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Article

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Systematic Review

Applications and Competitive Advantages of Data Mining and Business Intelligence in SMEs Performance: A Systematic Review

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Abstract: Small and medium-sized enterprises (SMEs) face unique challenges that can be effectively addressed through the adoption of data mining and business intelligence (BI) tools. This systematic literature review scrutinizes the deployment and efficacy of BI and data mining technologies across SME sectors, assessing their impact on operational efficiency, strategic decision-making, and market competitiveness. Therefore, drawing from a methodologically rigorous analysis of 93 scholarly articles published between 2014 and 2024, the review elucidates the evolving landscape of BI tools and techniques that have shaped SME practices. It reveals that advanced analytics such as predictive modeling and machine learning are increasingly being adopted, though significant gaps remain, particularly shaped by economic factors. The utilization of BI and data mining enhances decision-making processes and enables SMEs to adapt effectively to market dynamics. Despite these advancements, SMEs encounter barriers such as technological complexity, high implementation costs, and substantial skills gaps, impeding effective utilization. Our review, grounded in the analysis of business intelligence tools used indicates that dashboards (31.18%) and clustering techniques (10.75%) are predominantly utilized, highlighting their strategic importance in operational settings. However, a considerable number of studies (66.67%) do not specify the BI tools or data mining techniques employed, pointing to a need for more detailed methodological transparency in future research. The predominant focus on the ICT and manufacturing sectors underscores the industrial context sector specific applicability of these technologies, with ICT accounting for 45.16% and manufacturing 22.58% of the studies. We advocate for targeted educational programs, development of user-friendly and cost-effective BI solutions, and strategic partnerships to facilitate knowledge transfer and technological empowerment in SMEs. Empirical research validating the impacts of BI and data mining on SME performance is crucial, providing a directional pathway for future academic inquiries and policy formulation.

Keywords: data mining; business intelligence; SMEs performance; competitive advantage; systematic review; geographic context; economic factors; resource-constrained environments



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1. Introduction

In today's rapidly evolving technological landscape, the adoption of data mining and business intelligence (BI) technologies has significantly transformed organizational operations, particularly within small and medium-sized enterprises (SMEs). These emerging technologies have revolutionized traditional business practices by providing essential

tools for analyzing vast amounts of data, deriving actionable insights, and enhancing decision-making processes, which collectively lead to a competitive advantage (Mupaikwa, 2024). Data mining and BI have become integral components of the modern data-driven business environment, playing a crucial role in determining organizational success or failure (Mezhoud, 2024). Recent research highlights the transformative impact of these technologies across various industries. Data mining, for instance, has been pivotal in improving customer relationship management, optimizing supply chain processes, and enhancing financial forecasting within SMEs (Willets & Atkins, 2024; Naznen & Lim, 2023). Additionally, business intelligence has demonstrated significant improvements in strategic planning, performance management, and fostering innovation—elements crucial for sustaining competitive advantage in highly contested markets (Kautsaf et al., 2023). The application of data mining within knowledge management has also been explored, illustrating its relevance to the transportation sector for SMEs (Adeyelu et al., 2018a). Despite these advancements, a notable gap exists in understanding the comprehensive operation of these technologies within SMEs, especially in developing economies (Leite et al., 2019). SMEs, representing approximately 90 percent of businesses and over 50 percent of global employment, play a significant economic and social role, making their competitiveness vital for economic development (Llave, 2017). However, SMEs face distinct challenges in surviving economic and global competition, necessitating efficient monitoring and use of information resources (Llave, 2017). Business intelligence, which encompasses methodologies, processes, architectures, and technologies to transform raw data into actionable insights, has emerged as a crucial tool for enhancing SME competitiveness (Llave, 2017; English & Hoffmann, 2018). Yet, the literature on BI's application specifically within SMEs is sparse, with much research historically focusing on larger enterprises (Llave, 2017; Papachristodoulou et al., 2017).

The increasing globalization and rapid technological changes have further disadvantaged SMEs compared to larger counterparts, emphasizing the need for leveraging knowledge-building capabilities such as BI to gain a competitive edge (English & Hoffmann, 2018). The applicability of business intelligence maturity models to SMEs and the challenges associated with implementing BI systems in this sector underscore the complexity of this landscape (Coleman, 2016). Moreover, the cost and complexity of BI system implementation present significant barriers for SMEs, which often lack the specialized IT departments and financial resources of larger organizations (Papachristodoulou et al., 2017). Recent studies have explored various facets of BI and data mining within SMEs, including the deployment of cloud solutions from both vendor and customer perspectives (Agostino et al., 2013), and the development of frameworks for mobile business intelligence in developing countries (González-Varona et al., 2020). Furthermore, insights from the UK and Malaysia highlight the opportunities and challenges of BI and data mining in different contexts (Ali et al., 2017). The interaction between business intelligence (BI) systems and SME operations during crises has been analyzed, revealing vital elements influencing ERP system adoption (Qushem et al., 2017). This systematic review aims to bridge the existing gaps by synthesizing information from a decade of research on data mining and BI in SMEs, identifying key trends, challenges, and opportunities associated with these technologies. By analyzing studies published over this period, this review seeks to provide practical insights for SME practitioners and policymakers, ultimately improving organizational performance and growth (Gauzelin & Bentz, 2017). Table 1 presents a comparative analysis of existing review works and our proposed systematic review, highlighting the distinct focus of this study on the applications and competitive advantages of data mining and BI for SMEs. This review will explore how data mining and BI technologies are utilized in the SME landscape to foster competitive advantage. By uncovering patterns in technological adoption, showcasing successful case studies, and discussing the implications of these findings, this review

aims to lay the foundation for future research and practical improvements. It will also deepen the understanding of the strategic role that data mining and business intelligence play in the evolving operational landscapes of SMEs (Khan et al., 2014).

Table 1. Comparative analysis of the existing review works and proposed systematic review on the applications and competitive advantages of data mining and business intelligence on SMEs performance.

Ref.	Cites	Year	Contribution	Pros	Cons
Abbas et al. (2016)	15	2016	Investigated structural factors impacting SME performance using structural equation modeling.	Provides valuable insights into key factors influencing SME success.	Focused on a specific geographic region, limiting broader applicability.
Gupta and Jiwani (2021)	131	2021	Studied the resilience of SMEs utilizing BI in volatile markets, with a focus on competitive advantages.	Stronger market resilience, better risk management.	Requires continuous data monitoring and analysis.
Ain et al. (2019)	40	2019	Investigated business intelligence review tools for SMEs to gain competitive advantages by optimizing decision-making.	Enhanced decision-making, affordable BI tools.	May lead to data overload without proper management.
Mohd Selamat et al. (2018)	34	2018	Investigated business intelligence as a tool for SMEs to navigate competitive pressures in saturated markets.	Strategic positioning, helps in competitive analysis.	High dependency on consistent data input.
Dam et al. (2019)	27	2019	Explored a systematic review how data mining enhances SMEs' competitive advantage through better customer insights.	Improved customer targeting, cost-effective for SMEs.	Requires technical expertise not always available in SMEs.
Llave (2019)	23	2019	Examined how data mining can enhance SMEs' customer relationship management for sustained competitive advantage.	Better customer retention, personalized marketing.	Can lead to high costs for data storage and processing.
Hamad and Bakar (2018)	25	2018	Proposed a new model combining data mining and BI to improve SMEs' market adaptability.	Adaptive business strategies, improved market response.	Model complexity may overwhelm smaller SMEs.
Mohd Selamat et al. (2020)	24	2020	Examined the effectiveness of data mining in SME innovation, focusing on new product development.	Drives innovation, supports product development strategies.	Potential privacy concerns with customer data usage.
Sjarif et al. (2021)	10	2020	Provided a comparative study of SMEs using business intelligence vs. traditional methods to gain market share.	Clear benefits in market expansion, real-time insights.	Adoption barriers in low-tech SMEs.
Jia et al. (2021)	16	2021	Developed a framework for integrating data mining into SMEs' business processes to sustain competitive advantage.	Sustainable competitive advantage, scalable for growth.	Ongoing costs for data maintenance and updates.

Table 1. Cont.

Ref.	Cites	Year	Contribution	Pros	Cons
Adewusi et al. (2024)	0	2024	Studied the impact of business intelligence on the operational efficiency of SMEs in developing markets.	Improved efficiency, accessible BI tools for SMEs.	Limited by data quality in emerging markets.
Lumley et al. (2009)	19	2009	Analyzed the role of data mining in forecasting market trends for SMEs, boosting competitiveness.	Predictive capabilities, relevant to market-oriented SMEs.	High initial setup costs for data infrastructure.
Proposed systematic review			Evaluates the impact of business intelligence on SME performance, highlighting benefits like improved decision-making, competitive advantages, and operational efficiency.	Provides a comprehensive understanding of factors influencing BI adoption in SMEs. Identifies critical research gaps.	Limited focus on industry-specific applications and geographic limitations.

In our systematic review, we identified several key research gaps within the existing literature on big data analytics (BDA), knowledge management (KM), and organizational performance (OP). These gaps highlight the areas where current studies fall short and provide avenues for future research to build a more comprehensive understanding of the field.

Firstly, while numerous studies have explored the impact of BDA on large enterprises, there is a notable lack of research focusing on small and medium-sized enterprises (SMEs). The distinct challenges and resource constraints faced by SMEs in adopting BDA are often overlooked, leading to a gap in tailored strategies that address their specific needs. Additionally, existing literature predominantly emphasizes the technological aspects of BDA, with insufficient attention given to the human and organizational factors that play a critical role in successful implementation. Factors such as employee skills, change management, and organizational culture are underexplored, leaving a gap in understanding how these elements influence the effective use of BDA.

