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Generative AI and Augmented Business Analytics for Managerial Decision-Making: A Scopus-Based Bibliometric and Thematic Analysis, 2019-2026

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ABSTRACT

The business landscape is changing with the introduction of generative AI and augmented analytics, which transform business intelligence from descriptive reporting to a more conversational experience, from automatic insight generation to the ability to explain decisions or use AI to guide managerial judgment. In this study, fragmentation is tackled by conducting a bibliometric and thematic analysis of 92 documents retrieved between 2019 and 2026 from the Scopus database. The analysis includes performance analysis, citation analysis, country and source mapping, keyword co-occurrence, bibliographic coupling and thematic mapping using Bibliometrix/Biblioshiny, and Excel. The results indicate a young field that is growing quickly with 77.2% of documents published in 2025-2026, and an annual growth rate of 63.32%. The corpus is dominated by conference papers, which reflects the early dissemination of knowledge, and the core conceptual vocabulary includes business intelligence, large language models, artificial intelligence, generative AI, natural language processing and augmented analytics. The thematic structure indicates that the field is characterized by a focus on decision making, language models and business intelligence, and the need for trust, explainability, effectiveness of validation, data governance and human-AI collaboration is not fully integrated. The study makes a significant contribution by shifting the focus from GenAI as a mere technical extension of BI to a new decision-intelligence capability. It also proposes a conceptual framework linking generative AI, augmented analytics, business analytics capability, managerial decision quality, governance mechanisms and business performance.

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1. Introduction

The use of business analytics to transform data into reports, dashboards, forecasts and performance indicators is a traditional approach that has been used for many years. Previous business intelligence and analytics studies focused on data warehousing, analytical processing, and visualization and decision support as ways that organizations can enhance information processing and manager decision effectiveness (Chen et al., 2012; Cao et al., 2015). With time, this field has shifted from retrospective reporting to predictive and prescriptive analytics, as scholars started to consider analytics as a strategic organizational capability instead of an information system (IS) per se (Gupta & George, 2016; Wamba et al., 2017; Mikalef et al., 2019).

The new wave of generative AI is poised to disrupt this trend even more. Non-technical managers can interact with data through conversational interfaces instead of analysts or static dashboards, thanks to the capabilities of large language models, retrieval-augmented generation, AI agents, natural-language querying, automated data storytelling and text-to-SQL systems (Alghamdi & Al-Baity, 2022; Handler et al., 2024; Alparslan, 2025). These changes move business analytics from an expert-centric to a more democratic and participatory decision-support environment. Meanwhile, they bring in new risks of hallucination, data leakage, insufficient validation, and lack of transparency in model reasoning and overreliance on machine-generated recommendations (Dwivedi et al., 2023; Raisch & Krakowski, 2021; Dell'Acqua et al., 2026).

Conceptually, the academic literature on this transition is still quite fragmented, and is growing rapidly. Other studies are centered on enhanced analytics and automated data preparation, data visualization and insight generation. Others look at LLM in the context of business intelligence, consumer insight extraction, conversational business analytics, process mining, explainability, decision support systems or AI governance. There have been some recent bibliometric studies that have broadly mapped the field of business intelligence and organizational decision-making (Hajj et al., 2019; Alsaudi & Alhur, 2025), and another recent study focused on the augmented analytics and generative AI in business intelligence (Mekimah et al., 2024) as a field from 2019 to 2025. However, these studies do not fully reveal how generative AI and augmented analytics work together to revolutionise managerial decision-making processes via the mechanisms of business analytics capability, trust, explainability, governance, validation and human-AI collaboration.

The literature thus examined from the past 7 years (2019–2026) has been published in Scopus-indexed journals. This article therefore explores the literature published in Scopus-indexed journals regarding Generative AI and Augmented Business Analytics for Managerial Decision Making in the last 7 years (2019–2026). The study is driven by the desire to go beyond mere description of the growth of publications and to create a map of the field that is theoretically informed. In this context, bibliometric and network-analytic approaches can be of great value to uncover patterns of intellectual structure, thematic concentration and fragmentation which can be challenging to discern through narrative review alone (Donthu et al., 2021; Zupic & Cater, 2015). For algorithmic management, a recent bibliometric study shows how the science-mapping evidence can highlight the fragmentation of the technical, organizational, and governance-oriented streams of the field, a methodological approach that can also be applied to the field of business analytics with GenAI.

The paper has three contributions to make. First, it offers a map of a research field, as captured by Scopus, that has been gaining visibility, particularly since 2023. Second, it recognizes the dominant contributors, sources, countries, documents, communities of key words and research fronts that drive the field. Third, it creates a conceptual framework to place GenAI-assisted augmented analytics as a decision-intelligence capability that requires the interaction between the technology and the analytics capability, managerial judgment and governance mechanisms. These contributions are aimed at enabling further research that is cumulative, theoretically sound and practically relevant to the organizations using AI-powered analytics.

1.2. Research Questions

RQ1: What is the trend of the volume, growth and composition of documents of generative AI and augmented business analytics for managerial decision-making as indexed in the Scopus database from 2019 to 2026?

RQ2: Who, from where and in what countries and institutions do the key publications and collaborations in this research field appear?

RQ3: What are the most influential documents in the field and what do they tell about the shift from traditional BI to LLM-powered decision support?

RQ4: What are the conceptual themes and the associated communities of keywords in the literature, and how do they demonstrate the integration of GenAI, augmented analytics, business intelligence and decision support?

RQ5: What are some contemporary research fronts that can be seen in the bibliographic coupling, and what are some underdeveloped themes that need further theoretical and empirical research?

2. Literature Review

2.1 From Business Intelligence to Augmented Analytics

Business intelligence is well known to be a collection of technologies, processes and organisational practices that enable the access, analysis and managerial decision making based on data. According to classic BI research, the value of information systems can be achieved when analytical outputs are integrated into business processes and decision routines instead of being considered as separate technical products (Elbashir et al., 2008; Chen et al., 2012). The extension of this logic was business analytics which focused on statistical modeling, predictive analysis, machine learning, and data-driven business capabilities. Empirical results indicate that analytics can enhance the effectiveness of decision making when it helps organizations to build up the capability of information processing and create a data-driven environment (Cao et al., 2015).

It is essential to recognize the capability perspective to gain insight into the business value of analytics. Big data analytics capability is not just about the data or tools; it is a toolbox of tangible and intangible resources such as data infrastructure, technical skills, managerial support, data driven culture and organizational learning (Gupta & George, 2016). From a business research perspective, having analytics capability is also found to be beneficial for firm performance, innovation and competitive advantage when intertwined with dynamic capabilities and business process transformation (Wamba et al., 2017; Mikalef et al., 2019; Akter et al., 2016). This is significant in the present study as generative AI does not automatically generate decision value. The impact of its contribution will depend on how well organizations can integrate, validate, and control AI-generated insights into their current decision-making processes.

Augmented analytics is the next phase of this evolution. Unlike traditional BI, where analysts are responsible for picking the data, creating dashboards and taking meaning out of the data, augmented analytics automates or augments parts of the analytics cycle by leveraging AI, machine learning, and natural language generation to select data, build dashboards and take meaning out of the data. AI-based augmented analytics can aid in data preparation, feature identification, pattern recognition, visualization and insight generation, minimizing the gap between business users and analytical outcomes (Alghamdi & Al-Baity, 2022). However, the augmented analytics option also has issues of interpretation and accountability as automated insight generation can mask the underlying assumptions of management that must be considered when making consequential decisions.

2.2 Analytical Tools for Business Intelligence

Generative AI intensifies the shift from expert-led analytics to conversational and AI-assisted analytics. Large language models can be used to summarize unstructured data, create code, translate natural-language questions into SQL queries, generate a narrative from analytical results, and enable managers to explore other interpretations of business problems. LLMs are more versatile decision support tools than previous support tools, as they can be used for problem formulation, information search, and alternative generation and explanation in the same conversational interface (Handler et al., 2024). The adaptability is one of the reasons why they hold value for managerial decision making, yet it adds extra unpredictability in how managers need to gauge, confirm and believe the results of AI.

This is a new research front that has been demonstrated in recent studies from the Scopus corpus. In the field of marketing, LLM has proven useful in analyzing huge quantities of unstructured textual data, such as consumer reviews, and deriving insights from the service provided (Praveen et al., 2024). This study examines research on Business-RAG and LLM-based Business Insight Extraction (BIE) workflows, highlighting how enterprise data and documents can be linked to the business insight extraction workflow (Arslan & Cruz, 2024; Weng et al., 2025). Alparslan (2025) also states that while natural-language interfaces have the potential to alleviate technical hurdles for end users, the accuracy of the queries generated by these interfaces and the reliability of the validation mechanisms will affect the effectiveness of this research.

