmentally dependent and mediated by the data-centric culture, comes as a strategic means of talent management and competitive advantage, although theoretical frameworks remain rare [25]. In the context of SME, business intelligence and analytics adoption can be divided into three maturity phases depending on managerial and technical factors with the core aspect of successful transformation residing in leadership competencies, contextual factors, and digital readiness, and is more likely to be successful during disruptive times, such as the Covid-19 pandemic [26]. Together, these works indicate that there is a two-fold potential in analytics to become the force of performance, innovation, and talent management, yet they also present risks and situational issues that organizations must overcome to turn to sustainable value.

3.1.5 Cluster 5 (Purple): Sustainability, adoption challenges, and emerging trends in BIA

Evidence from Malaysian manufacturing companies demonstrates that business intelligence strongly influences sustainability performance through big data analytics capability, which acts as both a determinant and mediator, though green knowledge management shows no moderating effect [27]. In the SME environment, conceptual work outlines the problems of adoption, and the major drivers of adoption were found to be change of management, sharing of knowledge, information quality, and managing IT projects. It has highlighted perceived usefulness and ease of adoption as major drivers in BI system acceptance [28]. Research in the government sector describes the necessity to implement integrated models that integrate business intelligence and analytics with performance management. Case evidence indicates that effective implementations require not only technology but proper processes, skilled individuals, and sound governance as well as the organizational ability to provide effective BIA projects [29]. According to a bibliometric review of global literatures, big data and AI-based BI applications are becoming a focal point of research, specifically in healthcare, hospitality, and 5G technology, with predictive analytics serving as the driving force behind future developments and practical applications toward disruptive events like COVID-19 [30]. Together, these points of views highlight the cross-dimensional application of BI and analytics to increasing sustainability, steering implementation, improving performance management, and evolving the trend of innovation in any field.

3.1.6 Cluster 6 (Sky blue): BIA as a catalyst for innovation and value creation across industries

Digital platform capabilities play a pivotal role in driving technological innovation by leveraging strategic information flows and quality, with business intelligence analytics enhancing the impact of strategic information on innovation outcomes [31]. In the context of medium enterprises that are experiencing the transformation of Industry 4.0, the value of business intelligence and analytics can be achieved not only by the means of resources and capabilities but by promoting the organisational learning and developing adaptive cultures [32]. Evidence highlights that market orientation improves innovation and subsequently market performance, with business analytics capabilities and IT infrastructure acting as critical enablers under conditions of market turbulence [33]. The comparative study of the tourism industry proves that business intelligence enhances technology adoption and business efficiencies whereas business analytics advance forecasting insights and customer engagement approaches [34]. Collectively, these perspectives underscore the diverse but complementary roles of BI and BA in shaping innovation, strengthening performance, and enabling value creation across industries. Further research studies should consider cross-sectoral comparisons and situational enabling factors that define the strategic effectiveness of BI and BA in complex environments.

3.1.7 Cluster 7 (Orange): Business intelligence and analytics in management accounting and process effectiveness

This cluster is concerned with the impact of Business Intelligence and Analytics (BIA) on changing the nature of management accounting and effectiveness of internal processes. The studies draw attention to the fact that BIA is not only a technical system, but also a mediating mechanism and also a set of capabilities which act as the link between central transactional systems (like ERP) and more advanced management accounting methodologies and decision support. Rikhardsson and Yigitbasioglu [35] trace the evolution of BIA in the research on management accounting, and also deem there to be a need for more attention to how analytics is used in planning, controlling, and assessing performance. Youssef and Mahama [36] demonstrate empirically that BI serves as a mediator between ERP and management accounting practices enabling rich reporting and more informed managerial decisions. Al-Edenat and Alhawamdeh [17] add the individual-level dimension by showing the significant and positive effect of the BI/BA competencies in employees on the effectiveness of processes, pointing to the value of analytics in management accounting, which is dependent on both the systems available and the competencies of the people who utilise them.