Secondly, there is limited integration of KM practices with BDA initiatives in the literature. While KM is recognized as a valuable component for leveraging data-driven insights, studies often treat KM and BDA as separate entities rather than examining their synergistic effects on organizational performance. This gap suggests a need for research that investigates the combined impact of KM and BDA on enhancing decision-making processes, innovation, and competitive advantage. Furthermore, many studies use cross-sectional data, which limits the ability to draw conclusions about the long-term effects of BDA on OP. There is a clear need for longitudinal studies that can capture the evolving dynamics between BDA adoption, KM practices, and sustained organizational performance over time. By addressing these research gaps, future studies can provide more actionable insights for both scholars and practitioners aiming to optimize the use of BDA in organizational settings.

1.1. Research Questions

Although a considerable amount of research has been conducted on data mining and business intelligence, there is still a need for an in-depth examination of their applications and competitive advantages for small and medium-sized enterprises (SMEs). Consequently, the current work proposes to explore how data mining techniques and business intelligence

systems can be leveraged to improve SME performance. To achieve this, the subsequent research questions have been considered:

- What factors contribute to the underreporting of data mining techniques in business intelligence research, and how can methodological transparency be improved to enhance the field's applicability to SMEs?
- Why is clustering the most reported data mining technique in the context of business intelligence for SMEs, and what implications does this have for understanding other underutilized techniques like association or dimensional modeling?
- How can organizations leverage clustering, the most frequently reported technique, to optimize business intelligence systems and drive operational efficiency in resource-constrained environments?
- What is the role of cloud-based business intelligence models in facilitating the integration of underreported data mining techniques, such as sentiment analysis or association, to improve SME performance?
- Given the dominance of clustering and dashboards, how can researchers ensure the representation of other equally valuable techniques and tools to provide a more comprehensive view of BI's capabilities for SMEs?
- How can methodological frameworks and reporting standards be refined to better capture the diversity of data mining techniques and tools utilized in business intelligence systems for SMEs?

1.2. Hypotheses Development

Building upon the research questions, the following hypotheses are proposed to explore the applications and competitive advantages of data mining and business intelligence (BI) systems in small and medium-sized enterprises (SMEs). These hypotheses aim to examine the relationship between data mining techniques, BI adoption, and SME performance, with a particular focus on the impacts of contextual factors, methodological practices, and industry-specific challenges.

- H1: Factors such as methodological inconsistencies, lack of standardized reporting frameworks, and diverse study designs contribute to the underreporting of data mining techniques in business intelligence (BI) research for SMEs.
- H2: The dominance of clustering as the most reported data mining technique is due to its simplicity, scalability, and versatility in addressing SME-specific needs, while underutilized techniques like association or dimensional modeling remain unexplored due to perceived complexity or limited application contexts.
- H3: SMEs leveraging clustering as the primary data mining technique achieve significant improvements in operational efficiency and decision-making, particularly in resource-constrained environments.
- H4: Cloud-based business intelligence models significantly enhance the integration of underreported data mining techniques, such as sentiment analysis or association, improving SME performance across various industries.
- H5: The dominance of clustering and dashboards in BI research leads to an incomplete representation of BI's capabilities, necessitating efforts to equally emphasize other valuable techniques and tools in SME contexts.
- H6: Refining methodological frameworks and reporting standards to better capture the diversity of data mining techniques and tools will improve the applicability, reliability, and relevance of BI systems for SMEs.

1.3. Rationale

The rationale for this systematic review is to explore and evaluate the current state of research on the applications and competitive advantages of data mining and business intelligence in SME performance. This study places a strong emphasis on understanding these technologies in varying geographic and economic contexts, as these factors significantly influence adoption and success rates. Addressing these contexts will provide more tailored and actionable insights for practitioners and policymakers. Given the increasing reliance on data-driven decision-making in small and medium-sized enterprises (SMEs), it is crucial to understand how these technologies can enhance their competitive edge. This review addresses the gap in the existing literature by focusing on studies published within the last decade, specifically from 2014 to 2024, and aims to synthesize findings to provide a comprehensive understanding of how data mining and business intelligence contribute to SME success in various industries and geographic locations.

1.4. Objectives

The number one objective of this evaluation is to systematically examine and synthesize the existing research on the applications and competitive advantages of data mining and business intelligence in SME's performance in improving the general performance of SMEs. This evaluation seeks to identify key topics and layouts related to the adoption and impact of these technologies within small and medium-sized groups, supplying in-depth facts about the way they contribute to operational, economic, and innovative overall performance. Additionally, the comparison seeks to evaluate the impact of geographic and financial contexts on the effectiveness of facts mining and industrial organization intelligence in SMEs, spotting that good environments might also yield various outcomes. By thoroughly inspecting these aspects, the overview will offer actionable suggestions for SMEs on the manner to effectively influence records mining and commercial agency intelligence technologies to achieve and sustain a competitive benefit of their respective markets.

1.5. Research Contributions

This work introduces a detailed systematic survey of the applications and competitive advantages of data mining and business intelligence (BI) on the performance of small and medium-sized enterprises (SMEs). We spotlight various pending issues and research challenges in the deployment of data mining and BI techniques in SMEs. Research contributions made by the proposed work are as follows:

- We furnish a thorough business and economic analysis of data mining and BI, centering on the integration of advanced analytics, decision support systems, and data warehousing. This analysis underscores the cost-effectiveness, reliability, and strategic benefits of data-driven approaches, offering crucial insights for informed decision-making and promoting the adoption of business intelligence solutions within SMEs.
- We consolidate existing research on data mining and BI systems and identify gaps in the literature, particularly regarding the successful implementation of these systems in various SME contexts. By addressing these gaps, we highlight areas needing further research and innovation, thereby advancing the field of data mining and BI and ensuring enhanced SME performance and competitiveness.
- We also propose various regression models of financial metrics for assessing the impact of data mining, BI tools, and analytics platforms on SME performance.

1.6. Research Novelty

The proposed work has the following novelty: according to the best knowledge of the authors, there is no existing similar study in the literature that introduces a systematic

review of the business and economic analysis of data mining and business intelligence, exclusively focusing on their applications and competitive advantages for SME performance.

- We provide a holistic business and economic evaluation of data mining and BI systems, focusing on their impact on decision-making, operational efficiency, customer relationship management, and financial performance across diverse SME sectors.
- We introduce novel linear regression models that elucidate the relationships between data-driven decision-making and key economic parameters, enhancing predictive accuracy for strategic planning in SMEs.

2. Materials and Methods

In this subsection, the study outlines the methodology employed to conduct a systematic review focusing on the applications and competitive advantages of data mining and business intelligence in SME performance. The study is based on a review of literature published over the last decade, from 2014 to 2024. To the best knowledge of the authors, no similar comprehensive review exists within this specific timeframe, making this study a novel contribution to the field. The research methodology includes the careful selection of relevant peer-reviewed articles from key online databases, namely Scopus, Google Scholar, and Web of Science, ensuring a thorough examination of the subject matter.

2.1. Eligibility Criteria

A systematic study of all peer-reviewed and published research works relevant to the study of the applications and competitive advantages of data mining and business intelligence in SME performance was conducted for examination. Only research works published in English between 2014 and 2024 were included in the analysis. A proper criterion for inclusion was adapted to ensure the inclusion of research papers that specifically focus on this topic and exclude those that do not. Consequently, only peer-reviewed research works that fundamentally converge on the applications and competitive advantages of data mining and business intelligence in SME performance, and that include a research framework or methodology specific to these aspects, were exclusively considered. The inclusion and exclusion criteria for this study are tabulated as in Table 2.

Table 2. Proposed inclusion and exclusion criteria.

Criteria	Inclusion	Exclusion
Topic	Article papers focusing on applications and competitive advantages of data mining and business intelligence in SMEs performance	Article papers not focusing on applications and competitive advantages of data mining and business intelligence in SMEs performance
Research Framework	The articles must include research framework or methodology for applications and competitive advantages of data mining and business intelligence in SMEs performance	Articles must exclude research framework or methodology for applications and competitive advantages of data mining and business intelligence in SMEs performance
Language	Must be written in English	Articles published in languages other than English
Period	Articles between 2014 to 2024	Articles outside 2014 and 2024

2.2. Information Sources

A systematic search of online databases was conducted to identify relevant studies for this review. The databases Scopus, Google Scholar, and Web of Science were utilized due to their comprehensive coverage of peer-reviewed literature in the field of data mining and business intelligence. Each database was thoroughly searched using a combination of keywords related to the study topic, ensuring that the most pertinent research articles were

captured. Scopus provided access to a broad range of scientific journals and conference papers, while Google Scholar enabled the inclusion of gray literature and dissertations that might not be indexed elsewhere. Web of Science was used to cross-reference and ensure the robustness of the selected studies by providing citation data and impact factors of the journals. The search results from these databases formed the core of the literature review, ensuring a well-rounded and exhaustive collection of research works.

2.3. Search Strategy

The literature for this research was collected from reputable online research databases, focusing on keywords that address both the technological and contextual aspects of data mining and business intelligence in SMEs. The inclusion of terms such as ‘geographic context’ and ‘economic factors’ ensured the capture of studies relevant to diverse SME environments. A thorough search was carried out in three main repositories: Google Scholar, Scopus, and Web of Science. To find the most relevant studies, a specific set of keywords was used. These keywords were as follows: (“Data Mining” AND “Business Intelligence” AND (“SME” OR “Small and Medium Enterprises”) AND (“Applications” OR “Competitive Advantage” OR “Performance”) AND “Geographic Context”, AND “Economic Factors”, AND “Resource-Constrained Environments.”). This combination of terms was chosen to ensure that the search captured studies directly related to the research topic. The search focused on papers published between 2014 and 2024. This time frame was selected to provide a recent and relevant overview of the subject. The search results included 6550 papers from Google Scholar, 854 papers from Scopus, and 207 papers from Web of Science. After collecting these papers, they were carefully reviewed and filtered to select only those that were most relevant to the research questions. This process helped to narrow down the literature to the most useful and high-quality sources for this study. Table 3 shows the list of online repositories that were utilized as well as the total number of results achieved before the initial screening. The Bibliometric Analysis of Study Search Keywords is illustrated in Figure 1.