The studies indicate that the use of GenAI for analytics is shifting from experimentation to enterprise use. The current literature, however, tends to be more focused on the development of tools, prototyping and technical viability, rather than on the quality of managerial decisions, governance and the resultant long-term effects on organizations. This imbalance is in line with the broader research in AI in organizations, which posits that while AI can improve organizational decision-making, human-AI complementarity, interpretability and professional judgment and organizational design (Jarrahi, 2018; Shrestha et al., 2019; Benbya et al., 2020) should be considered.

We need to focus on the points below in managerial decision making, human-AI collaboration and responsible use.

Managerial decision-making is not simply a matter of selecting among the data that is present. It involves problem framing, situational judgment, interpretation of ambiguous data, and stakeholder negotiation and accountability for results. Classical decision theory highlights the nature of human irrationality when making decisions under complexity and uncertainty; this has been a fundamental argument for the need for decision-support systems (Simon, 1979). AI supporting decision systems hold the promise to complement managerial cognition by providing enhanced speed, search and pattern recognition. However, the usefulness of their products is contingent on the way human-AI interaction is designed and the roles of the algorithm and managers in the collaboration process (Jarrahi, 2018; Shrestha et al., 2019).

The automation-augmentation paradox applies particularly in this area. While organizations promote AI as a complement to human judgment, the technologies can also automate tasks or diminish the human discretion or generate hidden reliance on opaque technologies (Raisch & Krakowski, 2021). In a business setting, the paradox is the fact that as AI tools provide managers with rapid insights, they are also exposed to inaccuracies in their outputs, misleading explanations, or over-reliance on the AI's recommendations. The jagged technological frontier of experimental research indicates that AI can enhance productivity and quality for certain knowledge tasks, but not for others that are beyond the capabilities of the system (Dell'Acqua et al., 2026).

This means that trust and explainability are not an afterthought, but integral features that make GenAI-powered analytics practical for management. The acceptance of AI by humans relies on notions of competence, predictability, transparency and alignment with expectations (Glikson & Woolley, 2020). Explainable AI research also provides arguments that, when decisions matter, managers and customers need to be provided with explicable reasoning, not just predictions (Rai, 2020). When it comes to business analytics, explainability needs to be paired with data governance, validation and accountability since managers are not just interpreting the results of AI; they are taking action on it.

2.3 Gap Analysis and Study Positioning

The literature presented above shows a definite gap. Business intelligence research provides an understanding of the report and decision support aspects of using data systems in an organization. Business analytics capability research is an explanation of performance value of data, talent, technology and organization routines. In the field of generative AI research, scientists will explore the potential applications of LLMs for tasks such as language, code, summarisation, and knowledge-work automation. But this convergence of streams isn't fully developed. There is no focused bibliometric and thematic study that traces the joint influence of GenAI and augmented analytics on the managerial decision-making through business analytics capability, trust, explainability, governance and performance mechanisms in the field.

This gap is important as the literature is not yet too large to map, but too small to be used as evidence for a research agenda. The present Scopus corpus is small (92 documents), but 77.2% of these were published between 2025 and 2026, suggesting that it is a field that is rapidly emerging rather than a mature field with stable theories. The preponderance of conference papers also indicates that the field is still at an early stage of development, and requires conceptual integration and methodological consolidation. This study is a step toward bridging the gap by offering a structured overview of the field's growth, contributors, citation base, conceptual vocabulary, thematic clusters and future research directions.

Table 1. *Gap Analysis and Contribution of the Present Study*

Literature Stream	What is Already Known	Remaining Gap	How this Study Responds
Business intelligence and decision support	Explains dashboards, reporting, information processing and BI-enabled decision support.	Less attention to GenAI, conversational querying, LLM-generated insight and post-2023 decision-support challenges.	Maps the shift from BI to LLM-enabled and augmented decision support.
Business analytics capability	Explains how data, technology, talent and culture support performance and decision quality.	Does not fully account for GenAI-specific issues such as hallucination, prompt design, retrieval, validation and AI agents.	Links GenAI-enabled analytics to capability development and performance outcomes.
Generative AI and LLM applications	Shows technical and practical applications in text mining, consumer insight, coding and knowledge work.	Often lacks a managerial decision-making lens and does not consolidate the field bibliometrically.	Identifies research fronts where LLMs are connected to business analytics and decision support.
Trust, explainability and AI governance	Explains responsible AI requirements and human-AI trust mechanisms.	These issues remain dispersed and weakly integrated with business analytics research.	Positions governance, explainability and validation as boundary conditions of GenAI-enabled decision value.

3. Research Methodology

3.1 Research design

This study uses a bibliometric and a thematic science-mapping design. Bibliometric analysis is suitable since the aim is to explore published literature, not to test a primary data causal model. It allows for the longitudinal analysis of publication trends, productivity of sources, authorship, country collaboration, impact of publications, conceptual structure, and emerging research fronts. The study adopts the recommended bibliometric procedures for business research and transforms the study from descriptive indicators to interpretive insights through the use of science-mapping techniques (Donthu et al., 2021; Zupic & Cater, 2015).

Only Scopus bibliographic database is used. Scopus is a curated and source-independent abstract and citation database with extensive coverage across the scientific, technical, medical, social science and management literature. This is appropriate for a field which ranges from business analytics to information systems, decision sciences, and computer science. It also means that you're not as likely to get duplicate and inconsistent records when you combine the data from several indexing systems (Visser et al., 2021).

3.2 Search Strategy and Data Extraction

The number of documents included in the dataset for analysis was 92 documents in Scopus that were published between 2019 and 2026. The corpus was exported with bibliographic metadata, author keywords, index keywords, abstracts, source information, citation counts, affiliations and references. The year 2026 is an incomplete year and hence its output is interpreted with caution and not considered as a sign of decline.

Table 2: *Search and Extraction Protocol*

Element	Specification
Database	Scopus only
Timespan	2019-2026
Search field	Title, abstract and keywords
Core concepts	generative AI, large language models, augmented analytics, business intelligence, business analytics, decision support and managerial decision-making
Document types retained in the provided corpus	Article, review, conference paper, conference review, book, book chapter and short survey
Final analytical corpus	92 documents
Search/extraction date	July 12, 2026.

This working search logic was structured in 3 concept blocks. The first block introduced the concepts of GenAI and LLM, such as generative AI, generative artificial intelligence, large language models, LLMs, ChatGPT, AI agents and agentic AI. The second block focused on analytics-related terminology, augmented analytics, AI-assisted analytics, automated analytics, business analytics and business intelligence. The third block focused on decision terminology such as managerial decision-making, management decisions, decision support systems and data-driven decision-making. The last query should be run as is in Scopus since exact query transparency is critical for replication.

3.3 The Analytical Preparation and Screening of Written Texts

The study was conducted with a PRISMA informed logic of identification, filtering, eligibility checking and final inclusion. A total of 92 records were identified in the final Scopus export that were eligible for analysis. Titles and abstracts and keywords were screened for relevance to generative AI, augmented analytics, business intelligence, business analytics, decision support and managerial decision making. Typically, records that are not related to a business, analytics or decision-support application would be eliminated at this point. The dataset was also duplicated and inconsistent variants of keywords were verified before being imported into the bibliometric workflow (Page et al., 2021).

The keywords were particularly important due to the overlapping labels. Changes have been made to harmonize the terms GenAI, generative AI and generative artificial intelligence. For the purposes of interpreting clusters, LARGE LANGUAGE MODEL, LARGE LANGUAGE MODELS and LLMs were considered synonymous. The same attention was given to business intelligence, BI, business analytics, decision support systems, data-driven decision-making, natural language processing and augmented analytics. This normalization makes the results of co-word analysis and thematic mapping more comprehensible.

3.4 Bibliometric Tools and Techniques

Bibliometrix/Biblioshiny in R was employed for descriptive and thematic analysis because it allows for a comprehensive science-mapping workflow: import data, summarise the bibliographic data, analyse sources, analyse authors, create conceptual maps, perform thematic analysis and collaboration analysis (Aria & Cuccurullo, 2017). The output of VOSviewer (e.g. style) were used for network visualization because it is capable of creating and visualizing bibliometric networks like keyword co-occurrence, co-authorship, citation, co-citation and bibliographic coupling networks (van Eck & Waltman, 2010). Tables were checked, terms were cleaned and publication ready tables were prepared using the software Excel.

The analysis covered the scientific production per year, the composition of the documents, the productivity of the sources, the productivity of the authors, the productivity of institutions, the productivity of countries, country collaboration, the analysis of citations, the frequency of keywords, the evolution of keywords, the co-occurrence of keywords, the bibliographic coupling, and the thematic mapping. These methods demonstrate both the quantity of research generated and the intellectual and conceptual structure of the discipline.

