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# Artificial intelligence and business intelligence in small and medium enterprises: A bibliometric review of emerging research directions

**Nasrul Effendy Mat Nasir [1,*], Hapini Awang [2], Nur Suhaili Mansor [2] and Azlini Awang [1]**

[1]Politeknik Tuanku Syed Sirajuddin, Perlis, Malaysia; nadzeffendy@gmail.com; azlini@ptss.edu.my
[2]Universiti Utara Malaysia, Kedah, Malaysia; hapini.awang@uum.edu.my; nursuhaili@uum.edu.my

[*]Corresponding Author: nadzeffendy@gmail.com

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**Abstract**

Artificial Intelligence (AI) and Business Intelligence (BI) are advancing decision-making and strategic management in Small and Medium Enterprises, thereby improving competitiveness and digital sustainability. While there is a plethora of research on the application of AI and BI in SMEs, the literature is scattered. It varies in its understanding, frameworks, and methodologies, making it challenging to integrate the available knowledge. Prior reviews lack depth and focus, providing little to no commentary on publication patterns, foundational ideas, and prospective research paths. This work attempts to fill this research gap with a bibliometric analysis of AI and BI in SMEs, based on a sample of publications from Web of Science and Scopus from the period of 2015 to 2025. This analysis aims to address significant gaps in the literature by measuring publication volumes across countries and by authors worldwide, using digital maps, collaboration networks, co-occurring keywords, and co-citation and thematic mapping techniques to monitor the research productivity and intellectual geography of the discipline. The results obtained demonstrate the presence of several significant and nascent research areas, improving our understanding of the essential technological, scientific and strategic research advancements in these fields. This review draws on relevant theory and policy concerning the UN Sustainable Development Goals (SDGs 2030), especially SDG 8 (Decent Work and Economic Growth), and SDG 9 (Industry, Innovation and Infrastructure), which strengthen the value and relevance of this bibliometric analysis in shaping the adoption and sustainability of AI–BI within the context of SMEs.

**Keywords**: artificial intelligence; bibliometric analysis; business intelligence; small and medium enterprises; technology adoption

## 1. Introduction

Artificial Intelligence (AI) and Business Intelligence (BI) are increasingly recognized as critical enabling data-driven decision-making and strategic management, particularly within Small and Medium Enterprises (SMEs) [1]-[2]. AI-driven analytics, including machine learning and predictive capabilities, combined with BI systems that transform large volumes of structured and unstructured data into actionable insights, enable firms to move beyond descriptive analytics towards predictive and prescriptive decision-making [3]. This shift enhances organizational responsiveness, competitiveness, and strategic agility in dynamic market environments [4].

The role of AI-BI is especially significant for SMEs, which constitute a substantial proportion of the global economy and play a central role in employment creation, innovation, and economic growth [5]-[6]. Despite their strategic importance, SMEs face persistent challenges in adopting AI–BI systems due to limited resources, technological readiness constraints, skills shortages, and perceived implementation risks [7]-[8]. These constraints differentiate SMEs from large enterprises and make the adoption and effective utilization of AI–BI technologies more complex, reinforcing the need for focused scholarly investigation within SME contexts [5], [9].

Over the past decade, a growing body of literature has examined AI, BI, and their applications in SMEs, reflecting increasing academic and practical interest in intelligent technologies for organizational decision-making [10]-[11]. Existing studies are distributed across information systems, management, entrepreneurship, and digital transformation research streams [2], [12], [13]. Several narrative reviews and systematic literature reviews have attempted to synthesize this expanding body of work [1], [14], [15]. However, prior reviews tend to focus on specific aspects such as technology adoption drivers, isolated application domains, or selected methodological approaches, offering limited insight into the broader structural, conceptual, and intellectual evolution of AI–BI research in SMEs [14]-[15]. Earlier reviews rarely examine publication patterns, collaborative structures, dominant research themes, and foundational theoretical influences in an integrated and systematic manner [15]-[16].

To address this gap, the present study conducts a comprehensive bibliometric review of AI and BI research in SMEs using publications indexed in the Web of Science and Scopus databases from 2015 to 2025. By applying a multi-method bibliometric framework, including publication trend analysis, bibliographic coupling, keyword co-occurrence, and co-citation analysis [17]-[19]. This study provides a structured overview of research productivity, thematic orientations, and intellectual foundations within the field. This approach enables a more nuanced understanding of how AI–BI research in SMEs has progressed from early adoption-focused studies towards broader concerns related to performance, sustainability, and advanced analytics [11], [20].

Beyond mapping research trends, this review is conceptually anchored in the broader discourse on sustainable digital transformation. The integration of AI and BI within SMEs has direct implications for the United Nations Sustainable Development Goals (SDGs), particularly SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation and Infrastructure) [1], [7], [13]. AI–BI technologies support productivity enhancement, innovation capacity, and evidence-based decision-making, which are essential for fostering inclusive economic growth and strengthening digital infrastructure in SME ecosystems [4], [21], [22]. Rather than treating sustainability as a peripheral concern, this study positions AI–BI adoption and utilization as mechanisms that contribute to long-term organizational resilience and sustainable economic development [1], [7].

This study makes three primary contributions. First, it offers an indicator-based bibliometric synthesis that visualizes publication patterns, geographical distribution, and collaborative networks in AI–BI research on SMEs. Second, it employs methodological triangulation by integrating multiple bibliometric techniques to reveal the thematic and conceptual structure of the field with greater rigor and reproducibility than prior reviews [17]-[19]. Third, it identifies emerging research directions and persistent gaps, providing actionable insights for researchers, policymakers, and practitioners seeking to support the strategic and sustainable adoption of AI–BI systems in SMEs.

Consequently, this study intends to address the objectives as proposed through contributions, which include the following:

1. To visualize the patterns of publications and the spatial extent of the AI in BI in SMEs.
2. To identify the main thematic and conceptual arrangements that dominate the field.
3. To ascertain the intellectual roots and various new patterns of research within AI and BI in SMEs.

By addressing these objectives, this study contributes a systematic and evidence-based overview of AI and BI research in SMEs and establishes a foundation for future theoretical and empirical advancements.