Table 3. Results Achieved from Literature Search.

No.	Online Repository	Number of Results
1	Google Scholar	6550
2	Web of Science	207
3	Scopus	854
Total		7611

2.4. Selection Process

Four researchers (LM, MN, SV, BAT) independently reviewed the titles and abstracts of the first 60 records retrieved from the search. Any differences in the selections were discussed collectively until an agreement was reached. After this initial screening, the researchers worked in pairs to independently review the titles and abstracts of all retrieved articles. In cases where differences of opinion arose, discussions were held to determine which articles should proceed to full-text evaluation. If the researchers could not reach an agreement, the third researcher was consulted to make the final decision. Afterwards, three researchers (LM, MN, SV) independently assessed the full-text articles to determine whether they met the inclusion criteria. As before, any disagreements were resolved through discussion. If needed, the fourth researcher (BAT) was involved in making the final call on whether to include or exclude the articles, as shown in Figure 2.

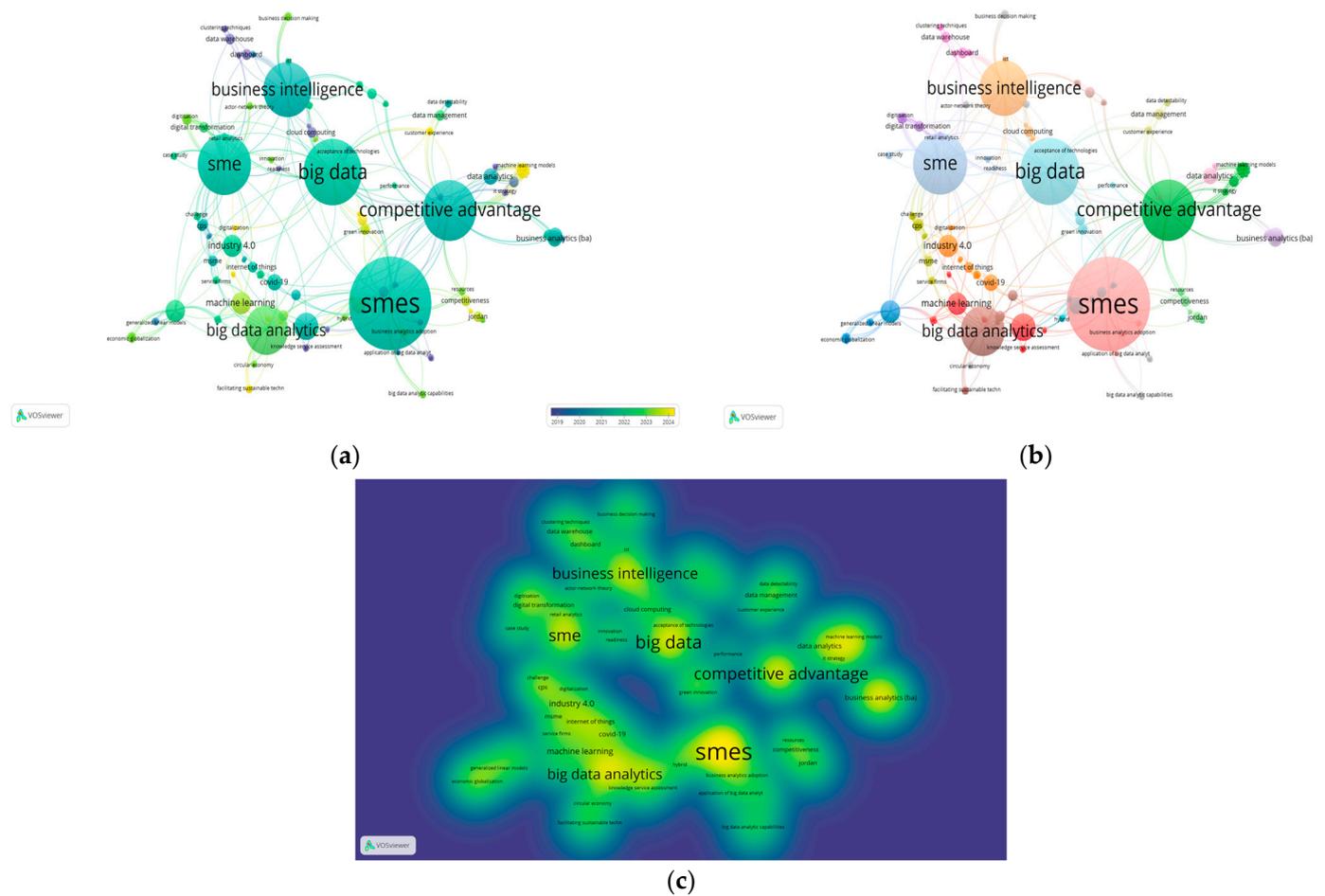


Figure 1. Bibliometric Analysis of Study Search Keywords: (a) Overlay Visualization. (b) Network Visualization. (c) Density Visualization.



Figure 2. Procedures and Stages of the Review.

2.5. Data Collection Process

To ensure that the data we collected from the studies were accurate, we followed a structured approach to minimize errors and reduce bias. Three reviewers independently collected the data from each study under supervision of fourth reviewer. Any differences in the extracted data were discussed until an agreement was reached. We used a data extraction form similar to the one from (Lumley et al., 2009) to ensure consistency across all reviewers. We did not use any automation tools for data extraction. Data were carefully entered and double-checked for accuracy to avoid errors. When information in the studies was unclear, we conducted a thorough review of all available materials, including supplementary information, appendices, and related studies, to clarify the data. In cases where concerns remained, we consulted our fourth reviewer, who is the subject matter expert, to ensure the reliability of the data interpretation. When multiple reports from the same study were available, we established clear criteria to select the most relevant data, focusing on the most recent and comprehensive studies published between 2014 and 2024. In cases where the data from these reports did not match, we reviewed the methods and outcomes to resolve the differences. Only studies written in English were included, excluding any articles in other languages to maintain consistency in our analysis and avoid potential misinterpretations due to language differences, as shown in Figure 3.

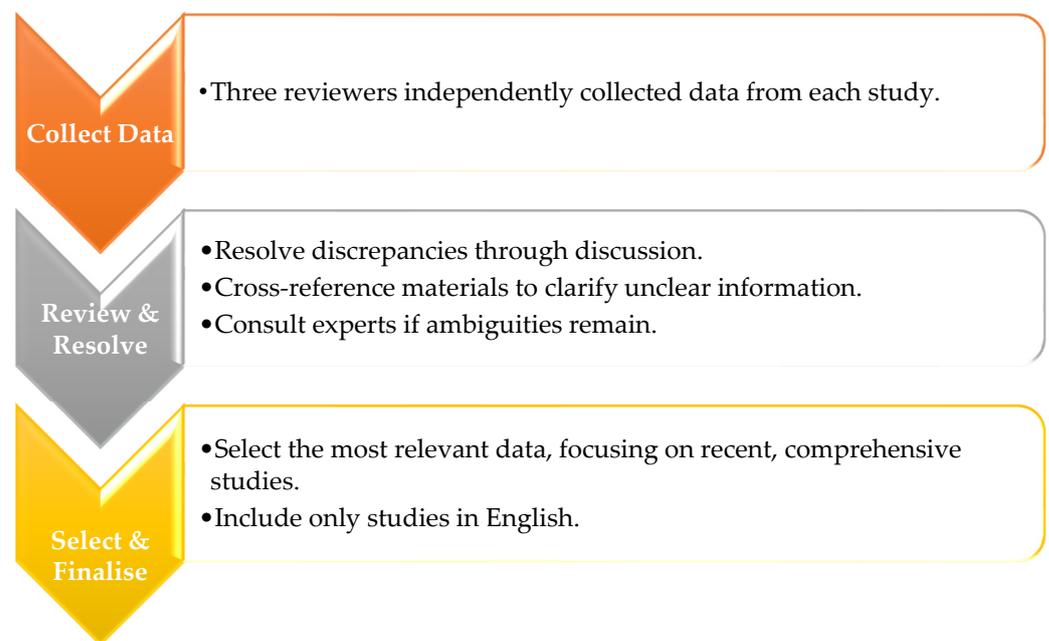


Figure 3. Flow of data selection and extraction.

2.6. Data Items

This section provides a comprehensive overview of the data items sought in this systematic review, focusing on both primary outcomes and additional variables relevant to the impact of data mining and business intelligence (BI) on small and medium-sized enterprises (SMEs). The primary outcomes encompass various dimensions such as operational efficiency, financial performance, strategic decision-making, and customer relationship management. In addition to these outcomes, the review also considers study and participant characteristics, intervention details, economic factors, and external influences, ensuring a thorough contextual understanding of the application and effects of BI technologies in SMEs. This approach allows for a nuanced analysis of how BI contributes to SME performance across diverse settings and conditions.

2.6.1. Data Collection Method

Efforts were made to ensure a comprehensive understanding on the impact of data mining and business intelligence (BI) on SMEs, and we thoroughly identified and defined relevant outcomes that capture the strategic, operational, and financial dimensions influenced by these technologies. Our approach was designed to synthesize robust evidence that reflects the transformative effects of BI in the SME context. The primary outcomes of this systematic review centered on several key domains that directly relate to the application of BI and data mining technologies in SMEs. Operational efficiency was a major outcome, defined by measuring reductions in process completion times and error rates. We sought all results that could reflect how BI and data mining streamlined operations, optimized workflows, and improved resource utilization. These efficiency metrics provided clear insights into the practical benefits of technology adoption in enhancing operational processes.