4. Results

4.1 Corpus Profile

The final corpus was composed of 92 documents from 73 sources published between 2019 and 2026 that have been indexed by Scopus. A total of 2,633 references and 281 authors were collected, with an average of 3.2 co-authors per reference. The mean document age was 1.11 years, further supporting the very recent literature. The mean number of citations per document was 2.685, which should be treated with prudence, since a large part of documents in the corpus were published in 2025 and 2026.

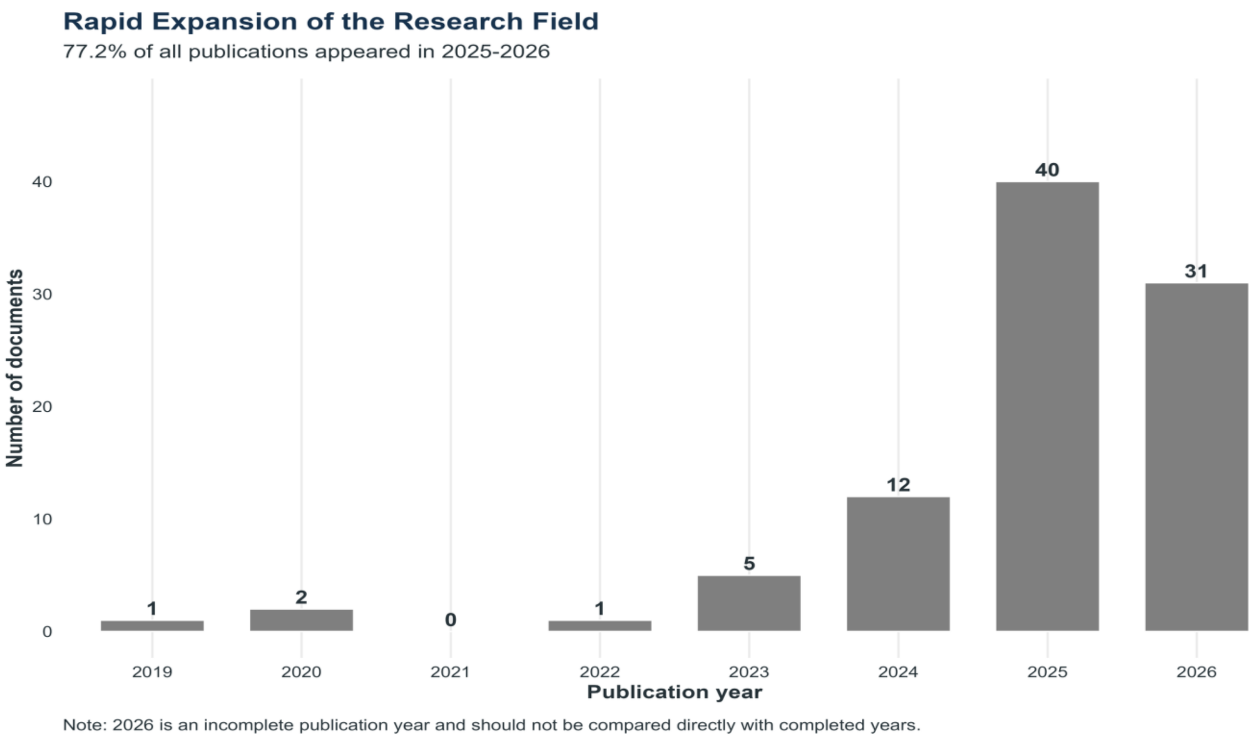
Table 3: *Main Information About the Scopus Corpus*

Indicator	Result
Timespan	2019-2026
Sources	73
Documents	92
Annual growth rate	63.32%
Document average age	1.11 years
Average citations per document	2.685
References	2,633
Authors	281
Single-authored documents	11
Co-authors per document	3.2
International co-authorships	16.3%

4.2 Annual Scientific Production

Annual publication output confirms that this is an emerging and rapidly accelerating field. The corpus contains only one document in 2019, two in 2020, one in 2022 and five in 2023. Output increased to 12 documents in 2024, then rose sharply to 40 documents in 2025. The 2026 count is already 31 documents in an incomplete year. Overall, 71 documents, or 77.2% of the corpus, were published in 2025-2026. This pattern suggests that scholarly attention accelerated after the mainstream diffusion of generative AI and LLM-based tools into business and analytics environments.

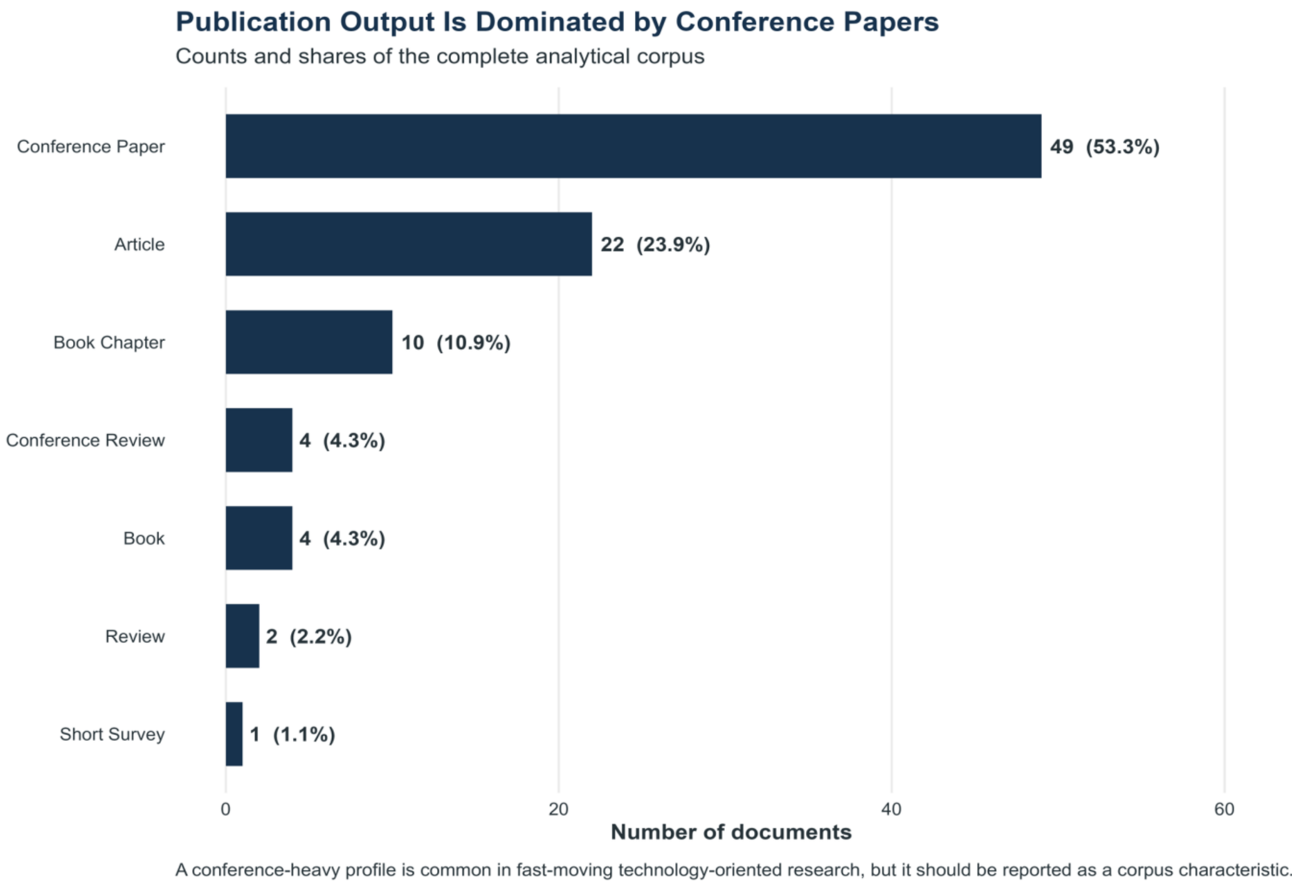
Figure 1: *Annual scientific production in the Scopus corpus from 2019 to 2026.*



4.3 Document-type Composition

The document-type distribution indicates that the field is still in a formative phase. Conference papers account for 49 documents, representing 53.3% of the corpus. Articles account for 22 documents, while book chapters, books, conference reviews, reviews and short surveys make up the remainder. This profile is typical of rapidly developing technology fields, where conference venues often disseminate early prototypes, frameworks and experimental applications before journal-based consolidation occurs. It also means that citation impact should be interpreted carefully because conference papers, book chapters and recent journal articles have different citation trajectories.