3.2 Co-occurrence Analysis

In the co-occurrence analysis, a threshold was applied to determine the minimum number of occurrences of a keyword. This is to ensure the reliability and significance of the mapping results. From the 1269 keywords identified, a minimum occurrence threshold of 5 was set, together with the use of thesaurus (as shown in Table 3), leading to 47 keywords that met the inclusion criteria for the co-occurrence network. An occurrence threshold of 5 was selected because it retained keywords with sufficient frequency to form stable, meaningful co-occurrence links while excluding low-frequency terms that appear in only one or two papers and whose inclusion would fragment the network into many small, uninterpretable clusters. Thresholds below 5 (e.g., 3 or 4) in this dataset produced over 150 qualifying keywords, generating a visually congested and analytically unclear network map. Thresholds above 5 (e.g., 8 or 10) reduced the keyword pool to fewer

than 30 terms, omitting conceptually important but moderately frequent keywords such as "SME," "supply chain management," and "sustainability." The threshold of 5 therefore maximises thematic coverage while ensuring that each retained keyword has established co-occurrence ties across multiple publications, supporting the reliability of cluster formation. This filtering process improves the analysis by focusing on the most representative and frequently occurring terms in the dataset.

Table 2. List of seven clusters ranked based on the number of publications

Cluster No. & Colour	Title	Number of publications	Representative publications
1 (Red)	Foundations and Strategic Value of Business Intelligence and Analytics	10	Trieu, (2017), Llave, (2017), Oesterreich et al., (2022), Belhadi et al., (2019)
2 (Green)	Business Intelligence and Analytics as Drivers of Performance and Strategic Development	8	Al-Okaily et al., (2023), Calof et al., (2015), Wee et al., (2023), Jayender (2021)
3 (Blue)	Analytics, Organizational Capabilities, and Sustainability in Decision-Making	7	Di Vaio et al., (2020), Bag & Rahman, (2024), Zhu & Li, (2023), Enad Al-Qaralleh & Atan, (2022)
4 (Yellow)	Risks, Ambidexterity, and Human Capital Dimensions of BIA	7	Rana et al., (2022), Božič & Dimovski, (2019), Gurusinghe et al., (2021), Hoang & Bui, (2023)
5 (Purple)	Sustainability, Adoption Challenges, and Emerging Trends in BIA	5	Cheng et al., (2023), Alsibhawi et al., (2023), Yahaya et al., (2019), Chen et al., (2022)
6 (Sky Blue)	BIA as a Catalyst for Innovation and Value Creation Across Industries	5	Liu et al., (2023), Bordeleau et al., (2020), Ashrafi & Zare Ravasan, (2018), Jiménez-Partearroyo et al., (2024)
7 (Orange)	Business Intelligence and Analytics in Management Accounting and Process Effectiveness	3	Al Edenat (2022), Youssef (2021), Rikhardsson (2018)

Table 3. List of keywords ranked based on the co-occurrences

Rank	Keyword	Occurrences	TLS	Cluster
1	Business Intelligence	117	414	4
2	Data Analytics	55	305	1
3	Big Data	46	239	1
4	Artificial Intelligence	54	223	1
5	Decision Making	35	196	5
6	Business Analytics	39	163	4
7	Information Analysis	32	158	4
8	Analytics	26	145	1
9	Competitive Intelligence	23	139	2
10	Predictive Analytics	21	111	2
11	Information Use	16	108	2
12	Information Systems	15	106	2
13	Machine Learning	18	99	2
14	Information Management	14	86	1
15	SME	17	84	1

The results show that "business intelligence" (TLS = 414, occurrences = 117) and "data analytics" (TLS = 305, occurrences = 55) are the most prominent keywords in the network, highlighting their central role within the field. Keywords such as "artificial intelligence" and "big data" appear between major clusters, suggesting that they connect multiple research themes and are relevant across different areas of study. Cluster 3 (Blue), which includes terms such as "digital transformation" and "knowledge management", forms a relatively cohesive group with strong internal relationships. However, its weaker links to other clusters indicate that this stream of research remains somewhat distinct from the broader BIA literature. Several keywords, including "data visualisation" and "organisational agility", appear on the periphery of the network. Although these topics are currently less prominent, their presence may point to areas that are gaining attention and offer opportunities for future research.