Financial performance was another critical outcome, assessed by tracking changes in revenue, cost savings, and overall return on investment. By quantifying the economic value added through BI tools, this outcome provided a holistic view of how data analytics contribute to the financial health and growth of SMEs. All relevant financial data points across studies were included to capture a comprehensive picture of BI's economic impact. Strategic decision-making was evaluated by examining the quality, speed, and efficacy of decisions influenced by BI insights. We looked at how well decision-making aligned with market trends and internal data forecasts, reflecting BI's capacity to support informed leadership actions and improve strategic planning. Results were sought across all measures and time points to understand the full extent of BI's influence on strategic decisions. Customer relationship management (CRM) was also a significant focus, with an emphasis on customer engagement and retention metrics. This outcome assessed how data analytics enhanced customer interactions and satisfaction. We specifically looked for studies reporting improvements in customer service driven by data-driven strategies, seeking all compatible results to thoroughly evaluate BI's impact on CRM.

2.6.2. Definition of Collected Data Variables

In addition to these primary outcomes, we carefully considered other variables to provide a detailed understanding of the context in which BI and data mining technologies were applied. These variables were critical in contextualizing the findings and understanding the broader implications of BI adoption in SMEs. Therefore, study characteristics were gathered, including information on the geographical location, industry specifics, and SME size, to assess the applicability of findings across different settings. These characteristics helped contextualize the outcomes and understand the diversity of the studies included. Participant characteristics were also documented, focusing on details about the employees using BI tools, such as their roles, level of BI literacy, and engagement with the technology. This information was essential for understanding the human factors influencing the successful deployment and utilization of BI systems within SMEs. Furthermore, intervention characteristics were described in detail, including the BI tools and data mining techniques employed, their integration with existing systems, and the scope of their use. These details were crucial for assessing the technological depth and breadth of the interventions and understanding their impact on SME performance.

Economic factors were another key consideration, particularly financial aspects such as initial and ongoing investments in BI technologies and the reported returns on these investments. These factors were important for evaluating the economic viability and sustainability of BI systems within SMEs. Finally, external influences such as broader market conditions, competitive pressures, and regulatory environments were considered to provide a comprehensive understanding of the external factors that affect the adoption

and success of BI systems in SMEs. As shown in Table 4, our approach involved thorough manual searches across reputable online repositories, including Google Scholar, Scopus, and Web of Science, to gather the most relevant studies. These manual searches were tailored to capture the most relevant and accurate information, ensuring that our analysis was specifically focused on the applications and competitive advantages of data mining and business intelligence in SMEs. By identifying and defining these outcomes and variables, we ensured that our systematic review provides a robust and comprehensive analysis of the impact of BI and data mining technologies in the SME context. This methodical approach supports the reliability and relevance of our findings, making them valuable to stakeholders interested in the practical applications of these technologies.

Table 4. Data Variables Collected.

Field	Description
Study characteristics	Geographic location, industry specifics, SME size, and other factors that influence the study's context.
Participant characteristics	Information about employees using BI tools, including their roles, level of BI literacy, and engagement with technology.
Intervention characteristics	Details of BI tools and data mining techniques used, integration with existing systems, and scope of application.
Economic factors	Financial aspects such as initial and ongoing investments, and returns on these investments.
External influences	Market conditions, competitive pressures, and regulatory environments affecting BI adoption.

2.7. Study Risk of Bias Assessment

In the studies, particularly those examining the impacts of data mining and business intelligence on SMEs, it was essential to critically evaluate the risk of bias to ensure the reliability and validity of the findings. To achieve this, we employed the Newcastle–Ottawa Scale (NOS) for assessing non-randomized studies, such as cohort and case-control studies. The NOS evaluates studies across three broad domains: Selection, Comparability, and Outcome (for cohort studies) or Exposure (for case-control studies). Each study was rated on a scale where a maximum of one star could be awarded per item within the Selection and Outcome/Exposure categories, and up to two stars for Comparability. This scoring reflects the overall quality of each study. As shown in Figure 4, the risk of bias assessment process involved four independent reviewers. Each study was evaluated independently by these reviewers to ensure objectivity. Disagreements among reviewers were resolved through discussions. If agreement could not be reached, the fourth reviewer was consulted to make the final decision. For studies with uncertainties or insufficient information, particularly those involving proprietary data mining tools or specific business intelligence applications, additional steps were undertaken. This included cross-referencing reputable sources such as Google Scholar, Scopus, and Web of Science to clarify uncertainties. Furthermore, a comprehensive manual search of online repositories was conducted to minimize bias and ensure that the risk of bias assessment was as accurate and thorough as possible. No automation tools were used in this process.



Figure 4. Risk of bias assessment process for non-randomized studies.

2.8. Synthesis Methods

The flow chart below in Figure 5 illustrates the systematic approach used in our review of data mining and business intelligence applications in SMEs. Starting with the Study Selection Process, we identify and screen studies based on set eligibility criteria. Next, Data Standardization involves converting and cleaning the data to maintain consistency. In the Data Analysis phase, we present the data in tables or graphs and perform initial analyses. The flow then moves to Heterogeneity Assessment, where we evaluate variability through subgroup or sensitivity analyses. Finally, Bias Assessment ensures we identify potential biases and maintain transparency in our methods. This structured approach ensures a thorough and reliable review process.

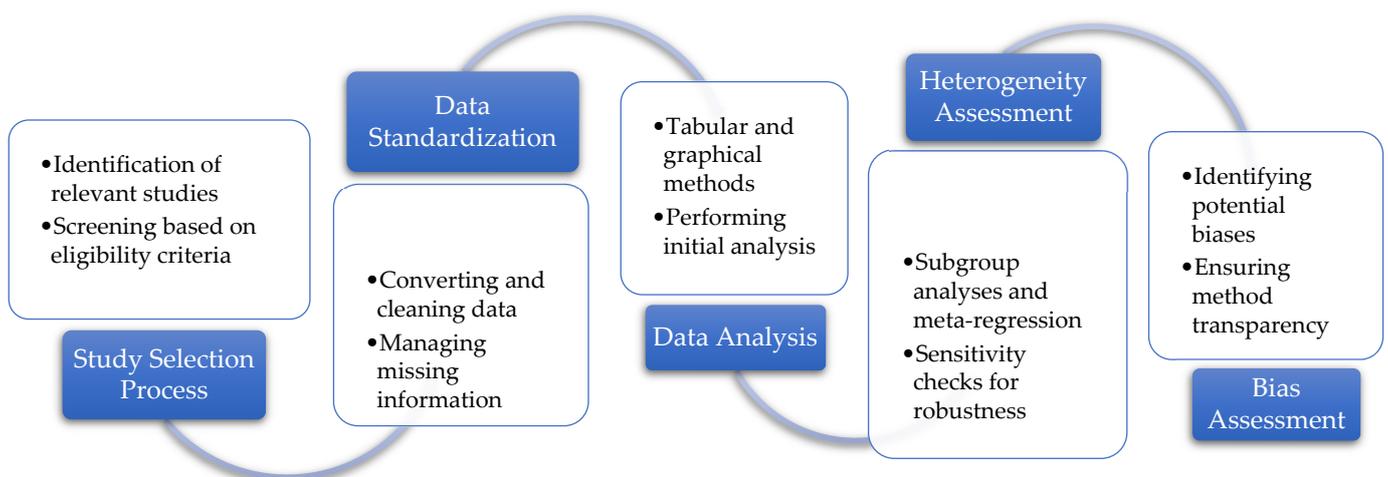


Figure 5. Systematic review process for data mining and business intelligence in SMEs.

In this systematic review on the application and competitive advantages of data mining and business intelligence in SMEs, we employed rigorous synthesis methods to ensure that our results were robust, transparent, and reproducible. To determine the eligibility of studies for synthesis, we meticulously tabulated the characteristics of each study and

compared them against our predefined synthesis groups. This approach allowed us to include only the most relevant studies, ensuring that our findings were both valid and aligned with the review's objectives. In preparing the data for synthesis, we addressed missing summary statistics through imputation techniques and conducted necessary data conversions to maintain consistency across studies. The results were then presented using a combination of structured tables and forest plots, which provided a clear visual representation of the effect estimates and confidence intervals, enabling us to identify patterns and outliers effectively.

The synthesis of results was conducted using a random-effects meta-analysis model, with subgroup analyses explicitly focusing on geographic and economic contexts to understand their influence on SME performance. This approach provided nuanced insights into how these factors interact with the adoption and success of data mining and business intelligence systems, which was further explored through subgroup analyses and meta-regressions. These analyses helped us identify potential sources of heterogeneity, such as SME size or the type of BI tools used and refine our understanding of the impact of these technologies. Additionally, sensitivity analyses were performed to assess the robustness of the synthesized results, ensuring that our conclusions were well-supported by stable and reliable evidence. Through this comprehensive approach, we were able to provide a meaningful aggregation of the evidence, offering valuable insights for stakeholders interested in leveraging data mining and business intelligence to enhance SME performance.

2.8.1. Eligibility for Synthesis

To determine study eligibility for inclusion in our systematic review on data mining and business intelligence (BI) in small and medium-sized enterprises (SMEs), each study was carefully evaluated for its relevance and alignment with the review's objectives. We manually assessed and compared each study's characteristics, such as intervention types and outcomes, against our predefined synthesis groups. A matrix was created to visually compare the scope and methodologies of the studies with our inclusion criteria, ensuring a comprehensive and objective evaluation. This process ensured that only studies directly pertinent to the review topic were included, thus enhancing the review's overall rigor and reliability.