Figure 2: *Document-type Composition of the Scopus Corpus.*



4.4 Sources, Authors and Institutions

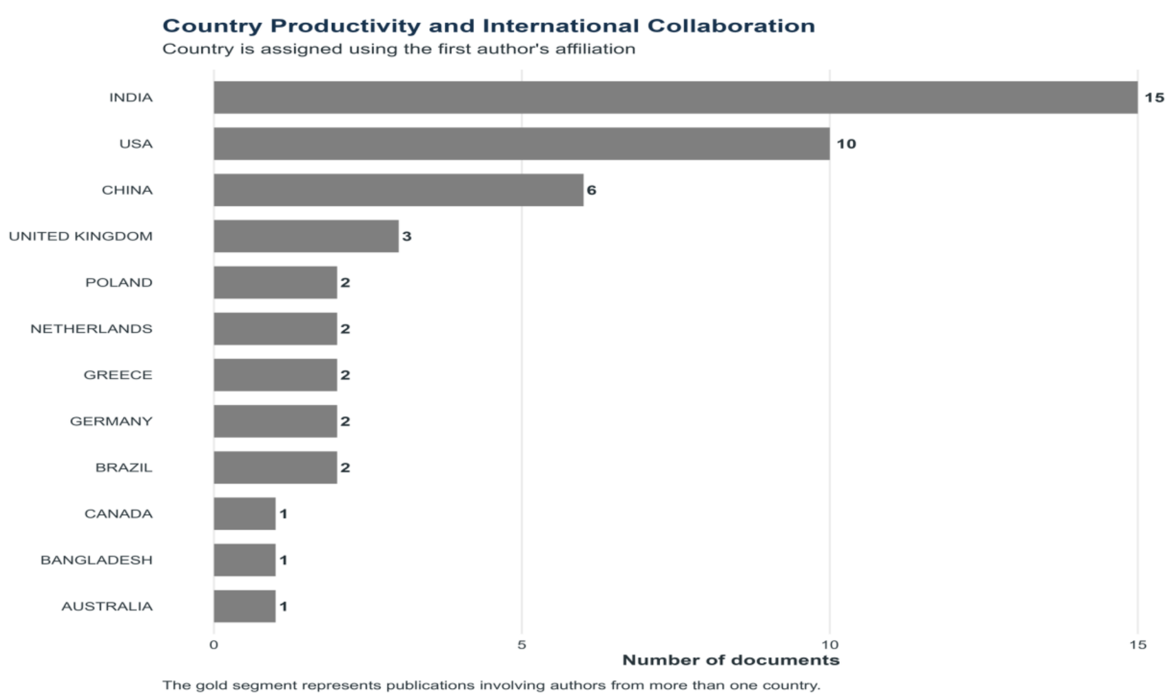
The source and author structure shows a dispersed field rather than a strongly consolidated journal community. Lecture Notes in Networks and Systems is the most productive source with seven documents, followed by Communications in Computer and Information Science with five documents. The appearance of conference proceedings and edited volumes among leading sources reinforces the conclusion that the field is still developing through applied and technical channels. Author productivity is also dispersed. Suresh A. is the most productive author with three documents, while several other authors have two documents. No single author or source currently dominates the field, indicating that a stable intellectual core is still being formed.

Figure 3: *Leading Publication Sources and Authors in the Scopus Corpus.*

4.5 Country Productivity and Collaboration

Country-level analysis shows that India is the leading first-author country with 15 documents, followed by the United States with 10 documents and China with six documents. The United Kingdom contributed three documents, while Brazil, Germany, Greece, the Netherlands and Poland each contributed two. This distribution shows that the field is not limited to traditional North American and Western European research centers. The prominence of India is notable and may reflect the strong presence of AI, software engineering, analytics education and conference publication activity in the corpus. However, international co-authorship is only 16.3%, suggesting that global collaboration remains relatively limited for a field with strong international business relevance.

Figure 4: *Country Productivity and International Collaboration in the Scopus Corpus.*



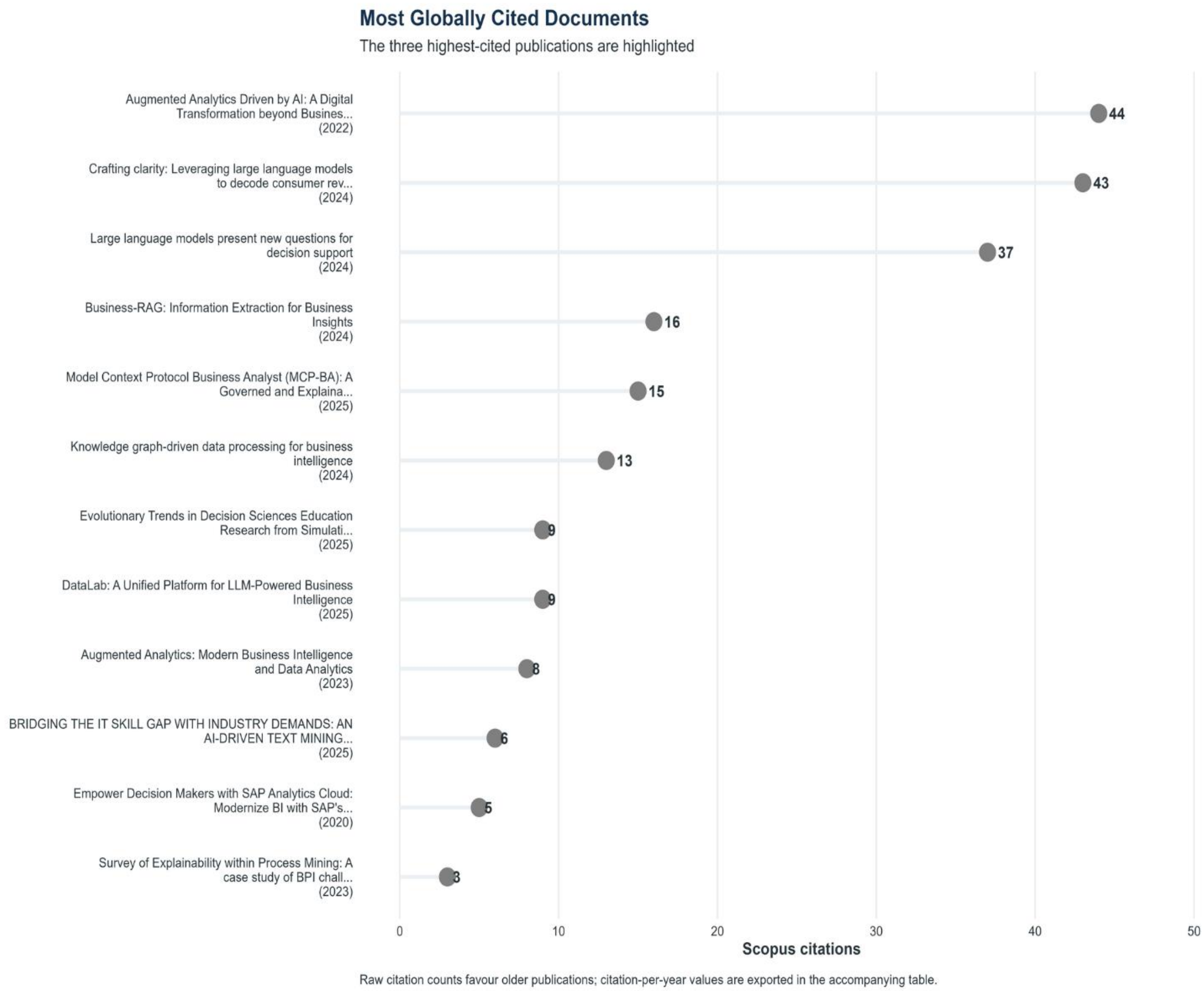
4.6 Citation Structure and Influential Documents

Citation analysis helps to locate the "intellectual footstones" of the field. Alghamdi and Al-Baity's 2022 article on AI-driven augmented analytics beyond business intelligence is the most cited document in the dataset, with 44 citations. The next two studies, with 43 and 37 citations respectively, are by Praveen et al., 2024 and Handler et al., 2024, respectively, on the use of large language models to decode consumer reviews and on the use of LLMs in decision support. The top documents highlight three interconnected areas of focus in the field: augmented analytics as a reimagining of BI, the use of LLM for business insight from unstructured data, and LLM as a new class of decision support technology (Alghamdi & Al-Baity, 2022; Praveen et al., 2024; Handler et al., 2024).