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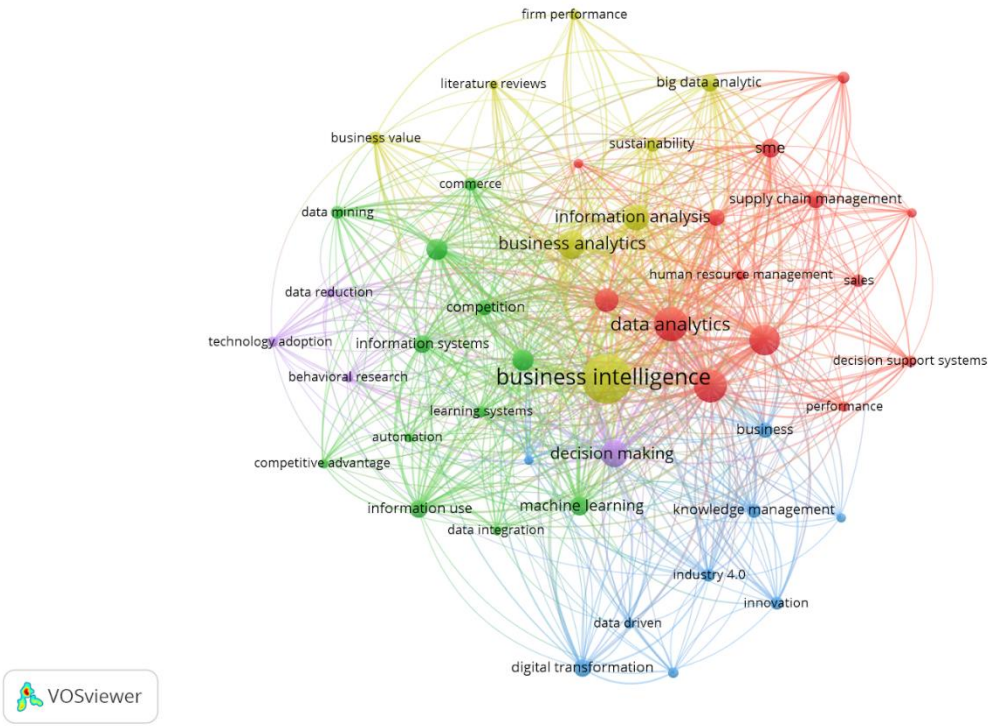


Figure 2. VOSviewer-generated keyword co-occurrence network of 47 BIA literatures

3.2.1 Cluster 1(Red): Technological infrastructure of data-driven decision making

Cluster 1 represents an overall view of technological and infrastructural foundations for data driven organisations. Having the highest total link strength and citation activity makes it the foundation layer upon other clusters. The main factors in this infrastructure are big data and data analytics as they occur the most. These factors act as the core stream to churn large scales of data into actionable insights. In recent years, organisations have been utilising cloud-based data platforms for managing data storage, artificial intelligence and machine learning algorithms to keep their data well organised and instantly accessible. Structuring big data and analytics by SME allows them to have efficient information infrastructure [37]. The keyword 'SME' is also highly ranked which indicates that even smaller business owners nowadays need these technologies, not only large corporations. Studies prove that big data and AI technologies improve SME sustainability and performance [38]. Analytics has also become a part of enterprise system and operational decision support [39]. This cluster also highlights how AI and advanced analytics affect management performance. Researchers and practitioners are increasingly working closely in this area as data analytics evolves into an essential tool for organisations [39].

3.2.2 Cluster 2 (Green): Strategic prediction for competitive advantage

This cluster explains the applications of predictive analysis techniques by organisations to stay ahead of other competitors. Competitive Intelligence is essential for organisations because it helps in better planning by understanding customer's preferences, competitor's strategies and market trends. Business value is able to be created with predictive analytics, [40]. For instance, a telecommunication company might use predictive analysis to reach their customers who are planning to cancel their contract by proposing customised offers that are better than their competitors as well as tailored to the customers' needs. Big data adoption strengthens a business competitive position over the others, [41]. Identifying critical risks and proposing strategies is important to bridge the gap between corporate practice and academic research, focusing on implementing Business Analysis in telecommunications [42].

3.2.3 Cluster 3 (Blue): BIA as a tool for strategic digital transformation

High citation index(h-index) for business performance and knowledge management shows that scholars constantly link BIA to performance outcome through strategic transformation. It is important for any transformation steps taken and how they perform to be driven by data and BIA, [23]. The appearance of data visualisation in this cluster indicates that digital transformation requires approval from top management and stakeholders authorisation which highlights the importance of data visualisation in decision making. Big Data, AI and BI works hand in hand to drive strategic digital transformation, [43]. Industry 4.0 has a strong influence of big data, BIA and digitalisation capabilities in driving its transformation, [44]. Cluster 3 has strong internal co-occurrence but none of the keywords appear among the top 15 keywords ranked by Total link strength attribute. This indicates that the cluster has a strong connection among internal concepts but less frequently discussed in global BIA topics. The keywords in this cluster are usually used in specific context discussions.