## 2. Materials and Methods

This section outlines the materials, data sources, and analytical procedures employed in conducting the bibliometric review. A systematic and reproducible bibliometric approach was adopted to examine the intellectual structure, thematic evolution, and research trends related to AI and BI in SMEs [15]-[16]. The methodological framework encompasses data collection and data analysis using established science-mapping techniques and specialized bibliometric tools.

### *2.1. Data Collection*

The research literature for this bibliometric review was sourced from the Web of Science and Scopus. These databases were chosen for their extensive coverage, indexing, and inclusion of high-impact, peer-reviewed journals which enhances the reliability and credibility of bibliometric datasets [23]-[24]. Keywords related to "artificial intelligence and/or Business Intelligence and/or small and medium enterprises (SMEs)" and terms associated with adoption and/or performance were used. Only journal articles and review papers were included in the review. To improve relevance, filters were applied to include only English-language, peer-reviewed publications and to exclude editorials, book chapters, conference papers, and other non-refereed works. The database search was completed in 2025, resulting in a collection of publications from 2015 to 2025, which were subsequently utilized for bibliometric analysis.

Citation information was drawn from Web of Science and Scopus, as these platforms provide strong citation metrics, are comprehensive in their abstracting and indexing of relevant information and data for highly ranked peer-reviewed publications and offer archiving standardized citation information and metadata [23]-[24]. Scopus covers business, management, information systems, and computer science to a greater extent than Web of Science [12]-[13],

[25]. By enhancing data coverage and reducing the limitations of each database, the two are combined. An extensive ssearch strategy was employed across titles, abstracts, and author keywords to ensure systematic and relevant coverage of the AI-BI in SMEs.

To achieve the aims of this study while ensuring data relevance and reliability, the study was delimited to peer-reviewed articles and review papers published in English between 2015 and 2025, and to a select range of document types. Excluded document types included, but were not limited to, conference papers, book chapters, editorials, notes, and non-refereed works, since there is a high lack of citation for non-refereed documents, and non-refereed documents also tend not to develop stable citation systems, which are needed for reliable mapping for bibliometric purposes [12]-[13]. This approach is the norm in the bibliometric field, especially in the research fields from which the data were drawn, and it would ensure that the data are of high integrity and robustness within the parameters.

Once the data were retrieved, bibliographic records were exported as CSV and Plain text (txt) files for easy integration with bibliometric analysis software. The exported records included all bibliographic details and all cited references. Pre-processing included removing duplicates, standardizing the names of authors and their institutions, and aligning keyword sets to minimize discrepancies arising from indexing differences between Web of Science and Scopus [19]. These processes were necessary to level discrepancies in constructed bibliometric networks [18].

The literature search was conducted using the Web of Science and Scopus databases. The search was performed within all fields using the following Boolean query*: ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning") AND ("business intelligence" OR "business analytics" OR "data analytics" OR "decision support system*") AND ("small and medium enterprise*" OR "SME*" OR "small business*" OR "medium enterprise*"). The initial search yielded 294 records from the Web of Science and 249 records from Scopus. Duplicate records were identified and removed during data preprocessing using ScientoPy based on DOI, title, and author metadata, resulting in minimal duplication approximately 1% in Web of Science and none in Scopus as shown in Figure 1.

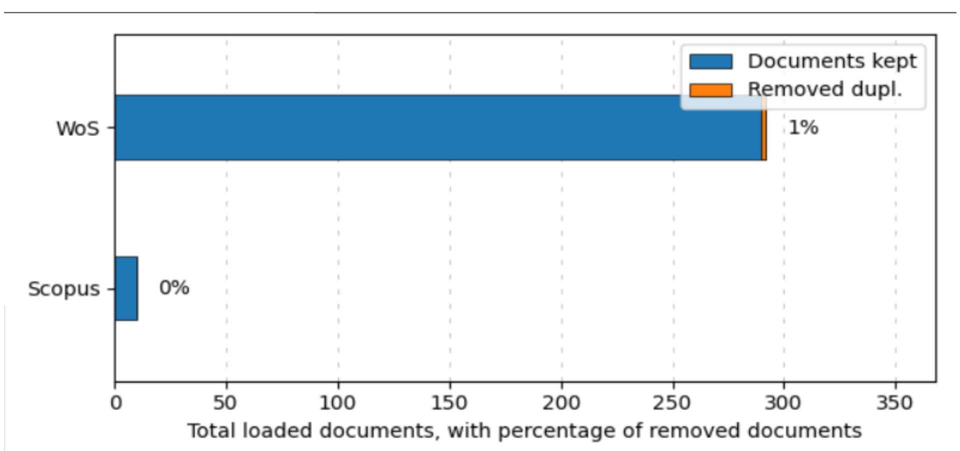


**Figure 1.** Data Collection from Web of Science and Scopus
Source: ScientoPy

*2.2. Data Analysis Method*

This study employed bibliometric analysis as a systematic, quantitative technique to assess scientific publications on the intersections of AI and BI in SMEs. This technique allows sifting through a considerable pool of academic publications and citation metrics to discern the structural development, intellectual pillars, and the evolution of a theme in a niche area [23]-[24]. An approach to scientific mapping from a quantitative perspective, applying bibliometric techniques to examine the structure and progress of AI and BI in SMEs [26]-[27]. The overall bibliometric workflow is illustrated in Figure 2, demonstrating the successive stages of research topic conception, data collection, scientific mapping and analysis. In addition, Figure 3 provides a PRISMA-style workflow diagram to clarify the search, screening, and inclusion steps, thereby improving the traceability and replicability of the bibliometric methods [28].

The analyses comprised two interconnected components that are performance analysis and scientific mapping. The performance analysis assessed research activity and its influence using bibliometric indicators, including the number of publications, total citations, average citations per document, and the h-index. These indicators were applied at the author, institution, country, and journal levels to identify leading contributors, influential publications, and primary research centers in the field of AI and BI in SMEs.

Scientific mapping techniques included co-authorship analysis, co-citation analysis, and keyword co-occurrence analysis. Co-authorship analysis principles studied patterns of collaboration among authors, institutions, and nations. This analysis revealed the social framework of the research domain. Concerning co-citation analysis, it discovered prominent works and the streams of influence by determining how often two works were cited together. This also included assessing patterns of keyword co-occurrence to derive the conceptual structure of research in AI–BI in SMEs and the principal research themes and their hotspots.