Table 4: *Most Globally Cited Documents in the Scopus Corpus*

Author(s)	Year	Document focus	Citations
Alghamdi & Al-Baity	2022	Augmented analytics driven by AI: A digital transformation beyond business intelligence	44
Praveen et al.	2024	Crafting clarity: Leveraging large language models to decode consumer reviews	43
Handler et al.	2024	Large language models present new questions for decision support	37
Arslan & Cruz	2024	Business-RAG: Information extraction for business insights	16
Patel et al.	2025	Model Context Protocol Business Analyst: A governed and explainable framework for enterprise analytics	15
Dey et al.	2024	A review of explainable AI and knowledge discovery themes in data mining literature	13
Akpan et al.	2025	Evolutionary trends in decision sciences education research	9
Weng et al.	2025	DataLab: A unified platform for LLM-powered business intelligence	9

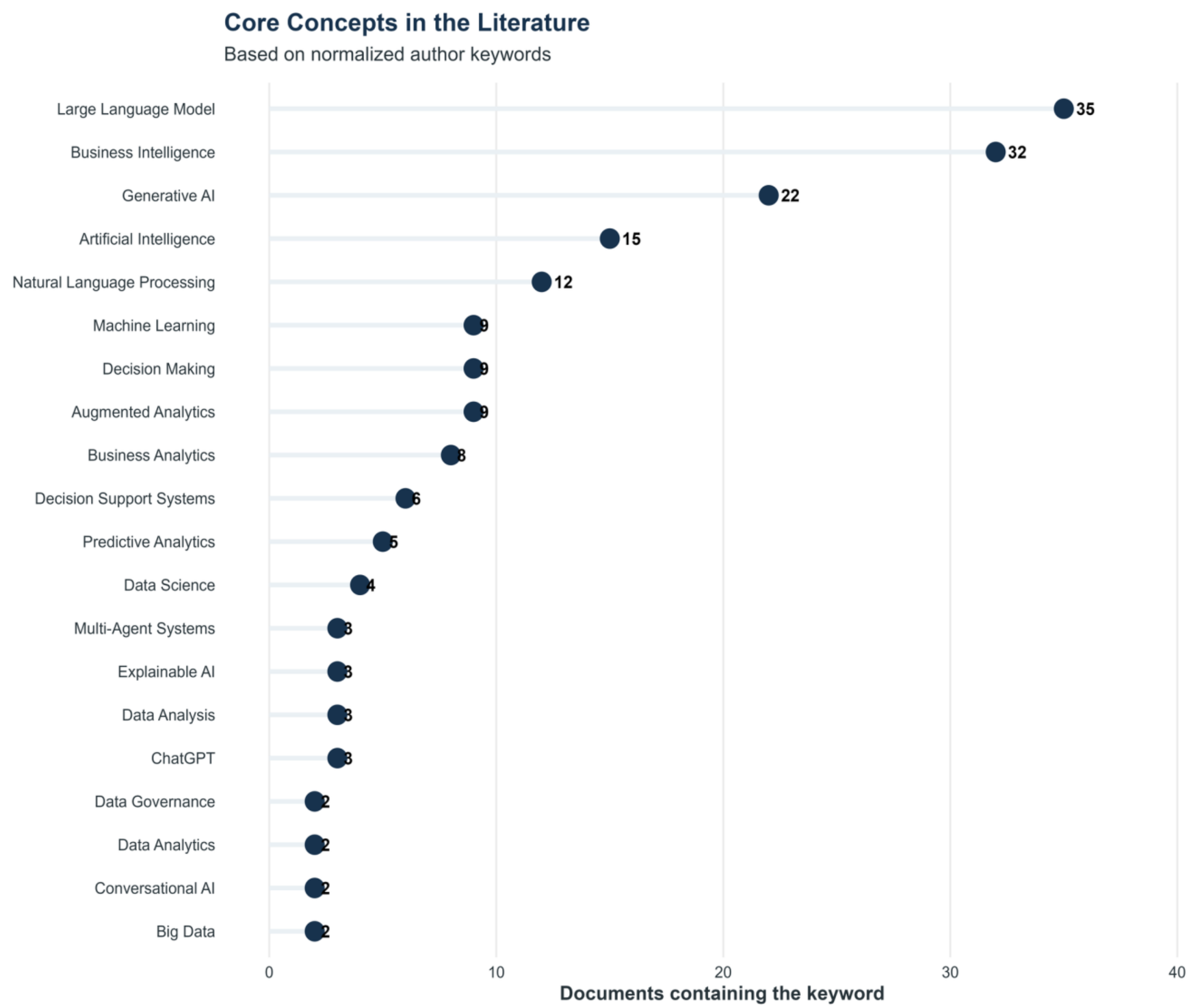
Figure 5: *Most Globally Cited Documents in the Scopus Corpus.*



4.7 Keyword Frequency and Conceptual Vocabulary

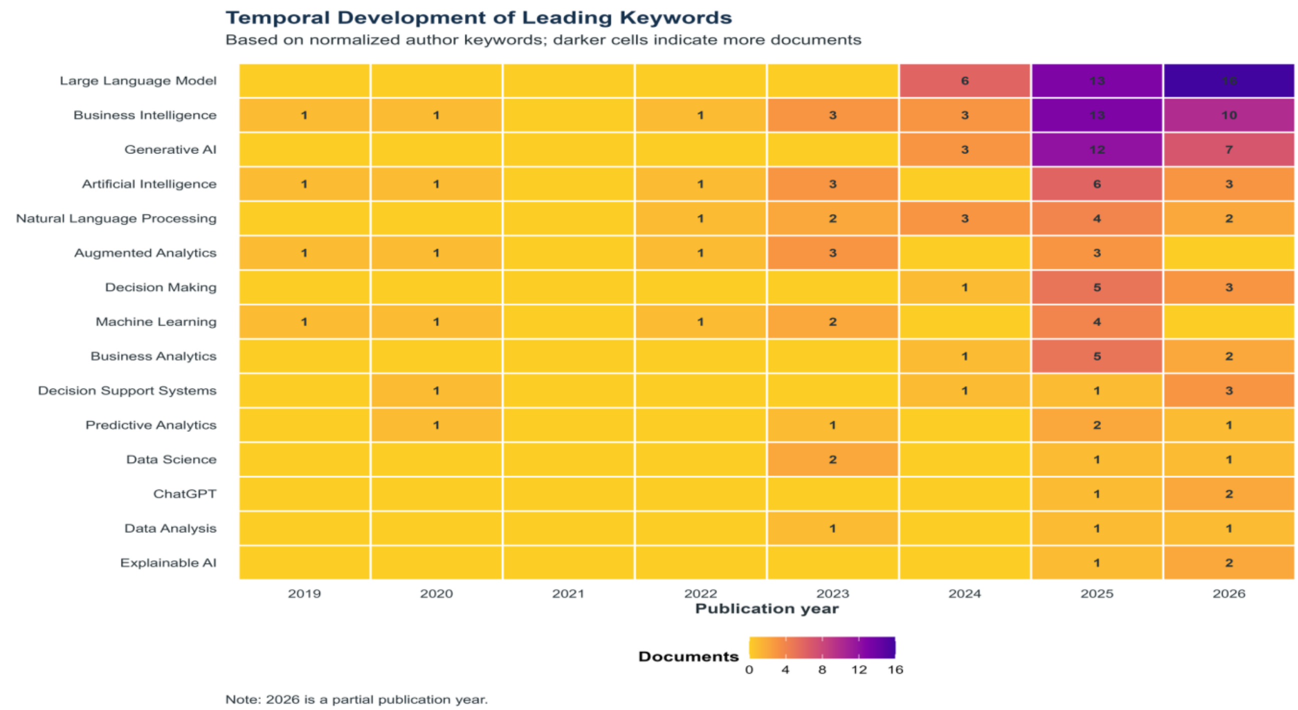
Conceptual vocabulary of the field is rooted in business intelligence, large language models, generative AI, artificial intelligence, natural language processing and augmented analytics from the keyword analysis. With the normalized output of keywords, the most common is large language model, followed by business intelligence, generative AI, artificial intelligence, natural language processing, machine learning, decision making, augmented analytics, business analytics and decision support systems. This pattern has been observed to be that the literature is not just an AI literature but a hybrid area where AI technologies are being understood in terms of BI, analytics and decision-support concerns.

Figure 6: *Core Keywords Based on Normalized Author Keywords.*



The keyword evolution heatmap also indicates that there were significant changes in the most recent years. The terms large language model, business intelligence, and generative AI, or artificial intelligence, are most prevalent in 2025-2026. This adds to the interpretation that the field is still developing their conceptual language. Business intelligence and decision-support terms have been around for a while, providing continuity with previous analytics research; more recently, the LLM and GenAI terminology is a new research agenda.