3.2.4 Cluster 4 (Yellow): BIA impact on organisation's performance

The cluster confirms that business intelligence and business analytics are framed as an integrated concept that combines tools and processes to support managerial decision making [15, 45]. BIA is perceived as a one-stop system in this cluster, combining the tools, data systems, analysis methods, and company procedures in making decisions by the management. The occurrence of "information analysis" as one of the keywords in this cluster explains the core process of BIA is examining data to find patterns and insights [13]. This key concept explains when the company studies data regularly to discover patterns and trends, and irregularities. It then applies these insights in making superior decisions concerning cost, productivity, customer service, risk, and strategy. Once this analysis is created into daily work, such as featuring dashboards, reports, alerts, and scenario models, it offers more timely, truthful, and futuristic information to a manager than the simple reports provide. The other meaningful information is the people. The cluster also emphasises that BIA develops skilled individuals who know how to solve real business issues through analysing data rather than just depending on software and tools [16, 45]. This means that benefits of BIA are dependent on the trained individuals to be able to read data and relate it to actual business issues. These are employees who know the business and the analysis, who can transform findings to action by altering processes, repositioning resources, redesigning products or tweaking strategy. The more employees are being developed with these skills, the more likely the decision making process will be evidence-based, less guess-work and more coordinated throughout the firm. The combination of integrated BIA systems and experienced personnel improves the efficiency of the operations, financial outcomes, innovation, and the overall competitiveness of the company.

3.2.5 Cluster 5 (Purple): Human and organization behaviour towards BIA adoption

Here, the discussion shifts from technology to human and organisation's discipline towards translating data into practical business value. Several factors have been identified to shape BIA adoption behaviour such as organisational, technological as well as social factors, [46]. In the real world, decision making might be different depending on the context. BIA investments are only profitable when it leads to decisions that generate better business results. The struggle of most organisations is the implementation of BIA recommendations after the adoption, [47]. An excellent BIA system may not guarantee a successful implementation if the organisation has not redesigned its decision making processes to use these insights.

Table 4. List of clusters ranked based on number of keywords that co-occurred

Cluster No. & Colour	Title	Number of Keywords	Representative Keywords
1 (Red)	Technological Infrastructure of Data-Driven Decision Making	14	Data Analytics, Big Data, Artificial Intelligence, Analytics, SME
2 (Green)	Strategic Prediction for Competitive Advantage	12	Competitive Intelligence, Information Use, Information Systems, Predictive Analytics, Machine Learning
3 (Blue)	BIA as a Tool for Strategic Digital Transformation	9	Data Visualization, Organizational Agility, Knowledge Management, Industry 4.0
4 (Yellow)	BIA Impact on Organization's Performance	8	Business Intelligence, Information Analysis, Business Analysis, Sustainability
5 (Purple)	Human and Organization Behavior Towards BIA Adoption	4	Behavioral Research, Decision Making, Technology Adoption

3.3 Implications

The insights generated from the bibliometric analysis of Business Intelligence and Analytics (BIA) research carry meaningful implications for both practice and theory. On the practical side, At the applied level, the results provide managers and decision-makers with advice on the ways in which BIA could be strategically adopted to enhance efficiency, promote innovation, and resilience within dynamic environments. On the theoretical side, the mapping of global scholarship offers a platform to support the development of conceptual clarity, covering unexplored contexts, and building integrative frameworks linking technical, organisational and human aspects of BIA.

Together, these implications highlight the way in which BIA is developing, out of a collection of technical tools, to serve as a revolution, shaping the organisations strategy, governance and long-term sustainability. Balancing sustainability and food security in agriculture involves adopting Industry 4.0 technologies such as blockchain, IoT, and AI, which not only enhance resilience and efficiency but help to face challenges including limited infrastructure, inequality, and lack of awareness; overcoming these barriers requires inclusive policies, strategic alliances, and capacity-building, with future directions focusing on long-term approaches, stakeholder engagement, and integration of emerging technologies [7].