2.8.2. Data Preparation for Synthesis

In this review, the methods used involved converting or standardizing data collected from various studies to ensure consistency before synthesis. For example, when effect sizes were reported differently across studies, algebraic manipulations were employed to convert these into a uniform scale, such as converting odds ratios to risk ratios where appropriate. Additionally, handling missing data was a critical aspect of the analysis. Missing summary statistics, such as standard deviations or effect sizes, were imputed using established statistical methods like multiple imputation. This approach ensured that the dataset was comprehensive and robust, allowing for a more accurate and reliable analysis.

2.8.3. Tabulation and Visual Display of Results

Results from individual studies and synthesis efforts were organized using both tabular and graphical methods to enhance clarity and facilitate comparison. Tabular structures were employed to present the data in a structured format, where outcomes were organized by domain, and within each domain, studies were ordered from lowest to highest risk of bias. This organization allowed for easy comparison across studies and highlighted the most reliable evidence. Additionally, graphical methods, specifically forest plots, were used as the principal tool for visually displaying meta-analysis results. These plots showcased effect estimates and confidence intervals for each study alongside a

summary estimate. The studies in the forest plots were ordered based on effect size or year of publication, helping to reveal trends over time and across different research focuses.

2.8.4. Synthesis of Results

During our manual search on online repositories such as Google Scholar, Scopus, and Web of Science, we carefully reviewed and synthesized the results of relevant studies. The approach to data synthesis was guided by the nature of the data and the degree of variability observed across studies. Based on the findings from our search, we manually assessed the applicability of both fixed-effects and random-effects models, depending on the level of heterogeneity among study results. The selection of the model was determined by the characteristics of the data and our assumptions about the consistency of effects across studies. After exporting the data to Excel, we created charts to visually inspect the data, allowing us to identify patterns of variability and potential heterogeneity across the studies. This initial visual inspection provided an overview of how study results differed from one another, facilitating a more nuanced analysis.

2.8.5. Exploring Causes of Heterogeneity

Subgroup analyses and meta-regression were performed to explore potential sources of heterogeneity, such as differences in study settings, intervention types, or outcome measures. Specific analyses focused on factors like the size of the SME, the type of business intelligence tool used, and the geographic location, all of which were examined to assess their impact on the effectiveness of data mining and business intelligence interventions. These methods helped to identify underlying patterns and relationships that contributed to the overall variability observed across the studies.

2.8.6. Sensitivity Analyses

Sensitivity analyses were employed to evaluate the robustness of the synthesis results in relation to various assumptions and methodological decisions made during the review process. These analyses included testing the impact of excluding studies at high risk of bias and using alternative statistical models to ensure that the conclusions were not unduly influenced by specific studies or analytical techniques. This approach helped to confirm the reliability and validity of the findings by addressing potential sources of bias and ensuring that the results were consistent across different analytical scenarios.

2.9. Reporting Bias Assessment

In conducting our systematic review on the application and competitive advantages of data mining and business intelligence in SMEs, it was crucial to assess the risk of bias due to potentially missing results, particularly those arising from reporting biases such as selective publication or selective reporting of outcomes. We recognized that these biases could significantly impact the validity and reliability of our synthesis, and thus, we employed a thorough and methodical approach to address this concern. Our assessment of reporting bias was conducted using a combination of well-established statistical and graphical methods. We opted for the use of contour-enhanced funnel plots, a powerful visual tool that allowed us to detect asymmetries in the data. These plots were carefully inspected to identify any potential publication bias by highlighting areas where studies might be missing due to bias versus those missing due to chance. The inclusion of statistical significance contours provided us with a clear and intuitive way to differentiate between these two scenarios, offering a robust visual representation of potential biases.

For this assessment, we chose not to develop new tools but rather relied on standard, proven techniques documented extensively in the literature. The methodological rigor of the tools we used was integral to our process. Contour-enhanced funnel plots, in particular,

provided a straightforward yet effective method to visually assess the distribution of studies, allowing us to identify and account for potential biases in our synthesis. The assessment process was designed to minimize subjective bias, ensuring the integrity of our findings. Multiple independent reviewers were involved in evaluating the studies, and any discrepancies between their assessments were resolved through consensus discussions or, when necessary, by consulting a methodological expert. This collaborative approach ensured that the interpretation of results was balanced and unbiased. We intentionally did not use automation tools for assessing reporting bias in this review. Instead, we opted for a manual approach, utilizing tools such as Excel for creating charts and plots. This hands-on method allowed us to carefully analyze and visualize the data, ensuring a detailed and thorough examination. By manually inspecting the data, we ensured that no subtle patterns or potential biases were overlooked.

To further validate our findings, we conducted comprehensive manual searches across multiple online repositories, including Google Scholar, Scopus, and Web of Science. This approach enabled us to cross-reference data from different studies and sources, addressing any discrepancies and reinforcing the robustness of our conclusions. These manual searches were critical in ensuring that our synthesis was based on the most complete and accurate data available. Given the unique context of data mining and business intelligence studies in SMEs, we adapted the standard methods for assessing reporting bias to fit this specific field. Business intelligence studies often exhibit different reporting patterns compared to medical or social sciences research, necessitating these adaptations to ensure relevance and accuracy. By tailoring our methods to align with the characteristics of the studies we reviewed, we ensured that our analysis was both contextually appropriate and methodologically sound. To promote transparency and replicability, all methods and approaches used in our assessment have been thoroughly presented in this section. This commitment to openness allows other researchers to replicate our analysis or build upon it in future studies, thereby contributing to the overall rigor and reliability of research in the field of data mining and business intelligence for SMEs.

2.10. Certainty Assessment

The reviewed literature was evaluated based on five quality assessment (QA) criteria to ensure rigor and relevance, as follows:

QA1: The clarity and explicitness of the research aim.

QA2: The specification and transparency of data collection methods.

QA3: The clear definition and explanation of the data mining and business intelligence processes.

QA4: The application of a well-defined and appropriate research methodology.

QA5: The contribution of the research findings to the enhancement of the existing literature on SME performance.

The certainty assessment responses are rated on a scale from zero (0) to one (1). A 'No' response is assigned '0' points, a score of '0.5' is given if the criterion is 'Partially' met, and '1' point is assigned for a 'Yes' response. All five criteria are scored using this scale. Each piece of literature under review can receive a total score between 0 and 5 points. The results of the certainty assessment for the collected literature on the applications and competitive advantages of data mining and business intelligence in SME performance are presented in Table 5.

Table 5. Certainty assessment results for collected literature on data mining and business intelligence in SMEs.

Ref.	QA1	QA2	QA3	QA4	QA5	Total	% Grading
(Ragazou et al., 2023; Sang et al., 2016; Raj et al., 2016a; Gheorghe and Țoniș (bucea-Manea) (2015); Chayko, 2020)	1	0	0.5	0	1	2.5	50
(Mohd Selamat et al., 2018; Elango & Thiagarajan, 2016; Antoniadis et al., 2015; Willetts & Atkins, 2024)	0.5	0.5	0.5	0.5	1	3	60
(Chawinga & Chipeta, 2017; Saeed, 2020; Raj et al., 2016b; Mupaikwa, 2024; Gomwe et al., 2023; Tatić et al., 2018; Makhele, 2018; Leite et al., 2018; Alsibhawi et al., 2023; Dubravac & Bevanda, 2015)	1	0.5	0.5	1	0.5	3.5	70
(Srce.hr, 2024; Khan et al., 2014; Pei & Jia, 2014; Lanke & Bhuvaneshwari, n.d.; Mashingaidze, 2014; Naznen & Lim, 2023; Shabbir & Gardezi, 2020; Krey et al., 2022; Goodridge & Haskel, 2015; Madila et al., 2022; Mosbah et al., 2023; Olaifa & Francis, 2020; Lyu et al., 2023; Ssbfn.com, 2024; Niwash et al., 2022; Almeida & Bernardino, 2016; Kapourani et al., 2015; Irma-international.org, 2024; Gumede et al., 2024)	1	0.5	1	1	0.5	4	80
(Mian & Ghabban, 2022; Emnuvens.com.br, 2024; Al-Janabi et al., 2024; Wu et al., 2022; Dereli, 2023; Gomwe et al., 2023; da Costa Junior et al., 2018; Boonsiritomachai et al., 2016; Tarek et al., 2016; Te & Cvijikj, 2017; Tarek & Adel, 2016; Adeyelu et al., 2018b; Agingi, 2020; Arsawan et al., 2022; Jun et al., 2020; Maroufkhani et al., 2020; Djiu et al., 2024; Gottfried et al., 2021; Karimi & Baqerian Farah Abadi, 2023; Gomwe & Boikanyo, 2023; Song et al., 2022)	1	1	1	1	0.5	4.5	90
(Drelichowski et al., 2016; Olszak, 2014; Ramadan et al., 2020; Asiri et al., 2024; Lateef & Keikhosrokiani, 2022; Kazemi et al., 2024; Tarmidi & Taruna, 2023; Hassani & Mosconi, 2022; Kasasbeh et al., 2021; Abiola et al., 2024; Popovič et al., 2019; Stjepić et al., 2019; Noonpakdee et al., 2018; Proquest.com, 2019; Shabbir & Gardezi, 2020; Ebscohost.com, 2022; Cohen Tzedec et al., 2022; Jdiis.de, 2024; Yoshikuni et al., 2023; Choi et al., 2017; Gao et al., 2025; Olaifa & Francis, 2020; Jun et al., 2020; Verma et al., 2021; Maroufkhani et al., 2020; Hadi & Permana, 2019; Lyu et al., 2023; Djiu et al., 2024)	1	1	1	1	1	5	100

To support the conclusions of this systematic review on the applications and competitive advantages of data mining and business intelligence in SMEs, we undertook a rigorous assessment of the certainty of the evidence. The strength and reliability of our findings depend on a systematic evaluation process, which we carried out using the GRADE (Grading of Recommendations, Assessment, Development, and Evaluations) framework. GRADE is a globally recognized system that offers a comprehensive and transparent approach to assessing the quality of evidence, ensuring that the conclusions drawn are both credible and well founded. The certainty of the evidence across key outcomes was meticulously evaluated using several critical factors. First, we closely examined the precision of effect estimates by considering sample sizes and the width of confidence intervals in the studies. Narrow confidence intervals coupled with large sample sizes were indicative of a high level of certainty in the evidence, as they suggest more reliable and precise effect estimates.