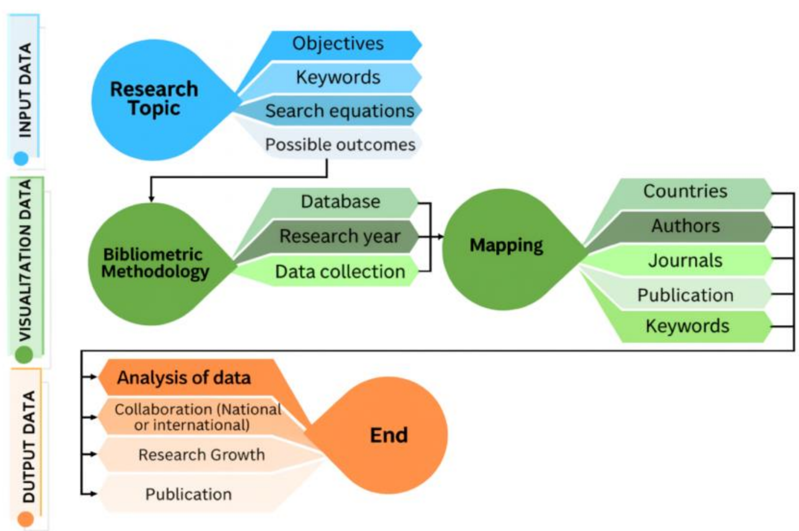


**Figure 2.** Bibliometric methodology
Source: Author's own elaboration designed using Adobe Illustrator.

### 2.3. Bibliometric Tools and Visualization

The analytical tools and data processing pipeline described in this study are illustrated in Figure 3. First, bibliographic data from the Web of Science and Scopus were filtered, extracted, and stored before being analyzed in Scientopy. VOSviewer, Bibliometrix (R), and Microsoft Excel. Scientopy was employed to examine the longitudinal evolution of research themes, thematic structures, and performance indicators [17]. VOSviewer was used for scientific mapping and visualization [11], [17]. Bibliometrix in R for the calculation of advanced bibliometric indicators and thematic analyses, and Microsoft Excel for descriptive statistics and data management [29].

The results of the bibliometric analysis were primarily visual. To represent the network of authors, keywords, and cited documents, network visualizations were used; to show the concentration of research and the focus of emerging research, density maps were used. In the interest of maintaining methodological transparency and reproducibility, we decided to keep the default values of all layout and visualization settings, as we mentioned before, except for very few cases.

While bibliometric analysis has strengths, it also has weaknesses. Because older papers have had more time to be cited, they are likely to receive more attention through citation-based indicators [30]. However, citation growth trends, average citation metrics, and temporal patterns mitigated this challenge to some extent. Publishing exclusively in English is likely to introduce some language bias in the dataset, but this decision ensures some degree of consistency and allows for wider geographical comparability [31]. The combination of Web of Science and Scopus libraries has mitigated the risk of database coverage bias [32]. Finally, there is minimal attention to the qualitative depth of patterns in the bibliometric methods, which means that the findings complement more detailed content analysis but cannot be considered a substitute for it.

In summary, the methods undertaken provide a robust, transparent, and reproducible framework for mapping the evolution, structure, and thematic orientation of the AI and BI research in SMEs. The combination of performance analysis and scientific mapping methods, along with the precise specification of the parameters used in this research, enables accurate interpretation of the bibliometric findings and provides a solid foundation for further study and evidence-based decision-making.

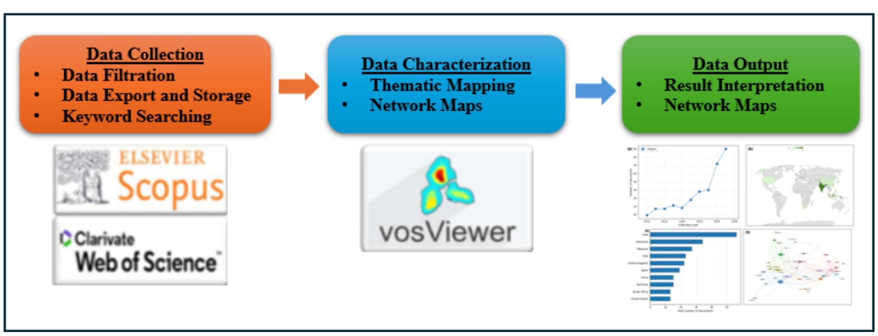


**Figure 3.** Analysis tools
Source: Author’s own elaboration designed using Adobe Illustrator.

## 3. Results

### *3.1. General Publication Trends*

This section provides a spatio-temporal overview of analytics AI and BI in SMEs retrieved from the Web of Science and Scopus Database. As shown in Figure 4 (a), the number of publications is projected to increase from 2015 to 2025 with minor fluctuations in the most recent years. This pattern reflects the sustained growth and relevance of integrating AI-BI across academia and SMEs.

In the first phase of the study, published between 2015 and 2017, the number of publications was low, at fewer than 20 per year. This is the stage where the value of AI survey was still limited, BI system was often perceived as complex and studies focusing on small sized firms were relatively scarce. This period reflects an emerging interdisciplinary research phase involving digital technologies, complex systems, and organizational structures.

From 2018 to 2020, the number of publications per year increased gradually from 17 to 18. The adoption of cloud-based BI platforms and the analytics as a service model coincided with increasing scholarly attention to data-driven decision-making in SMEs. During the same period, research increasingly examined the role of data-driven tools in relation to organizational competitiveness, productivity, and resilience. A significant increase in the publication output began in 2021 and continued in subsequent years. In 2021, there were 21 publications, and in 2022, this number increased to 25. This upward trend continued in 2023, followed by a marked increase increased in 2024 with 62 publications, while 64 publications output in 2025 remained at a comparatively high level. This overall increase in publications reflects the advancements in AI at the time, especially in predictive analytics and real-time decision-support systems. his was all amid the global prioritization of data-driven SMEs and the world's increased focus on digital transformation. The uncertainty brought by COVID-19 coincided with increased scholarly attention to analytics-driven decision-making among small enterprises [31], [33].