3.3.1 Managerial implications

Business Intelligence and Analytics (BIA) assists managers with a map of the way to enhance the performance of the organisation by inculcating the data-centric approaches throughout every level of the decision-making [48]. One of the central insights emerging from this analysis is the recognition that BIA effectiveness does not solely depend on technical systems but is significantly influenced by human skills, user participation, and leadership competencies. Managers are

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therefore encouraged to view BIA as a strategic investment in both technology and people [49]. By improving the data literacy of employees, educating them on analytical tools, and instilling confidence in underrepresented people, especially women, more welcoming and productive decision-making processes can be achieved. These initiatives result in not only effectiveness of the processes, but also lead to greater job satisfaction and employee engagement that further enhances the overall performance of an organisation [50].

Another important implication relates to the management of data quality and information resources. The results emphasise that system quality, training quality, and especially data quality are essential determinants of perceived benefits and user satisfaction with BIA systems. To the managers, this is to imply that along with investments made on the infrastructure of BIA, there ought to be investments in the maintenance of correct, reliable and well-structured data. Neglecting these aspects can undermine the credibility of analytics outputs and reduce trust in decision-making. Managers in SMEs, in particular, should allocate resources toward simple yet effective BIA solutions that balance affordability with reliability. Also, through structured monitoring tools like dashboards, managers are in a position to view the progress of the industrial programs, identify the early risks and make corrective actions on time consequently cutting the uncertainty factor and enhancing the resilience in the volatile markets [51]

Lastly, managerial decision making needs to become more and more intertwined with foresight and intelligence alongside BIA systems. Insights gained from the bibliometric mapping point to the potential of integrating external market signals with internal for uncertainty reduction and improve strategic planning. Managers should adopt a proactive orientation by leveraging BIA to anticipate future scenarios, identify emerging opportunities, and adjust organisational strategies accordingly. For example, industries such as manufacturing, nutraceuticals, or public services can benefit from foresight-driven analytics that guide investment decisions and policy alignment [52] In addition, SME managers should understand that the process of adoption of BIA is a progressive process with continuous skill development in the areas of data management, cultural fit, and investment decisions. With the practices embedded, managers are able to make BIA a supportive tool into a strategic capability that leads to long-term competitiveness and sustainable growth. Altogether, managerial implications can support the importance of the holistic approach of people-mechanisation-technology to unlock the potential of BIA [11].

3.3.2 Theoretical implications

Bibliometric mapping of BIA studies, in its turn, leads to the theory-building, as it helps to connect fragmented pieces of knowledge to a unified intellectual system. Determining seven different clusters that include foundations and performance drivers, risks, sustainability, and innovation will give a systematic perspective of the development of BIA knowledge. This synthesis moves the discussion of the theoretical debates out of the limited technical views to emphasise the multidimensional characteristics of BIA consisting of social, cultural, organisational, and contextual factors. This integration assists in overcoming the shortcomings of previous research that viewed BIA as more of an IT system rather than as a socio-technical ability that determines organisational performance and innovativeness. In this way, the analysis contributes to the conceptual clarity and builds the theoretical basis of the future research.

Another theoretical contribution can be defined as the focus on the under-researched settings, especially, SMEs and developing economies. A lot of the BIA literature is based in developed nations and with large corporations, but the study underlines the manner in which the size of organisations, amount of available resources, and cultural preparedness, affect adoption and results. The mapping highlights that it is necessary to apply BIA theories to smaller companies and new markets where the adoption is informed by the particular issues of limited resources, digital skills gaps, and strained infrastructures. This viewpoint takes the theoretical debate a step further and places diversity and inclusiveness in the centre of BIA scholarship, whereby theoretical constructs created in developed economies might not be applicable across a variety of contexts. Such a gap will be addressed as it will open the way to the context-sensitive frameworks that would be able to capture the realities of various organizational and national contexts.

Also, the findings provide theoretical possibilities to connect BIA to a broader field, including foresight, sustainability, and human capital development. Current theories focus more on efficiency and performance results, whereas the clusters found indicate that BIA is also useful in long-term policy-making, ambidexterity of innovation, and workforce empowerment. These intersections invite the creation of integrative theoretical frameworks that relate BIA to ideas of strategic management, organisational behaviour, and the sustainability literature. As an example, it is possible to theorise BIA as a resource of knowledge and as a dynamic capability, which helps organisations to balance between efficiency in the short term and long-term flexibility. These frameworks would not only include the technical aspects of BIA, but they would also explain the contribution of BIA to culture and governance and strategic foresight. The theoretical implication, overall, is that BIA scholarship is shifting to a more multifaceted and multi-layered concept, combining technological, human, and contextual aspects, which presents new avenues of theory generation in the management and information systems research.