Figure 7: *Temporal Evolution of Leading Normalized Keywords.*



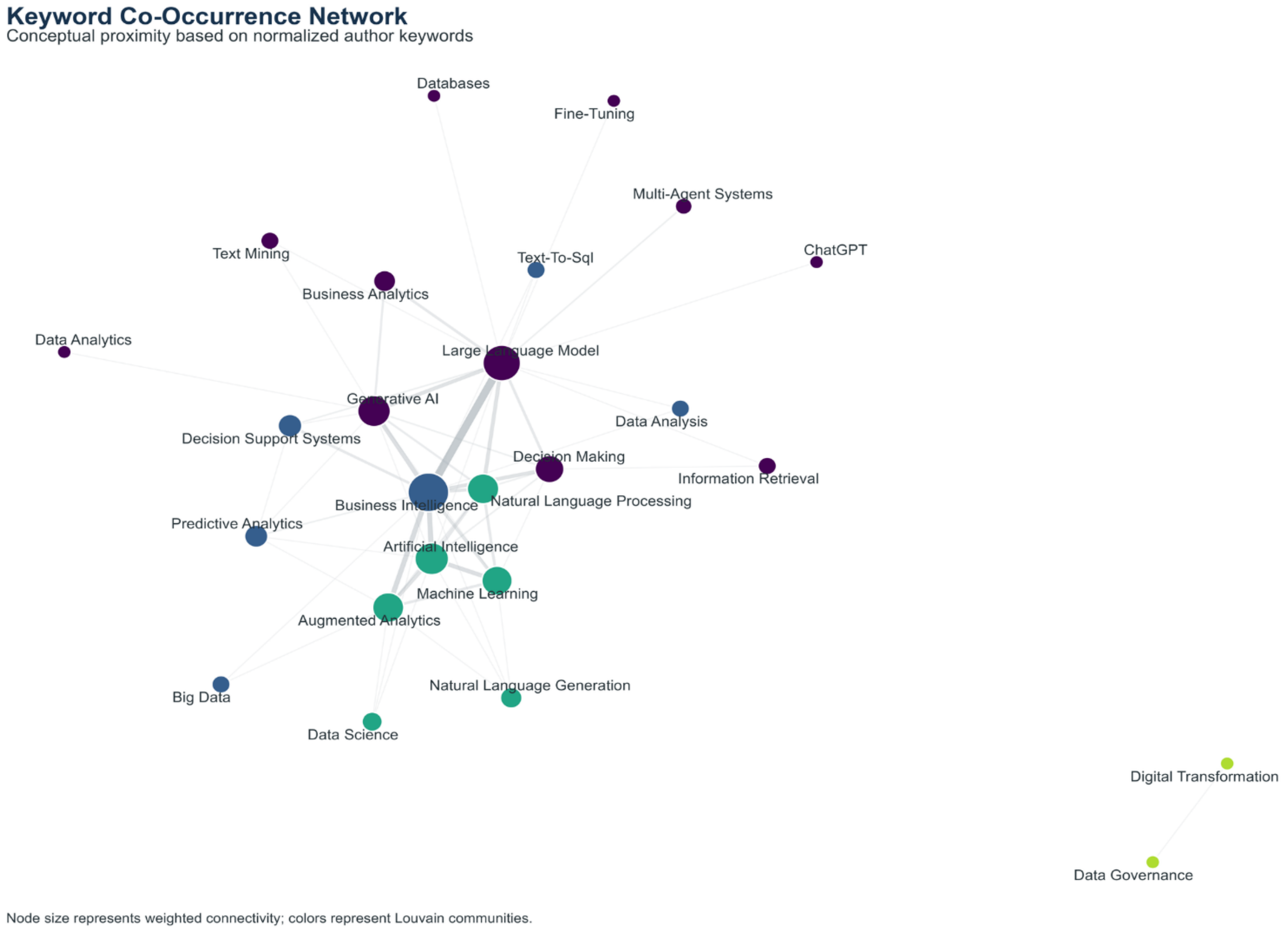
4.8 Keyword Co-occurrence Network

The co-occurrence network of the keyword has 4 communities. Business intelligence, large language model, artificial intelligence, generative AI, natural language processing and augmented analytics and machine learning are the strongest connected terms. Business intelligence is at the top of the network followed by large language model and artificial intelligence. This implies that the analytics tradition is still the primary conceptual linkage for GenAI applications. Large language models are the technology enabler and augmented analytics and natural language processing are the link between technology and business users. The technology enabler is large language models; the link between technology and business users is augmented analytics and natural language processing.

Table 5: *Central Nodes in the Keyword Co-occurrence Network*

Node	Network Strength	Community
Business Intelligence	77	2
Large Language Model	60	1
Artificial Intelligence	42	3
Generative AI	38	1
Natural Language Processing	34	3
Augmented Analytics	33	3
Machine Learning	30	3
Decision Making	25	1
Decision Support Systems	12	2
Predictive Analytics	11	2

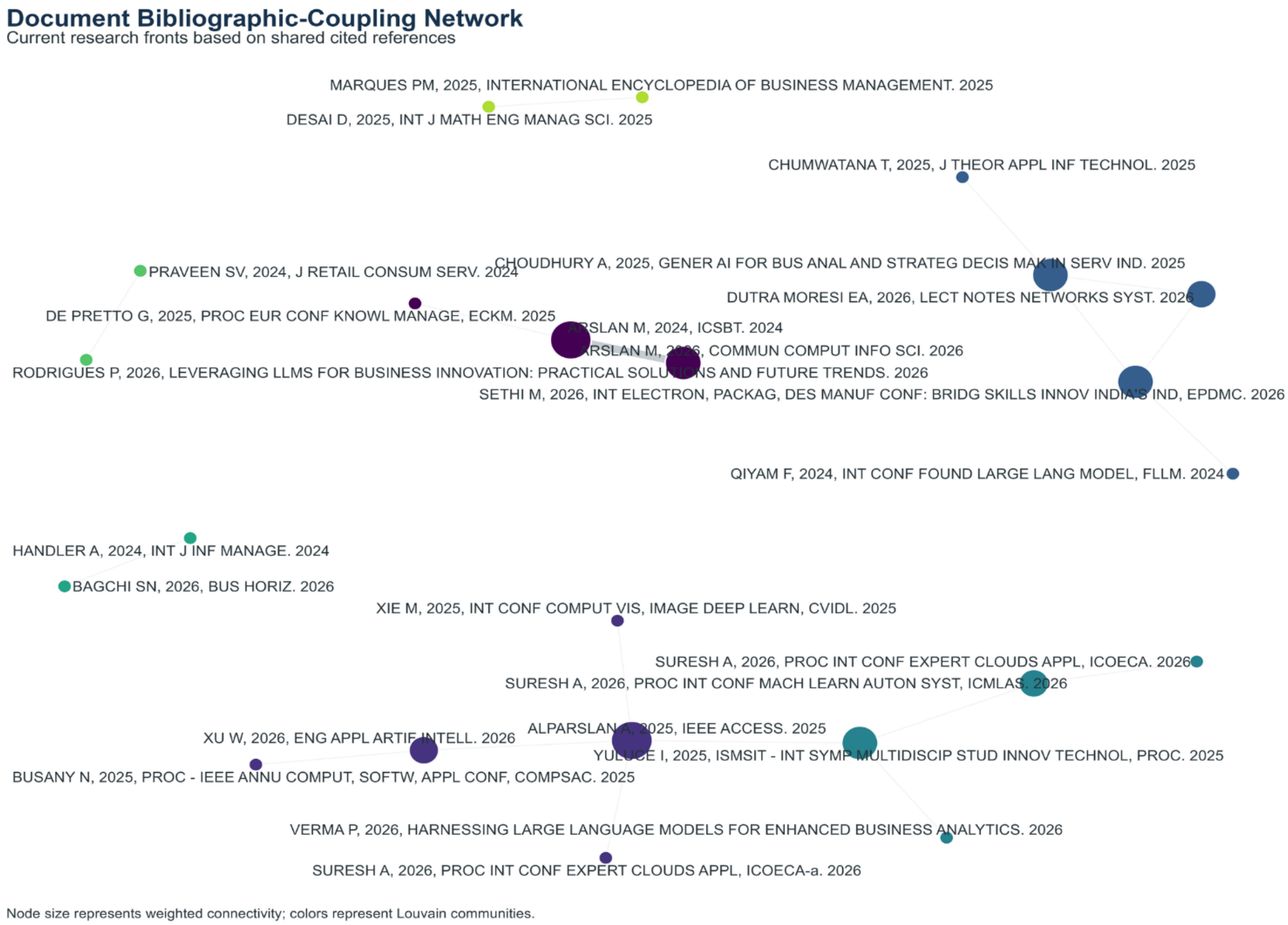
Figure 8: *Keyword Co-occurrence Network Showing the Conceptual Structure of the Field.*



4.9 Bibliographic Coupling and Current Research Fronts

Bibliographic coupling is a technique that characterizes contemporary fronts of research by coupling documents that cite each other. The document-coupling network has seven communities (subpopulations), meaning that the field is evolving along multiple partially connected fronts. The first front is information extraction with LLM and Business-RAG for generation of enterprise insights. The second front relates to conversational business analytics, validation effectiveness and Text-to-SQL. The third front is on the use of generative AI for business intelligence and strategic decision-making in services. A fourth is data governance, explainability and enterprise analytics frameworks. The network thus establishes that the field remains, for the time being, somewhat fragmented, on the one hand in terms of theoretical studies of the technical platforms, and on the other in terms of practical frameworks and decision-support applications.