There are also the geographical patterns of the articles published, reflecting the worldwide scope of AI–BI research in SMEs. As illustrated in Figure 4 (b). India recorded 34 publications, followed by United State 33 publications, the United Kingdom 26 publications and China with 25 publications. These countries are the most indicative of AI–BI importance in both emerging and developed economies.

Notably, contributions from European countries are also evident, with Italy (23), Germany (18), and Spain (18) among the most prolific. Such output confirms the continued interest in research and development in the digital transformation of SMEs in the European Union, which is also the result of policies that promote innovation, encourage data-driven entrepreneurship, and support the 4th Industrial Revolution [22]. At the same time, the South Korea (16), France (14) and Malaysia (14) also demonstrate considerable activity as shown by the number of publications, which confirms the existence of a diversified global research landscape.

Overall, in reviews of publication trends, there seems to be a shift from early-stage to fully developed, functional research in application-oriented studies. The rise after 2020 indicates that AI- BI in SMEs have matured into a key research area, associated with technological advancements of systems and increasing academic interest in data and analytics-driven organizational practices [7].

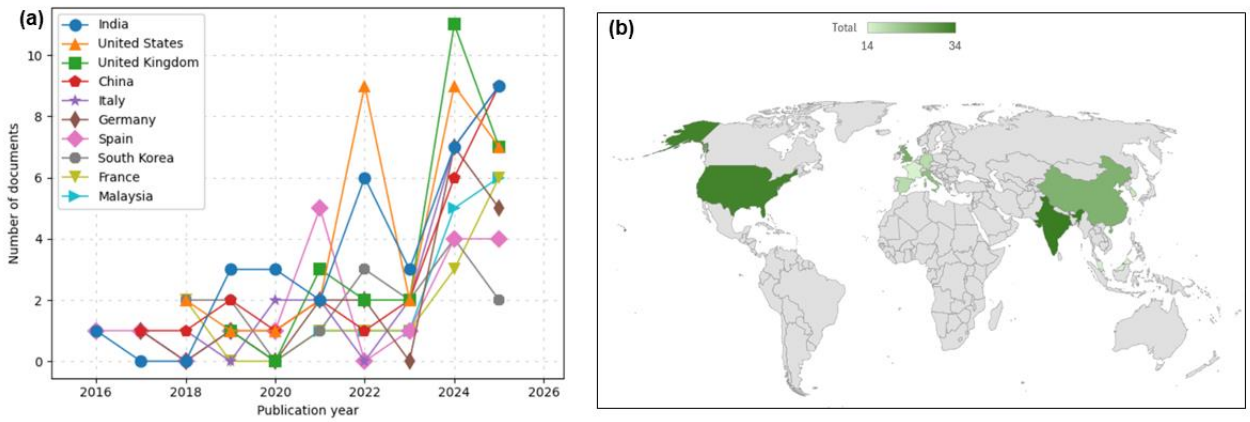


**Figure 4.** (a). Annual publication trends; (b). Geographical distribution of publications.
Source: WoS and Scopus database, analyzed using ScientoPy and Microsoft Excel, visualized using Microsoft PowerPoint.

*3.2. Performance and collaboration of countries*

This part analyses the countries involved in investigating AI-BI in SMEs, and how they are performing and cooperating globally. Using publication and co-authorship information from the Web of Science and Scopus database, the analysis shows the leading contributors and the cross-national research collaboration structure in this emerging area. Figure 5 (a) shows the research output from the top 10 countries. India leads with 34 publications, followed by the United States (33), the United Kingdom (26), and China (25). These countries' strong performances reflect the economic importance of SMEs both emerging and developed economic contexts.

Other European nations also make significant contributions. Italy (23), Germany (18) and Spain (19) show sustained scholarly interest in the transformation of SMEs through AI-BI technologies. These contributions are especially relevant to policy frameworks supporting innovation, entrepreneurship, Industry 4.0 adoption, and digital innovation related research in European SMEs. Among non-European contributors, China (25) exhibits a comparatively strong publication profile, indicating research potential in AI and analytics. South Korea (16), France (14), and Malaysia (14) further contribute to the overall research landscape.

In addition to the number of publications, Figure 5 (b) depicts networks of international collaboration through co-authorships. In this network, countries are the nodes, while the connections represent the degree of collaboration. As a result of high research output and extensive cooperation with the United States, the United Kingdom (labelled as "England" in the collaboration network), Germany, and several Asian countries, India is in the middle of the map.

Within the European region, Italy, the United Kingdom, Spain, and Germany are concentrated, indicative of strong interregional collaboration based on common research themes, institutional affiliations, and mobility programs. Malaysia demonstrates collaborative linkages, especially with countries in the same region and with some European and Anglo-Saxon countries. The collaboration network also shows that countries with moderate publication numbers can become strategically crucial as bridging nodes interlinking different subregional clusters. Such cross-country collaboration is essential for the organizational, technological, and contextual environments required for integrating AI-BI into SMEs [34]. Here, the solutions needed are usually interdisciplinary and cross-cultural.

On an overall basis, country level analysis shows that although AI–BI research geographically disperses across SMEs, there is a degree of occupational intensity in advancing AI–BI research in some developing economies, augmented by growing cross-country collaborations.