3.4 Limitations

Although this bibliometric analysis renders some important information about the intellectual organisation and development of Business Intelligence and Analytics (BIA) research, there are some limitations which should be admitted. First, the research uses Scopus database as a sole source of data. Even though Scopus is commonly known to have an extensive coverage of peer-reviewed literature, not all of the literature that is relevant in other indexing databases like Web of Science or Google Scholar are covered in Scopus. This dependency might have omitted certain powerful work

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especially those in some of the local journals or conference papers that are not indexed in Scopus. As a result, the dataset, while robust, may not represent the full breadth of scholarly contributions in the field.

Second, the analysis applied a citation threshold to ensure that only the most influential publications were included in the mapping process. While this approach enhanced the reliability of the findings by focusing on highly cited works, it may have overlooked recent studies that are relevant but have not yet accumulated substantial citation counts. Since bibliometric methods inherently favour established publications, the rapidly emerging themes, such as artificial intelligence integration, real-time analytics, or the role of BIA in digital transformation, may not be fully captured. This creates a potential time-lag effect where new but impactful research areas are underrepresented in the analysis [53].

Third, the study focuses primarily on quantitative mapping of publications, citations, and keyword networks. While this approach provides a clear visualisation of research trends and thematic clusters, it does not fully capture the depth of conceptual insights or methodological nuances present in individual studies. The reliance on keyword co-occurrence also assumes consistency in how authors use terms, which may not always be the case, leading to potential variations in cluster formation [54]. Moreover, the clusters have to be interpreted in a relatively subjective manner because the interpretation of the clusters presupposes that the meaning and coherence of the identified patterns should be attached with the help of qualitative judgment.

Combined, these restrictions point out that the findings can be understood as a systematic review but not as a final description of the entire BIA scholarship. Irrespective of these limitations, the research provides a powerful base to the discourse of the intellectual terrain of BIA and a framework through which prospective studies can be conducted to fill the gaps.

3.5 Future Research Avenues

It is based on the identified limitations that some promising directions can be offered in future research on Business Intelligence and Analytics (BIA). To begin with, the area of bibliometric analyses in the future research should be increased to include several databases including Web of Science, IEEE Xplore, or Google Scholar. This would guarantee a wider coverage where regional contributions, new conference papers, and different viewpoints that might not be found individually in Scopus would be captured. Cross-database comparisons would also be more successful at revealing research trends on a global scale and minimise the chance of not recognising a study that is important but not as popularly indexed.

Second, scientists should consider paying attention to the new themes which do not receive a large number of citations, yet which have a high potential to form the next generation of BIA scholarly studies. Among them are the role of BIA in digital transformation, the integration of artificial intelligence and machine learning into the BIA systems, real-time data analytics, the role of BIA in digital transformation, and blockchain-enabled intelligence. Tracing these new directions with the help of bibliometric mapping and case-based studies would assist in capturing the changing role of BIA in the ever-changing technological environments. Also, longitudinal studies of how research themes change over time might help illuminate the ways in which new trends are substituting, complementing, or adding to existing lines of research.

Third, future work must pay more attention to contextual aspects and especially to the experiences of small and medium-sized enterprises (SMEs) and organisations in developing economies. The existing BIA literature focuses largely on the largest companies operating in developed economies, creating a knowledge gap on how to address BIA barriers to adoption, skills gaps, governance complexities, and cultural preparedness elsewhere. Better theory and practice may be achieved through cross-sectoral and cross-country comparative research studies that discover the role institutional environment, resource limitations, and cultural expectations play in BIA adoption and performance. In addition, future studies may establish integrative models, which can relate BIA with sustainability, policy-making, and development of human capital, that is, it is not a technological system but a socio-technical capability.

In general, the way forward must be to become inclusive, interdisciplinary and flexible. With the help of the combination of cutting-edge bibliometrics tools and the approaches of the qualitative type, scholars can produce insights that address not only the current state of the BIA research but also its future. This would fortify theoretical advancement, steer managerial activity and make sure BIA remains a transformative force of competitiveness, resilience and sustained growth.