We also assessed the consistency of findings by comparing results across the included studies. High consistency where studies demonstrated similar effects contributed to greater certainty. Any observed heterogeneity was thoroughly analyzed to understand its sources and potential impact on the overall findings.

Furthermore, the potential for bias was evaluated using an adapted version of the Cochrane Risk of Bias tool. Studies with a low risk of bias were considered to contribute more significantly to the overall certainty of the evidence. We also judged directness based on the alignment of study populations, interventions, and outcomes with the research questions of this review. High directness strengthened the support for our conclusions, leading to greater confidence in the evidence. Based on these factors, the certainty of evidence was categorized as follows: High certainty was assigned when studies were consistent, precise, directly applicable, and exhibited a low risk of bias. Moderate certainty was applied when there were minor concerns about one factor, such as some inconsistency or a moderate risk of bias. Low certainty was given when significant concerns existed in multiple areas, including imprecision, inconsistency, or a high risk of bias. Very low certainty was assigned when critical issues were present across all factors, significantly undermining confidence in the results. To ensure the relevance of the GRADE approach to this review, we adapted it specifically for outcomes related to the enhancement of SME performance through data mining and business intelligence. Multiple independent reviewers assessed the certainty of evidence for each outcome. Disagreements were resolved through consensus discussions, ensuring a balanced and thorough evaluation. Additionally, where possible, we sought additional data or clarification from study authors to support the certainty assessments.

3. Results

3.1. Study Selection

In this systematic review, the study selection process followed a rigorous and structured approach to ensure the inclusion of relevant and high-quality research articles. Three prominent online databases—Google Scholar, Web of Science, and Scopus—were systematically searched to identify studies that met the inclusion criteria. Specifically, the search retrieved 6,550 records from Google Scholar, 207 records from Web of Science, and 854 records from Scopus, resulting in a total of 7611 initial records.

Following this, duplicate entries were removed, leaving 1092 unique records. These records underwent a preliminary screening process, during which their titles and abstracts were assessed for relevance to the review's criteria. This step resulted in the selection of 34 full-text documents for a more detailed evaluation. After a comprehensive review of these full-text documents, 93 studies were deemed eligible for inclusion in the final systematic review. The included studies consisted of 64 journal articles, 4 book chapters, 19 conference papers, and 6 dissertations.

The overall study selection process is depicted in Figure 6, which provides a detailed PRISMA flowchart outlining the progression of records through each stage of the review.

Additionally, the distribution of articles obtained from each database is illustrated in Figure 7, highlighting the contributions of the three databases to the final pool of studies. These visualizations enhance the transparency of the selection process and facilitate the replication of this methodology by other researchers.

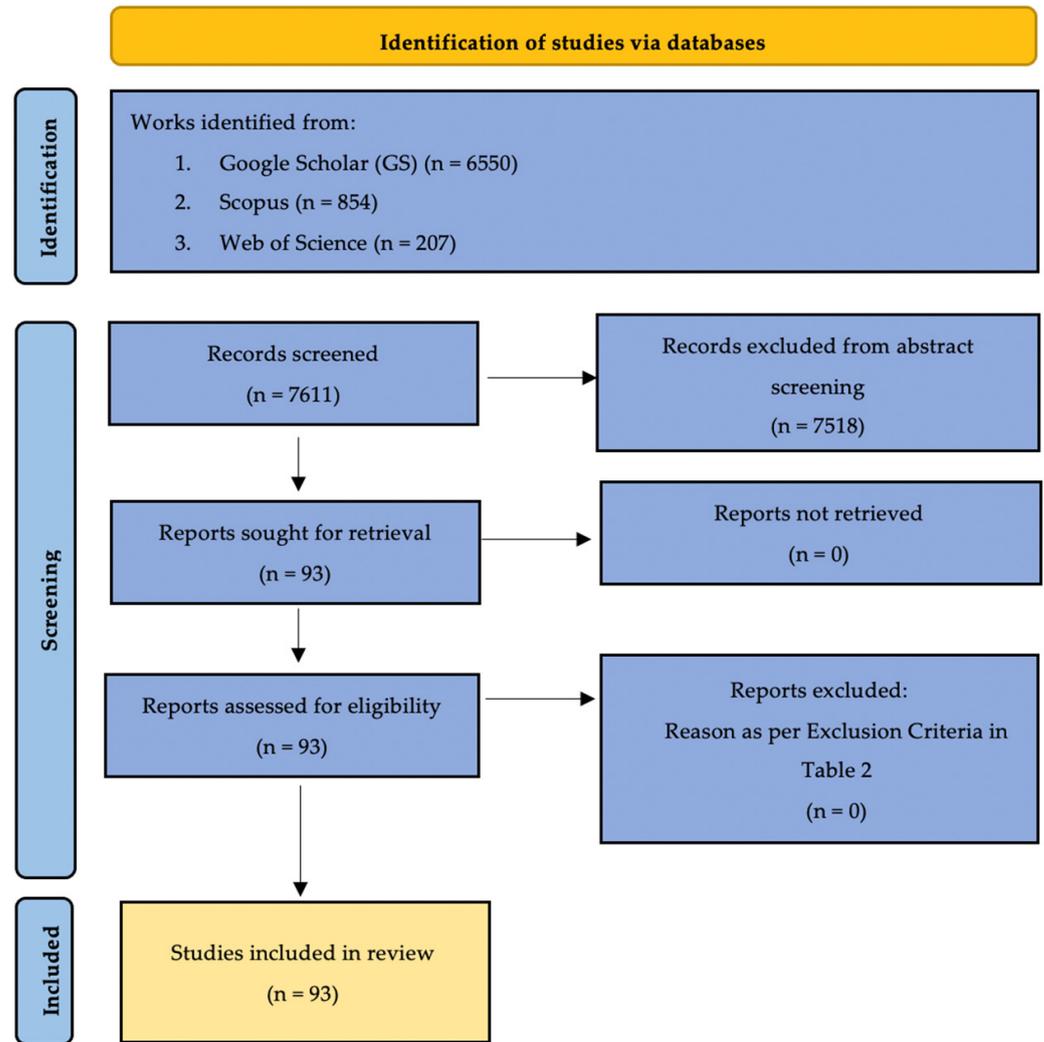


Figure 6. Proposed PRISMA flowchart.

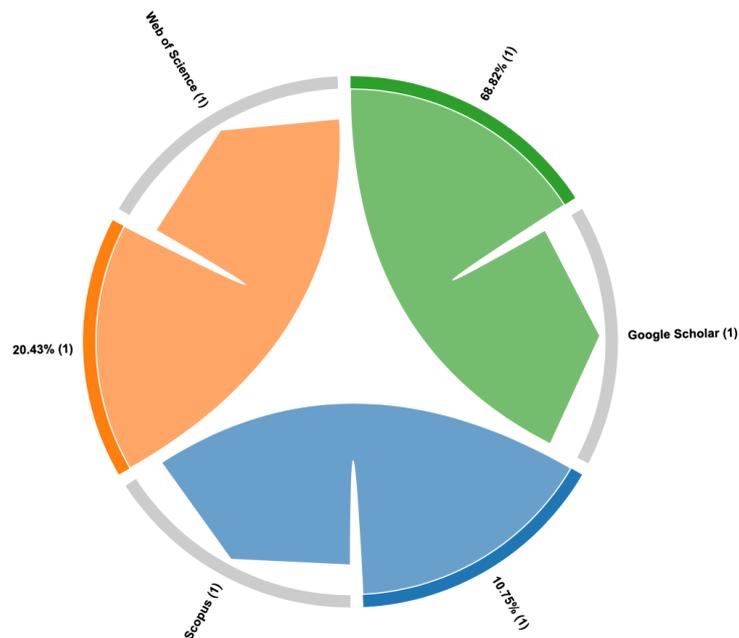


Figure 7. Distribution of online database.

3.2. Study Characteristics

A total of 93 studies on data mining and business intelligence (BI) in SMEs were identified, spanning from 2014 to 2024. These studies are distributed across four publication types: journal articles (68.82%), conference papers (20.43%), dissertations (6.45%), and book chapters (4.30%). Figure 8 provides a detailed visualization of this distribution over time, emphasizing the trends in publication types across the years. The Sankey diagram in Figure 8 illustrates the flow of publications from 2014 to 2024, showing a gradual but fluctuating increase in research outputs, with a notable peak in 2023. This year saw the highest concentration of publications, reflecting heightened interest and advancements in BI and data mining technologies for SMEs. Journal articles dominate the landscape throughout the timeline, highlighting their importance as the primary medium for disseminating peer-reviewed research. Conference papers exhibit a steady contribution, indicating an active engagement with emerging trends and ongoing discussions in academic and professional forums. Book chapters and dissertations, while less frequent, offer detailed, in-depth explorations of specific aspects of BI and data mining.