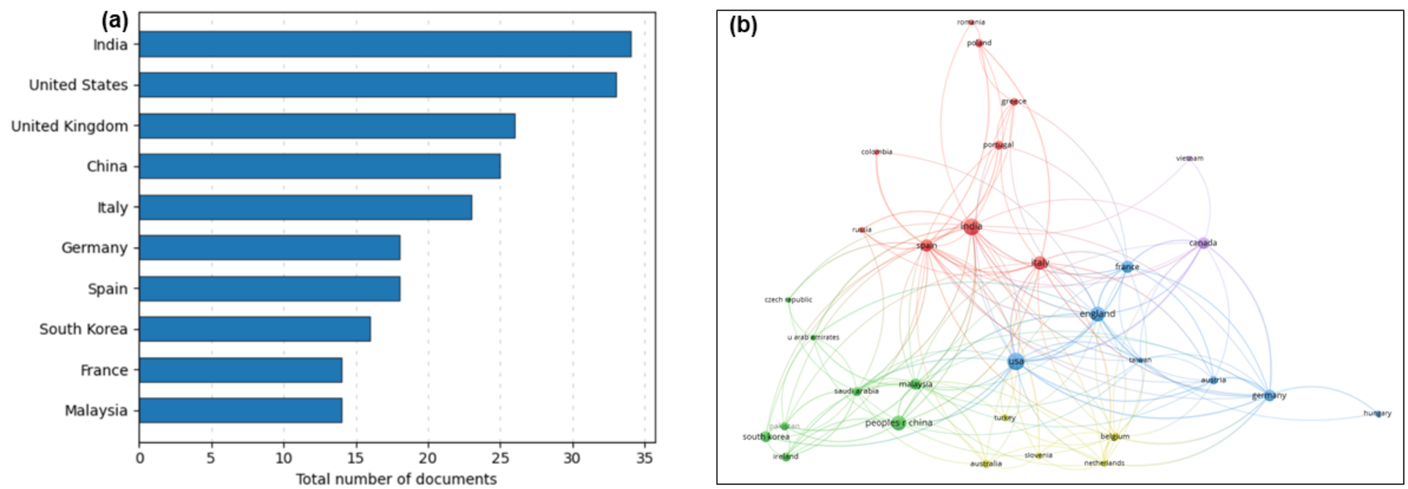


**Figure 5.** (a). Total number of AI-BI in SMEs by the top 10 most productive countries, based on Web of Science and Scopus database; (b). Country co-authorship network visualized using VOSviewer. Node size represents publication volume, while edge thickness reflects the strength of collaborative relationships. The network illustrates India's central position in international research collaboration, alongside dense regional collaboration patterns across Europe and Asia. Source: Analyzed using ScientoPy and visualized using VOSviewer.

### *3.3. Bibliographic Coupling Analysis*

Bibliographic coupling was performed to analyze the first thematic structure of AI and BI in SMEs at the document level. By sharing reference indices across documents, this method identifies more closely intertwined research streams and offers a perspective on the discipline's primary thematic orientations. The resultant coupling network, produced with VOSviewer, identifies four cohesive thematic clusters that reflect a systematically organized and maturing research environment, as shown in Figure 6.

Cluster 1 (Red) covers studies on the intersection of AI, digitalization and SMEs in the context of Industry 4.0. These studies address artificial intelligence adoption, digitalization, and technology adoption, along with associated costs and risks, as shown in Table 3. This stream focuses on adoption readiness and the implementation challenges SMEs face.

Cluster 2 (Green) studies AI-based information systems and their impact on SMEs performance. This cluster compiles studies on systems, information utilization, financial performance, sales, and competitive advantages, summarized in Table 1.

Cluster 3 (Blue), whose theme is sustainability, innovation and manufacturing of SMEs. The publications on this focus on the potential of AI and BI technologies for sustainable production, innovation, manufacturing efficiency, and other economic outcomes.

Cluster 4 (Yellow) covers the SMEs of business intelligence infrastructure and decision-making systems. The studies in this stream focus on cloud BI systems, computing, decision-making, and commercial processes. As shown in Table 3, this cluster highlights the value of tech infrastructure, particularly the cloud-based BI systems, in fostering data-driven decision-making in technology-scarce SMEs.

The outputs of bibliographic coupling show that AI–BI in SMEs is concentrated on four interconnected research streams: adoption and digitalization, performance outcomes, sustainability-oriented innovation, and decision support systems as shown in Table 1.

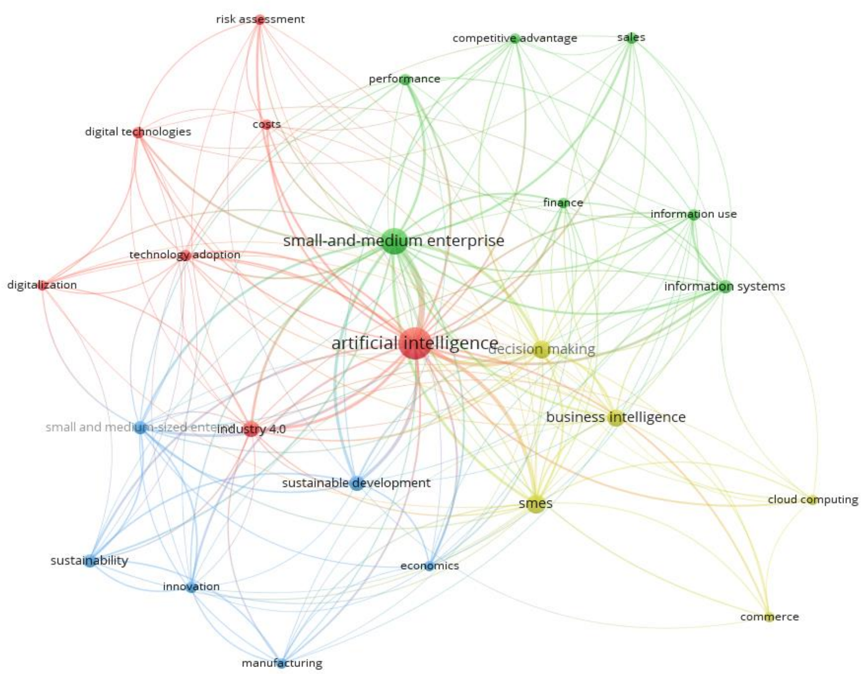


**Figure 6.** Bibliographic Coupling Network of AI–BI Research in SMEs
Source: Visualized using VOSviewer

**Table 1.** Thematic Clusters of AI–BI Research in SMEs Based on Bibliographic Coupling Analysis

| Cluster | Theme | Publication | Representative Publication |
|---|---|---|---|
| 1 (Red) | AI Adoption, Digitalization, and Industry 4.0 in SMEs | 7 | [21] |
| 2 (Green) | AI-Enabled Information Systems and SME Performance | 7 | [35] |
| 3 (Blue) | Sustainability, Innovation, and Manufacturing-Oriented SMEs | 6 | [36] |
| 4 (Yellow) | Business Intelligence Infrastructure and Decision-Making Systems | 8 | [20] |

A qualitative interpretation of these clusters suggests that the literature remains largely adoption-centric, with limited emphasis on post-adoption capability development and long-term organizational transformation within SMEs.