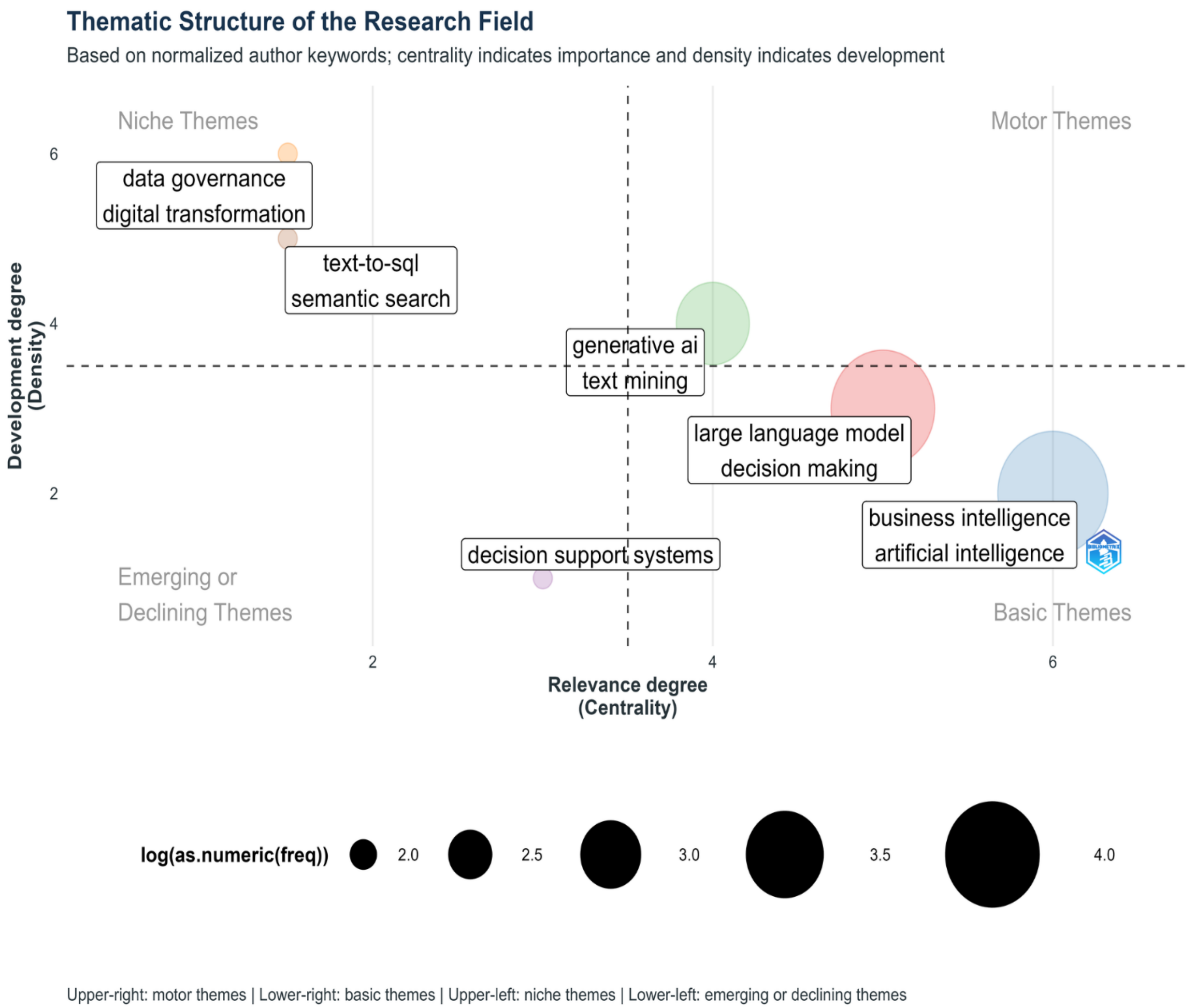
Figure 9: *Bibliographic-coupling Network of Current Research Fronts.*



4.10 Thematic Map

A maturity and centrality perspective on the field is given in the thematic map. Language models and decision making are themes that are relevant, but also have internal development which means that language model based decision support is becoming a motor theme. Business intelligence and artificial intelligence are listed as basic and transversal elements, that is, they are of central importance to the field as a whole, but do not necessarily have their own specialization within the field. Generative AI with text mining and data analytics, and data storytelling, seem to be emerging as a special theme, compared to data governance, digital transformation and human-AI collaboration, which are niche themes. The key takeaway is that governance-related themes are present and relevant but not yet core, although they are very relevant in practice to the managerial judgments that are made.

Figure 10: *Thematic Map Based on Normalized Keywords.*



5. Discussion

The findings indicate that augmented business analytics with GenAI is a nascent research area with fast growth, multiple publishing venues, a significant proportion of conference papers and a conceptually hybrid terminology. This robust growth in 2025 and 2026 reflects the rapid adoption and adaptation of LLMs and AI-powered analytics tools by scholars. But the field is not developed evenly. Technical themes like LLM, NLP, and Text-to-SQL and information extraction are progressing quickly, and organizational themes like trust, explainability, validation, human-AI collaboration, and governance are less entrenched within the mainstream network.

This pattern directly supports the gap argument of the study. Previous studies have shown that BI and analytics can enhance decision effectiveness when embedded in the organization's information-processing processes (Cao et al., 2015). It has also demonstrated that analytics capability can be beneficial to performance with the support of complementary resources and dynamic capabilities (Gupta & George, 2016; Wamba et al., 2017; Mikalef et al., 2019). The question now is not whether analytics matters, but how generative AI impacts the role of analytics systems in managerial decision making. The bibliometric results show that the answer to this question is just starting.

One of the key findings of the research is the transition from business intelligence (BI) as a reporting system to GenAI-powered analytics as an interactive decision-intelligence capability. In the classical approach, dashboards and reports are interpreted after the analysts have created data models for the business users. In the new model, managers are able to ask questions in plain English, get explanations generated and ask for other summaries and use conversational systems to interact with data. This alters the analytical division of labor within organisations. However, it also introduces new risks, such as the fact that decision-makers might not be aware of the assumptions, retrieval limits, hallucination risks, or validation boundaries of AI-generated outputs (Handler et al., 2024; Alparslan, 2025).