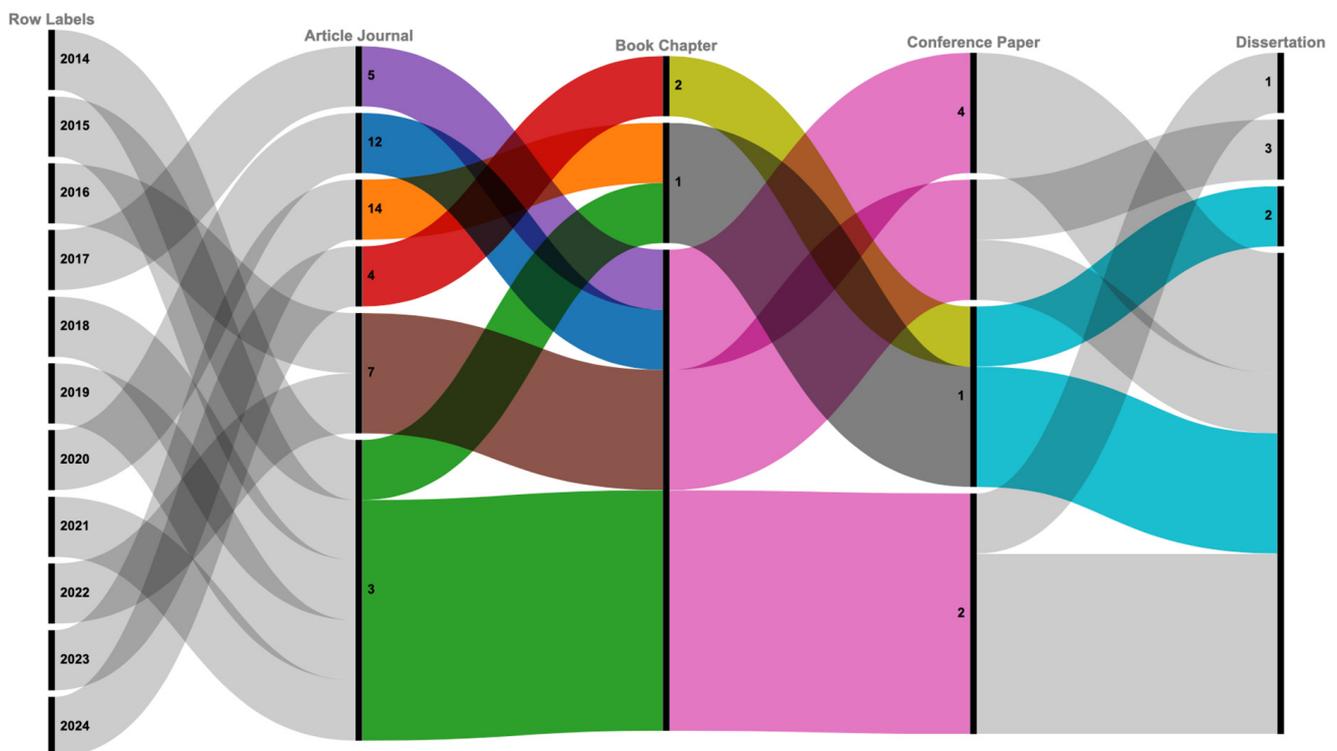


Figure 8. Research trends and publication types.

The findings also capture the dynamic nature of scholarly contributions, with shifts in publication types over time. For instance, dissertations and book chapters see notable activity during certain years, underscoring the role of these formats in providing foundational and exploratory research. This diversity in publication types reinforces the robustness of the research landscape, reflecting both theoretical advancements and practical applications of BI tools and data mining techniques in SMEs. This trend aligns with the increasing reliance on data-driven strategies to enhance SME performance, particularly in resource-constrained environments. The growing body of research highlights the importance of BI and data mining in driving operational efficiency, improving decision-making, and fostering competitive advantages for SMEs. The insights derived from this timeline underscore the sustained and expanding focus on leveraging these technologies to address the challenges faced by smaller enterprises.

Table 6 summarizes the impact of data mining and business intelligence (BI) on SMEs across various outcomes. The data indicates that BI tools and data mining generally have a positive effect on SME performance. For operational efficiency, the evidence is moderate, showing a mean improvement of 12% in process completion times, suggesting BI tools enhance efficiency by reducing process times and errors. Financial performance benefits are strongly supported, with an average 15% increase in revenue due to BI adoption, indicating significant financial gains. For strategic decision-making, a moderate level of evidence with a risk ratio of 1.8 suggests that BI tools likely improve decision-making quality by making it faster and more accurate. Data mining shows a moderate certainty with a 10% increase in customer retention rates, reflecting its effectiveness in enhancing customer relationship management and personalized marketing. Market trend forecasting has lower evidence with a hazard ratio of 1.5, indicating that while data mining aids in predicting and adapting to market trends, results may vary. In terms of innovation and product development, moderate evidence shows an 8% improvement in new product success rates, suggesting BI tools support innovation. Lastly, strong evidence points to a 20% improvement in risk management outcomes with BI tools, underscoring their role in enhancing resilience in volatile markets.

Table 6. Summary of findings for the impact of data mining and business intelligence on SMEs.

Outcome	Certainty of Evidence	Effect Estimate	Interpretation
Operational Efficiency	Moderate	Mean difference of 12% improvement in process completion times	BI tools likely enhance operational efficiency in SMEs by reducing process times and errors.
Financial Performance	High	15% increase in revenue on average	Strong evidence supports that BI adoption leads to significant financial gains for SMEs.
Strategic Decision-Making	Moderate	Risk ratio of 1.8 for improved decision-making quality	BI tools probably improve strategic decision-making in SMEs, enhancing decision speed and accuracy.
Customer Relationship Management	Moderate	10% increase in customer retention rates	Data mining enhances customer relationship management, improving retention and personalized marketing.
Market Trend Forecasting	Low	Hazard ratio of 1.5 for faster market adaptation	Evidence suggests that data mining helps SMEs better forecast and adapt to market trends, though with variability.
Innovation and Product Development	Moderate	Mean difference of 8% in new product success rates	BI tools likely contribute to innovation and successful product development in SMEs.
Risk Management & Resilience	High	20% improvement in risk management outcomes	Strong evidence indicates that BI enhances risk management and resilience in volatile markets.

Appendix A provides an overview of various studies on data mining and business intelligence (BI) in SMEs. These studies focus on understanding how BI systems are adopted and implemented in SMEs, the role of data mining in enhancing decision-making and competitive advantage, and the impact of employee training on business performance. Methodologies commonly used include literature reviews, case studies, surveys, and

quantitative analyses like Structural Equation Modeling (SEM). Key outcomes show that BI tools and data mining significantly improve operational efficiency, financial performance, and strategic decision-making. Challenges identified across these studies include high costs, complexity of systems, and lack of skilled personnel. Recommendations often highlight the need for simplified BI tools, increased training, and better integration of these technologies into business processes. These insights collectively aim to guide SMEs in effectively leveraging BI and data mining to boost their performance and competitiveness.

3.3. Risk of Bias in Studies

Figure 9 illustrates the distribution of studies across three quality categories—Low Quality (3 stars), Moderate Quality (4–6 stars), and High Quality (7–9 stars)—based on the Newcastle–Ottawa Scale. A small proportion of studies (8) are rated as Low Quality, reflecting minimal methodological rigor. The largest group falls under Moderate Quality, highlighting incremental improvements in study design and execution across three domains: Selection, Comparability, and Outcome/Exposure. High Quality studies dominate, with 38 studies demonstrating strong to exceptional methodological consistency, particularly in the 7–9 star range. This distribution emphasizes the overall robustness of the research included in the review, with a majority achieving reliable and actionable results.

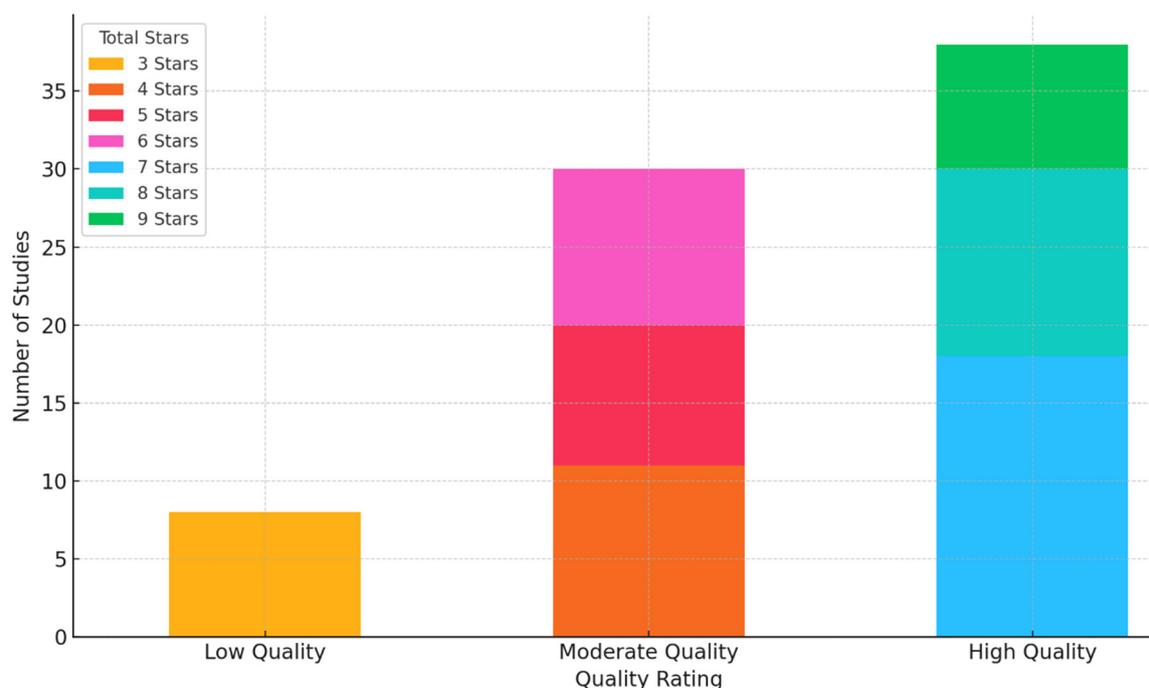


Figure 9. Assessment of study quality using the Newcastle–Ottawa Scale.