*3.4. Keyword Co-occurrence Analysis*

Keyword co-occurrence network visualization analysis is used to assess the degree of interrelationship between the concepts of AI and BI in the research domain. This analysis is conducted using the keyword(s) of the authors in VOSviewer using the complete counting method and a minimum threshold of five occurrences, which allows dominant and nascent research themes to be identified in the network visualization output based on the co-occurrence of the keywords. This research produced seven network visualization thematic clusters, demonstrating the network's conceptual breadth and sophistication as shown in Table 2.

Cluster 1 (Red) encompasses Artificial Intelligence aimed at improving financial inclusion and addressing bankruptcies among Micro, Small, and Medium Enterprises (MSMEs), including keywords such as AI adoption, artificial intelligence, fintech, blockchain, credit scoring, financial inclusion, and PLS-SEM.

Cluster 2 (Green) represents the research intersection of digital transformation, sustainability, and Industry 4.0. The main keywords in this cluster include digital transformation, digital technologies, digitalization, Industry 4.0, entrepreneurship, manufacturing, and sustainability.

Cluster 3 (Blue) concentrates on organizational context and SMEs typologies, identified by keywords such as enterprise resource planning, micro enterprises, small enterprises, and technology–organization–environment.

Cluster 4 (Yellow) focuses on business intelligence infrastructure and related decision support systems, including keywords such as business intelligence, cloud computing, decision support systems, and decision-making.

Cluster 5 (Purple) explores productivity, innovation, and the applications of AI–BI in smart manufacturing. The keywords innovation, productivity, and smart manufacturing relate to the application-oriented branch of research.

Cluster 6 (Cyan) comprises the technology acceptance and behavioral adoption models, as characterized by the keywords “technology acceptance model, technology adoption, mobile business intelligence”.

Cluster 7 (Orange) encompasses advanced analytics techniques, especially machine learning and deep learning.

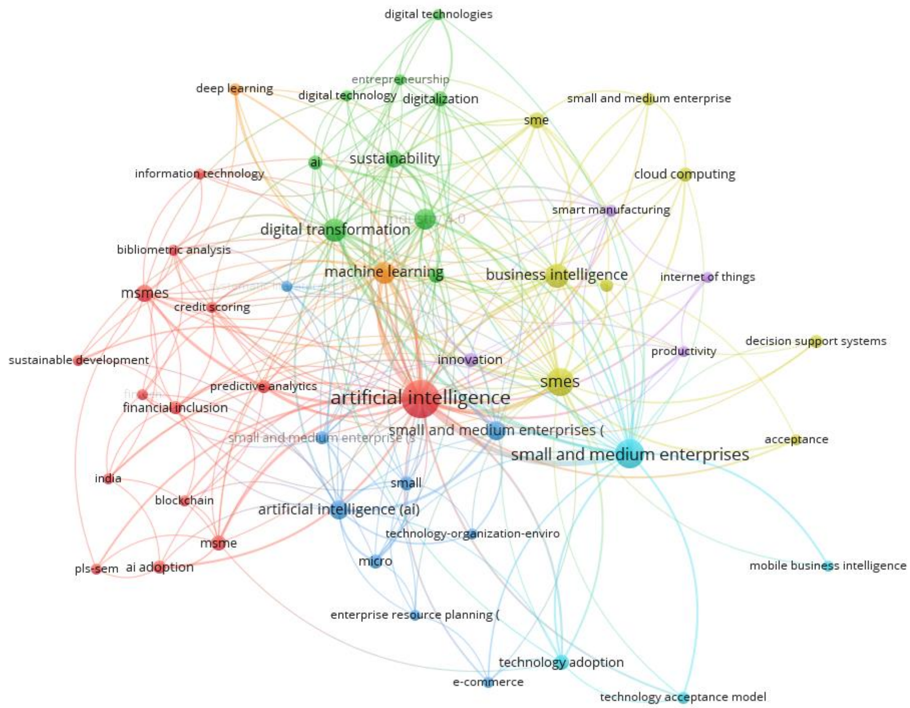


**Figure 7.** Keyword Co-occurrence Network of AI–BI Research in SMEs
Source**:** Visualized using VOSviewer

Generally, keyword co-occurrence analysis shows that AI–BI research within SMEs is progressing from adoption- and theory-led studies towards more complex integrations, including digital transformation, sustainability, BI infrastructure, and advanced analytics.

**Table 2.** Thematic Results of Keyword Co-occurrence Analysis on AI–BI Research in SMEs

| Cluster | Theme | Representative Keywords |
|---|---|---|
| 1 (Red) | AI Adoption, FinTech, and Financial Inclusion in MSMEs | AI Adoption; Artificial Intelligence; Fintech; Blockchain; Credit Scoring; Financial Inclusion; MSMEs; PLS-SEM |
| 2 (Green) | Digital Transformation, Sustainability, and Industry 4.0 | Digital Transformation; Digital Technologies; Digitalization; Industry 4.0; Entrepreneurship; Manufacturing; Sustainability |
| 3 (Blue) | Organizational Context and SME Typologies | Enterprise Resource Planning; Micro Enterprises; Small Enterprises; TOE Framework |
| 4 (Yellow) | Business Intelligence Infrastructure and Decision Support Systems | Business Intelligence; Cloud Computing; Decision Support Systems; Decision Making; SMEs |
| 5 (Purple) | Productivity, Innovation, and Smart Manufacturing | Innovation; Productivity; Smart Manufacturing |
| 6 (Cyan) | Technology Acceptance and Mobile BI Applications | Technology Acceptance Model; Technology Adoption; Mobile Business Intelligence |
| 7 (Orange) | Machine Learning and Deep Learning Techniques | Machine Learning; Deep Learning |

Qualitative synthesis of the keyword patterns reveals a gradual thematic shift from technology adoption models towards broader concerns related to sustainability, digital transformation, and advanced analytics, signaling the conceptual maturation of the field.