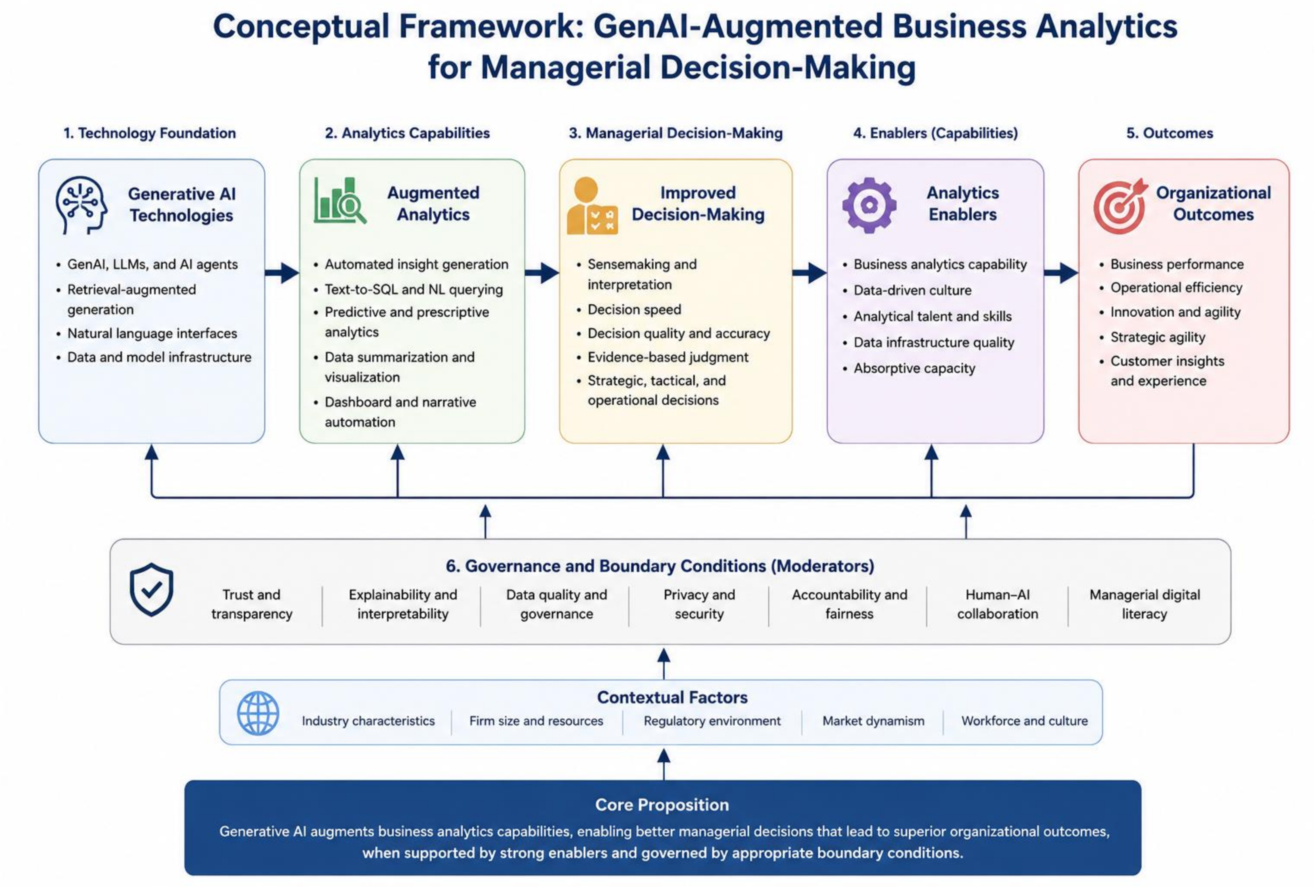
The results indicate that the theoretical integration of the field is needed to be stronger. The resource-based view and dynamic capabilities perspective can help explain how organizations can transform GenAI tools into analytics capability and business performance (Barney, 1991; Teece, 2007). Socio-technical and human-AI collaboration perspectives can account for the fact that the same tools can sometimes be used to enhance managerial judgment and sometimes lead to problematic dependence on opaque systems (Jarrahi, 2018; Raisch & Krakowski, 2021). Trust and explainability research can help to better understand the circumstances in which managers can and will appropriately trust AI-based recommendations (Glikson & Woolley, 2020; Rai, 2020). These views must be fused together, as GenAI-powered analytics is a technological, organizational, and cognitive process.

6. Conceptual Framework

The study suggests a conceptual model that connects GenAI technologies with business results via augmented analytics and managerial decisions based on the bibliometric results and literature review. The framework starts with technology layer, including LLM, AI agents, retrieval-augmented generation and natural language interfaces. These technologies provide an analytics layer that includes automated insight generation, conversational query, Text-to-SQL, predictive analytics, prescriptive analytics and data storytelling. The analytics layer adds to the business analytics capability when it is integrated into organizational routines, data infrastructure, talent and the culture of the organization.

The framework emphasizes that business value is created when the quality, speed and context of business decisions are enhanced by the addition of analytics. But the connection is not guaranteed. The governance and boundary conditions are trust, explainability, data quality, privacy, accountability, validation effectiveness, and human-AI collaboration and managerial digital literacy. These conditions are essential if GenAI is to speed up decision-making and reduce reliability or accountability. Under such circumstances, GenAI can boost business analytics capacity and aid performance, innovation, agility, and strategic responsiveness.

Figure 11. *Conceptual Framework Linking GenAI, Augmented Analytics, Business Analytics Capability, Managerial Decision-Making and Business Performance.*



7. Theoretical, Methodological and Practical Contributions

This study's theoretical contribution is to redefine the GenAI enhanced analytics as a decision-intelligence capability. This framing links business analytics capability, human-AI interaction, decision-support systems and responsible governance of AI. It takes the conversation from the technical question of whether LLM can create insights to the management question of how companies can use the outputs of the LLM to make decisions that are reliable and accountable.

The methodological contribution lies in the integration of the bibliometric mapping from the Scopus database and thematic interpretation. The study uses performance analysis, keyword analysis, bibliographic coupling and thematic mapping on a recent corpus representative of the current surge of research on GenAI since 2023. Thanks to the application of Bibliometrix/Biblioshiny and VOSviewer, transparency and replicability are enhanced, and a gap analysis and conceptual framework ensure that the paper is not just descriptive.

The practical contribution is for managers, analytics leaders and information systems professionals. The results suggest that organizations should not assess the effectiveness of GenAI-powered analytics based on performance metrics such as speed, automation, and ease of use for the user. They should also consider effectiveness of validation, data governance, explainability, user training, decision accountability and fit with current analytics capability. However, despite their importance to responsible managerial use, the thematic map of the field indicates that these governance issues are not well developed in the literature.

8. Future Research Agenda

Future research should shift from a tool-based approach to demonstration to one that is organizationally based. Additional studies of a longitudinal, mixed-method and field-based nature are required to assess whether the use of GenAI-powered analytics enhances decision quality and performance or simply speeds up the analysis. Further studies are needed in the process of learning to accept AI-generated outputs, who is held responsible when decisions are made based on AI-generated explanations and how governance processes will be established for AI-assisted analytics. Moreover, these relevant questions are important to address in future research;

- How do managers ensure that their trust in GenAI-generated business insights is accurate when model outputs are fluent but uncertain?
- What are the types of explanations that help non-technical managers to validate the recommendations without giving them false confidence?
- What is the impact of Text-to-SQL, semantic search and natural-language dashboards on analytical self-service behavior?
- How to use GenAI to assist, augment or defer to human judgment in strategic, tactical and operational decisions?
- What governance mechanisms are needed to audit, monitor and control AI-generated analytical recommendations?
- How do resource-limited organizations leverage GenAI powered analytics if data quality, talent and infrastructure are limited?
- Is there over time an improvement in decision quality, innovation, agility and firm performance through GenAI-enabled augmented analytics?

9. Limitations

There are some limitations of this study. First, it covers Scopus only, and not documents that are covered only in Web of Science, Dimensions, Google Scholar or domain-specific databases. Secondly, the analysis is based on a search strategy and a set of search terms (also known as the search vocabulary). Alternative terms may be used in relevant papers, but should be interpreted in the context of the language used throughout the paper. Third, 2026 is an incomplete year of publication, and should not be compared directly to completed years. Fourth, the corpus is contemporary, so that the number of citations is subject to fluctuations and may underestimate more recent but influential work. Fifth, the bibliometric analysis can reveal structures and patterns but may not directly prove the effectiveness of GenAI-driven analytics for enhancing managerial decision-making or business outcomes. Sixth, document-type heterogeneity is that conference papers, book chapters and journal articles are grouped together, which is acceptable for an emerging field and should be noted in interpreting the impact of citations.

10. Conclusion

This study traced research about generative AI and business analytics using these systems for managerial decision-making in the last seven years (2019–2026) published in Scopus-indexed journals. The analysis indicates that this field has a strong potential for acceleration, is emerging quickly, has a wide spread of sources and contributors, and has a conceptual structure focused on business intelligence, large language models, generative AI, artificial intelligence, and natural language processing and augmented analytics. The most influential documents show a shift from augmented analytics that are a digital transformation beyond BI to LLM supported decision support, consumer insight extraction, enterprise information retrieval and conversational business analytics.

The key takeaway is that Augmented Analytics with GenAI should be viewed as a new capability in Decision Intelligence. It isn't just about automating analytics tasks, it's about changing the way managers access, interpret, validate and act on data. The study provides a timely contribution by combining bibliometric evidence and a conceptual framework that connects technology, analytics capability, managerial decision making, governance and performance. Future research is needed to move beyond tool adoption to explore the conditions needed to responsibly, explainably and sustainably enhance decision quality with GenAI.

Data Availability Statement

For this study, the bibliometric data was downloaded from Scopus database and further processed in the R package "Bibliometrix" and "Biblioshiny" and in Excel. The figures and tables presented in this manuscript were created from the R bibliometric output provided. Authors should save the exact query history and extraction date used in the Scopus database for later replication, prior to journal submission.

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The authors have no competing financial or personal interests to disclose for this manuscript.

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AI used to remove grammatical errors and improve the sentences' structure. Although, data, results, interpretation and other key arguments are purely genuine and without AI intervention. Moreover, conceptual framework's visuals were enhanced with e help of AI.