4. Conclusions

Business Intelligence and Analytics (BIA) is an emerging area of research. It influences the way in which organisations develop value, make improved decisions and acquire competitive advantage in a constantly evolving business environment. Through the application of both bibliometric and co-occurrence analyses, this research maps the intellectual landscape of BIA by interpreting the main clusters, which manifest its foundations, driving elements of performance, organizational opportunities, risks, adoption aspects, sustainability issues, and innovation opportunities. The outcome highlights the fact that, BIA is not only a technical tool, but a socio-technical ability, which signifies unification of people, processes, and technology.

There are major practical and theoretical implications of the results. To managers, the analysis revealed the importance of building employee capabilities, data quality, and being able to establish BIA in strategic planning and foresight. For researchers, this study is valuable because it brings together fractured knowledge in unified groups, uncovers gaps in knowledge research, and indicates new theoretical frameworks to support the multidimensionality of BIA. Limitations related to the scope of the database, citation boundaries, and the methodological choice mean that the results should be considered as an informed overview and not the final description of the discipline in general.

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In conclusion, the paper presents opportunities in future research. Broader coverage of databases, investigation of new trends, including AI-based analytics and the advent of blockchain, and filling gaps in the focus of SMEs and developing economies will enhance both academic knowledge and managerial practice. The integrative and interdisciplinary strategy will also be of crucial benefit in tackling BIA as a transformational energy in all industries. Overall, this work is a source of continuing exploration of BIA, as it offers scholars, managers, and policymakers a better understanding of the nature of BIA as it exists in the present, challenges it faces, the opportunities it has to facilitate innovation, sustainability, and overall organisational development.

Acknowledgements
The author would like to acknowledge the academic guidance provided by supervisors and lecturers during the development of this research. This study was conducted as part of the first author's doctoral research at International Islamic University Malaysia. The authors also acknowledge the use of bibliometric analysis software and secondary data sources that supported the completion of this study. Any remaining errors are the responsibility of the authors.
AUTHOR ACTION REQUIRED: If specific individuals are to be named in the Acknowledgements, please provide each person's name and contribution and confirm consent to be acknowledged. Otherwise, please confirm the wording above.

Funding
AUTHOR ACTION REQUIRED: Please confirm all financial or material support and provide the full official funder name and grant/award number. If no specific funding was available, use the mandatory statement: "This study was not supported by any grants from funding bodies in the public, private, or not-for-profit sectors."

Declaration of Competing Interests
The authors declare no conflicts of interest.

CRediT Author Contribution Statement
Zahid Khair: Conceptualisation; Methodology; Data curation; Formal analysis; Visualisation; Writing – original draft.
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AUTHOR ACTION REQUIRED: The first-author roles above were mapped from the contribution description supplied in the manuscript. All authors must review and agree to the final CRediT statement.

Availability of Data and Materials
AUTHOR ACTION REQUIRED: Please provide the accessibility statement for the Scopus records, filtered bibliometric dataset, thesaurus file and VOSviewer outputs. If the processed datasets can be shared on request, the template permits: "The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request."

Ethics Statement
This study did not involve human participants or animal subjects. Ethical approval was therefore not required for this research.
AUTHOR ACTION REQUIRED: Please confirm the ethics statement above, including that only bibliographic/secondary data were analysed and no sensitive personal data were used.

Generative Artificial Intelligence Disclosure
AUTHOR ACTION REQUIRED: Please disclose any generative AI use, including tool name/version and purpose. If no generative AI tools were used, confirm the following statement: "No generative artificial intelligence tools were used in the preparation of this manuscript. All intellectual content is original and solely attributable to the authors."

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Appendix A
Filtered Dataset used for Bibliometric Coupling