*3.5. Co-citation Analysis*

This segment outlines the main frameworks guiding research on AI and BI in SMEs through co-citation analysis. Co-citation analysis offers insights into the development of core theories and significant scholarly works by examining how often references are cited together across various publications. This method is most effective in identifying the field's primary knowledge bases, which shape and advance the domain.

Strategists constructed a co-citation network of cited references based on the co-citation patterns. Held a minimum threshold of citations to include only the major and often co-cited works. The resulting network yielded several highly interconnected, distinct clusters, which, for clarity and in alignment with the journal's standard practices, we merged into four major intellectual foundations. These clusters of ideas, with representatives from the fundamental works, are outlined in Table 3.

The first intellectual cluster is rooted in the technological acceptance, diffusion of innovations, and organizational adoption behavioral frameworks in AI and BI in SMEs. It is based on the pioneering research of [22], [35], [37]. Such studies offer the foundational literature on the determinants of individuals' and organizations' adoption of AI-enabled BI systems, based on perceived usefulness, ease of use, and contextual readiness [20], [35], [36]. The second intellectual cluster focuses on the resource-based view (RBV), firm performance, and value creation. This cluster is dominated by the works of [38]-[39]. Such literature identifies information systems and analytics capabilities as central to an organization's strategic resource endowments, which can engender positive organizational outcomes and sustain competitive advantage. This literature serves as the basis for empirical studies that associate AI–BI capabilities with a variety of outcomes, including productivity and efficiency, as well as performance, in SMEs [22], [34], [37].

The third intellectual cluster focuses on Digital Transformation and Industry 4.0, as well as on the literature on analytics-driven organizational change. The foundational work of [22], [40] elucidated the impact of digital technologies, analytics, and AI on the reconfiguration of business models, organizational processes, and strategic planning in firms. This cluster offers a macro-level perspective on the adoption of AI and BI in SMEs [36], [38].

The fourth intellectual cluster examines the contributions of AI and intelligent and Advanced systems analytics in this area of the field. This cluster includes some of the earliest works in the field of artificial intelligence and analytics-based decision support, such as [41]. These scholars provide the conceptual and methodological foundations for studies that apply machine learning, predictive analytics, and intelligent systems to improve decision-making and automate processes in SMEs.

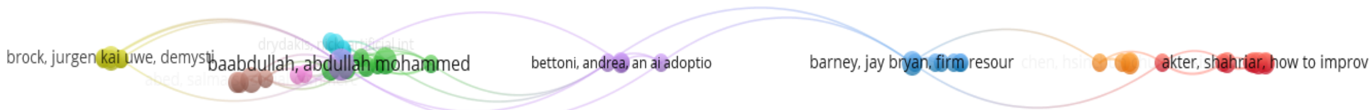


**Figure 8.** Author Co-citation Network Revealing the Intellectual Structure of AI and BI in SMEs
**Source:** Visualized using VOSviewer

**Table 3.** Intellectual Clusters of AI and BI in SMEs Based on Co-citation Analysis

| Intellectual Cluster | Core Theme | Representative Foundational References |
|---|---|---|
| 1 | Technology Adoption & Information Systems Foundations | [22], [35], [37] |
| 2 | Resource-Based View, Firm Performance & Value Creation | [38], [39] |
| 3 | Digital Transformation, Industry 4.0 & Analytics-Driven Change | [22], [40] |
| 4 | AI, Intelligent Systems & Advanced Analytics Foundations | [36], [41] |

Qualitative interpretation of the co-citation structure highlights a strong dependence on technology adoption and information systems theories, while organizational learning and dynamic capability perspectives remain comparatively underutilized.

## 4. Discussion

This study aims to synthesize research on AI-BI in SMEs and to perform a bibliometric analysis using trend, thematic, conceptual, and intellectual structure analyses. The evidence suggests that the AI-BI intersection in SMEs has shifted from being exotic and fragmented to a more organized, interdisciplinary field of study. From a qualitative synthesis perspective, this transition can be interpreted as reflecting a gradual consolidation of research themes rather than merely an increase in publication volume, alongside emerging efforts to integrate technological, organizational, and strategic viewpoints. This observed transition aligns with prior reviews that describe the gradual maturation of AI–BI research in SMEs from exploratory adoption studies towards more integrative and value-oriented investigations.

The bibliographic coupling analysis indicates that adoption and digitalization remain central areas of AI–BI research, showing that a lack of readiness, cost, and risk continue to prevent SMEs from engaging more with AI enabled systems [6]. However, the clusters of publications on performance, sustainability, and BI decision-making systems infrastructure suggest that the field is gradually shifting away from focusing solely on AI–BI adoption towards emphasizing the long-term value that the intersection of AI and BI can offer. This shift may be explained by the increasing recognition that technological adoption alone is insufficient without complementary organizational capabilities and learning processes. Qualitative interpretation of these clusters indicates that while adoption readiness remains dominant, post-adoption capability development and long-term transformation processes are still insufficiently examined. This finding is consistent with earlier studies that predominantly examined AI and BI adoption drivers while giving limited attention to post-adoption capability development and long-term organizational outcomes in SMEs

The use of keyword co-occurrence analysis also uncovers a more detailed understanding of the field's conceptual structure. Distinct conceptual sections focusing on advanced analytics, machine learning, and smart manufacturing highlight the increasing technical sophistication of AI–BI applications within SMEs. Meanwhile, the continued presence of technology adoption models and behavioral theories indicates that conceptual development within these frameworks remains partly rooted in traditional adoption models. From a theoretical standpoint, this suggests a misalignment between rapid technological advancement and the slower evolution of explanatory organizational theories. Qualitative synthesis of the keyword patterns suggests that theoretical advancement has not fully kept pace with the increasing technical sophistication of AI–BI applications. Similar concerns have been raised in prior literature, which notes that empirical advances in AI-enabled analytics often outpace the development of robust explanatory and organizational theories in SME contexts.