No	Author	Cluster	Citations	Total Link Strength (TLS)
1	Belhadi (2019)	1	174	9
2	Hayajneh (2022)	1	53	1
3	Llave (2017)	1	50	8
4	Lave (2018)	1	9	9
5	Oesterreich (2022)	1	68	17
6	Sanchez-Hughet (2022)	1	8	7
7	Subramaniam (2024)	1	7	4
8	Torres (2018)	1	212	8
9	Trieu (2017)	1	264	8
10	Ye (2023)	1	7	6
11	Al-Okaily (2023)	2	162	6
12	Ashal (2024)	2	20	7
13	Bany mohammed (2024)	2	64	4
14	Calof (2015)	2	46	1
15	Jayender (2021)	2	17	3
16	Llave (2019)	2	19	3
17	Solano (2024)	2	10	2
18	Wee (2023)	2	20	6
19	Arias-Pérez (2023)	3	21	5
20	Bag (2024)	3	48	3
21	Di Vaio (2022)	3	166	21
22	Enad Al-Garalleh (2022)	3	35	5
23	Paradza (2021)	3	42	4
24	Rajnoha (2024)	3	15	1
25	Zhu (2023)	3	60	1
26	Božič (2019)	4	178	20
27	Egwuonwu (2024)	4	16	16
28	Gurusinghe (2021)	4	70	8
29	Haftor (2021)	4	46	7
30	Hoang (2023)	4	23	8
31	Janković (2023)	4	68	2
32	Rana (2022)	4	303	19
33	Alsibhawi (2023)	5	21	2
34	Chen (2022)	5	23	3
35	Cheng (2023)	5	60	12
36	Mantri (2023)	5	14	1
37	Yahaya (2019)	5	8	1
38	Ashrafi (2018)	6	69	3
39	Bordeleau (2020)	6	125	10
40	Jimenez-Partearroyo (2024)	6	13	1
41	Liu (2023)	6	38	12
42	Shiau (2023)	6	15	4

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43	Al-Edenat (2022)	7	8	10
44	Rikhardsson (2018)	7	243	2
45	Youssef (2021)	7	23	2

Appendix B
Filtered Dataset used for Keyword Co-Occurrences

No	Keyword	Cluster	Total link strength	Occurrences	Avg Citations
1	analytics	1	145	26	38.3077
2	artificial intelligence	1	223	54	22.2963
3	big data	1	239	46	37.6522
4	cloud computing	1	34	5	4
5	data analytics	1	305	55	24.1455
6	decision support systems	1	46	7	45
7	enterprise resource planning	1	37	7	14.2857
8	human resource management	1	36	6	8.1667
9	information management	1	86	14	15.0714
10	performance	1	39	6	88.1667
11	sales	1	30	8	44.75
12	sme	1	84	17	12.6471
13	supply chain management	1	70	15	23.8
14	systematic literature review	1	29	5	38.6
15	automation	2	34	5	0.2
16	commerce	2	55	9	18.6667
17	competition	2	82	12	45.6667
18	competitive advantage	2	30	5	14.4
19	competitive intelligence	2	139	23	35.7391
20	data integration	2	32	5	1
21	data mining	2	63	9	51.8889
22	information systems	2	106	15	5.6667
23	information use	2	108	16	1.875
24	learning systems	2	56	7	22.1429
25	machine learning	2	99	18	23.7222
26	predictive analytics	2	111	21	14.5238
27	business	3	60	12	41.4167
28	business performance	3	33	5	28.2
29	data driven	3	23	5	17.4
30	data visualization	3	18	5	5.6
31	digital transformation	3	54	15	24.6667
32	industry 4.0	3	56	8	57.75
33	innovation	3	34	8	35
34	knowledge management	3	58	10	42.2
35	organizational agility	3	24	6	19.5
36	big data analytic	4	75	15	31.1333
37	business analytics	4	163	39	18.7179
38	business intelligence	4	414	117	23.2906
39	business value	4	45	8	61.5
40	firm performance	4	27	6	84.3333
41	information analysis	4	158	32	41.2188
42	literature reviews	4	30	5	37.2
43	sustainability	4	47	10	18.4
44	behavioral research	5	35	5	7.8
45	data reduction	5	33	5	0
46	decision making	5	196	35	19.6286
47	technology adoption	5	31	6	6

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Appendix C
Thesaurus used to unify similar terms

Label	Replaced by
business intelligence	business intelligence
business intelligence (bi)	business intelligence
business intelligence and analytics	business intelligence
business-intelligence	business intelligence
business intelligence systems	business intelligence
advanced analytics	analytics
analytics	analytics
big data analytic	big data analytic
big data analytics	big data analytic
data analysis	data analytics
data analytics	data analytics
decision making	decision making
decisions makings	decision making
jordan	
machine learning	machine learning
machine-learning	machine learning
small and medium-sized enterprise	sme
sme	sme
smes	sme
supply chain management	supply chain management
supply chains	supply chain management
sustainability	sustainability
sustainable development	sustainability

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