The insights from co-citation analysis also enrich this narrative by identifying the field's key intellectual foundations. The dominance of theories of technology adoption and information systems underscores the importance of behavioral and organizational theories in AI–BI adoption. Likewise, the significant influence of the resource-based view and performance literature highlights a growing perception of AI–BI capabilities as a source of competitive advantage and organizational success. However, this intellectual concentration also indicates a relative underrepresentation of organizational learning and dynamic capability perspectives, which are critical for explaining long-term transformation. From a qualitative perspective, this intellectual structure reveals a strong reliance on established theories, with limited integration of organizational learning and dynamic capability perspectives. This theoretical concentration echoes earlier reviews that highlight the dominance of technology adoption frameworks and call for broader integration of organizational learning and capability-based perspectives in AI–BI research.

A review of the literature indicates that although AI-BI in SMEs have advanced in terms of development and understanding, its potential remains underexplored, both theoretically and empirically. This assessment is not derived from individual results alone, but from a qualitative synthesis of the thematic, conceptual, and intellectual patterns identified through the bibliometric analyses. The synthesis of the thematic, conceptual, and intellectual frameworks underpins the research aimed at addressing the identified gaps.

### *4.1. Research Gap Identifies*

Building on the qualitative synthesis of the bibliometric findings, several theoretical, methodological, and contextual gaps can be identified. While previous studies primarily documented adoption determinants and technological readiness, the present bibliometric analysis reveals persistent gaps related to post-adoption transformation processes, contextual heterogeneity, and long-term value creation [42]. This gap may be attributed to the dominant focus of earlier research on initial adoption decisions rather than on sustained organizational change and capability development. This finding extends prior bibliometric reviews by explicitly highlighting post-adoption capability development as an underexplored dimension. Although there has been significant expansion in the scope of analysis of the intersection of AI, BI and SMEs over recent years, the earliest bibliometric studies on this relationship have identified multiple directions that are still in the early stages of development. As demonstrated by their relative prevalence, initial studies that focused solely on the acceptance phase of the relationship between AI and BI in SMEs overlooked the essential processes underlying actual transformation.

From an organizational behavior modification theory perspective, these early studies on the adoption of AI and BI in SMEs and their limited implementation in small organizations reveal a lack of integration with organizational learning-based behavioral frameworks. This theoretical imbalance reflects a reliance on intention- and acceptance-based models that are less equipped to explain long-term learning, adaptation, and capability accumulation. Co-citation analysis shows a strong preference for the theory of technology adoption over resource-based theory, which accounts for the absence of a unified approach.

Another contextual gap concerns the overrepresentation of specific regions and industries. Although developing and emerging economies are increasingly included in the literature, research remains unevenly spread across regions, with few comparative studies between countries and their institutional environments. This imbalance limits the explanatory power of existing findings regarding how regional regulatory environments, digital infrastructure, and cultural conditions shape AI and BI adoption outcomes in SMEs. Future research could benefit from cross-country and cross-sectoral analyses to understand how regional regulatory environments, digital infrastructure, and cultural factors influence AI and BI adoption and outcomes in SMEs. There is a clear need to allocate more research efforts to microenterprises and informal SMEs, which are often overlooked in empirical studies but are economically very significant.

The structure of concepts revealed by the keyword co-occurrence analysis indicates, to some extent, a separation between the advanced analytics literature and that of organizational impact studies. Although there is growing interest in predictive analytics, machine learning, and intelligent systems, the limited integration of these technical advances with studies on organizational outcomes suggests a disconnect between technological innovation and impact-oriented research. Consequently, a significant gap persists in studies assessing how advanced AI–BI techniques influence decision quality, innovation processes, and the sustainability of overall performance in SMEs.

Finally, the integration of societal and sustainability concerns in AI and BI in SMEs remains cautious. While sustainability its peripheral positioning suggests that sustainability considerations are often treated as secondary outcomes rather than as integral components of AI–BI strategy and value creation.

### *4.2. Future Research Agenda*

Future research on the intersection of AI-BI in SMEs should incorporate additional behavioral frameworks from organizational learning theory, definitional shifts in organizational control, and dynamic capabilities theory to better explain the adoption of AI-BI systems within SMEs. This theoretical expansion is necessary to move beyond intention-based explanations and to account for sustained learning, adaptation, and capability development over time.

Methodologically, the existing studies mainly rely on cross-sectional, quantitative survey designs, often employing structural equation modelling [8], [43], [44]. While useful for theory validation, these approaches fall short in capturing the complex, multidimensional, and longitudinal aspects of AI and BI adoption and use [9], [45]. This methodological dominance partly explains why post-adoption dynamics and long-term organizational transformation remain underexplored in the current literature. The gaps in the literature suggest future research should include longitudinal studies, qualitative case research, and mixed method approaches to explore how AI-BI capabilities evolve. These methodological recommendations are informed by a qualitative synthesis of the dominant research designs and thematic limitations observed in the literature.

Therefore, future research should go beyond technical feasibility to examine the implementation of advanced AI techniques, including managerial, ethical, and organizational considerations, and scrutinize these factors more critically within the context of business resource constraints. Such an approach would enable a deeper understanding of why certain AI–BI initiatives generate value while others fail to progress beyond experimental or pilot stages. Future studies should more thoroughly explore how AI–BI system adoption can promote environmental and social sustainability, as well as inclusive development, particularly in relation to the world's Sustainable Development Goals.

In conclusion, future AI-BI research in SMEs should shift from a primarily adoption-focused approach to more integrated, longitudinal, and contextually aware perspectives. This shift directly responds to the theoretical, methodological, and contextual gaps identified in the preceding discussion.

## 5. Conclusions

This study offers a structured bibliometric synthesis of research on artificial intelligence and business intelligence in small and medium-sized enterprises, providing insights into the evolution, thematic focus, and intellectual foundations of the field. By integrating thematic, conceptual, and co-citation analyses, the study highlights a shift from predominantly adoption-oriented investigations toward broader discussions of performance, value creation, and advanced analytics. Nevertheless, the synthesis reveals persistent theoretical and methodological limitations, particularly in relation to post-adoption transformation and long-term capability development. Overall, this review establishes a coherent knowledge base and identifies critical directions for future research aimed at advancing a more integrated and context-sensitive understanding of AI–BI in SMEs.

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