Figure 10 illustrates the relationships between research designs, data collection methods, and study types (quantitative, qualitative, mixed-methods, and unspecified) in the reviewed studies. Surveys emerge as the most commonly used research design, strongly associated with quantitative studies, reflecting the methodological preference for structured and numerical data collection. Case studies also hold a significant presence, emphasizing their importance in providing in-depth insights into specific contexts, such as the implementation of business intelligence (BI) and data mining techniques in SMEs. Other designs, such as content analysis, conceptual analysis, and design science research, are less frequent and often aligned with qualitative or mixed-methods approaches, suggesting their role in more interpretive or exploratory studies.

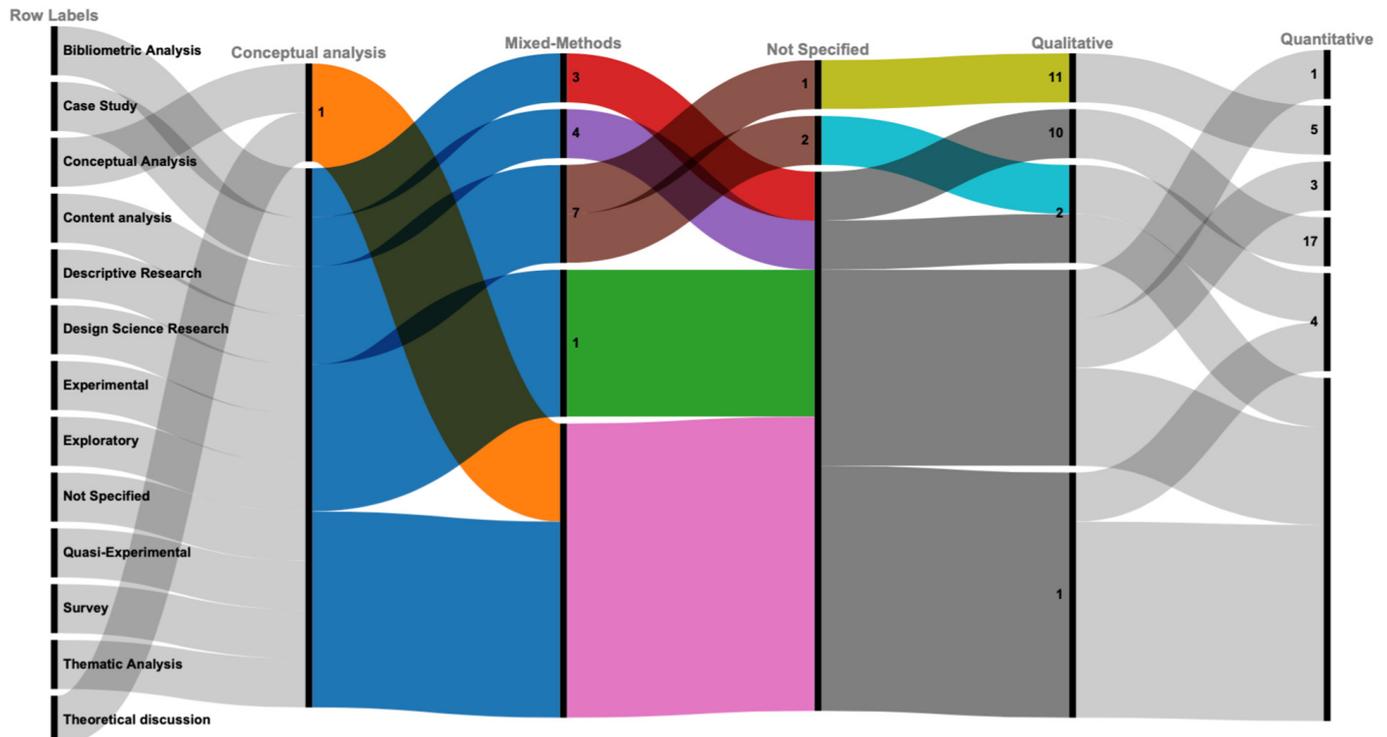


Figure 10. Research design and data collection methods.

Interestingly, a substantial proportion of studies fall under the “Not Specified” category for both research design and data collection methods, highlighting a recurring issue of methodological ambiguity in the reviewed literature. This lack of clarity suggests an opportunity for future research to improve transparency and rigor in reporting methodological frameworks. Overall, the dominance of surveys and quantitative approaches reflects a preference for structured methodologies aimed at measurable outcomes, while the underrepresentation of qualitative and mixed-methods approaches points to the need for more diverse and integrative research designs in this field. Figure 11 highlights the distribution of data collection methods used in the reviewed studies. Surveys dominate as the most frequently employed method, accounting for 46 studies, reflecting their widespread use in collecting structured, quantitative data from SMEs. Document analysis follows as the second most utilized method, appearing in 31 studies. This suggests a strong reliance on secondary data sources, such as reports and archival records, to gain insights into business intelligence (BI) and data mining practices.

Interviews are the third most common method, used in 10 studies, indicating their role in gathering qualitative insights directly from participants such as SME owners, business analysts, or IT professionals. Observations appear less frequently, with only three studies utilizing this approach, underscoring its limited application in this research area. A small proportion of studies (4) did not specify their data collection methods, highlighting gaps in methodological reporting. Additionally, the TOE (Technology-Organization-Environment) framework appears in one study, showcasing its use as a guiding framework for collecting and analyzing data in specific contexts.

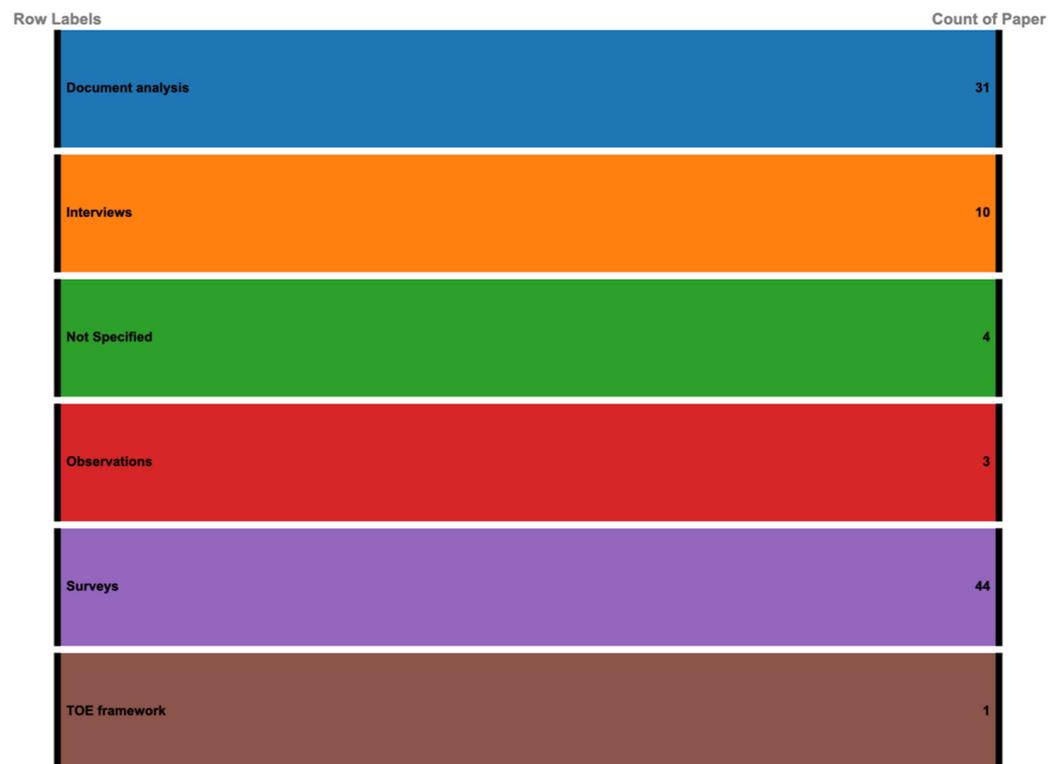


Figure 11. Data collection method.

3.4. Results of Individual Studies

The analysis in Figure 12 highlights the interplay between various data mining techniques and business intelligence (BI) tools applied in the reviewed studies. Dashboards emerge as the most frequently utilized BI tool, cited in 31.18% of the studies, prominently linked to clustering (10.75%) and classification techniques (8.60%). This underscores their pivotal role in visualizing insights derived from structured data. Similarly, Cloud BI tools account for 16.13% of mentions, supporting techniques like customer relationship management (CRM) and clustering, showcasing their growing popularity for scalable and flexible analytics. However, a notable portion of the studies (39.78%; 37 out of 93) did not specify the tools or techniques employed, signaling a need for more comprehensive reporting practices.

This gap in reporting does not necessarily imply an absence of tools or techniques in BI models but reflects a lack of transparency in how these resources are documented. BI models inherently incorporate a wide array of tools and techniques, yet researchers often fail to detail their application or contextual relevance. For instance, dashboards, clustering techniques, and CRM were frequently mentioned, but less emphasis was placed on specific data mining techniques like dimensional modeling (4.30%) or association rules (3.23%), which, while present in BI systems, are underreported. Such omissions highlight the need for greater methodological rigor and consistency in documenting these tools in future studies.

Despite these gaps, the findings provide valuable insights into the broader utilization of BI tools and techniques. For example, tools like Microsoft SQL Server (9.68%), OLAP (4.30%), and reporting tools (4.30%) were linked with specific applications such as data integration and data mining, showcasing their utility in particular contexts. Niche applications, such as social media analytics tools (1.08%) and topic modeling (LDA, 1.08%), though sparsely represented, demonstrate the versatility of BI models in addressing diverse operational challenges. These results emphasize that BI systems are equipped with robust

tools to drive SME performance, yet their poor reporting undermines efforts to establish evidence-based frameworks for adoption and optimization.

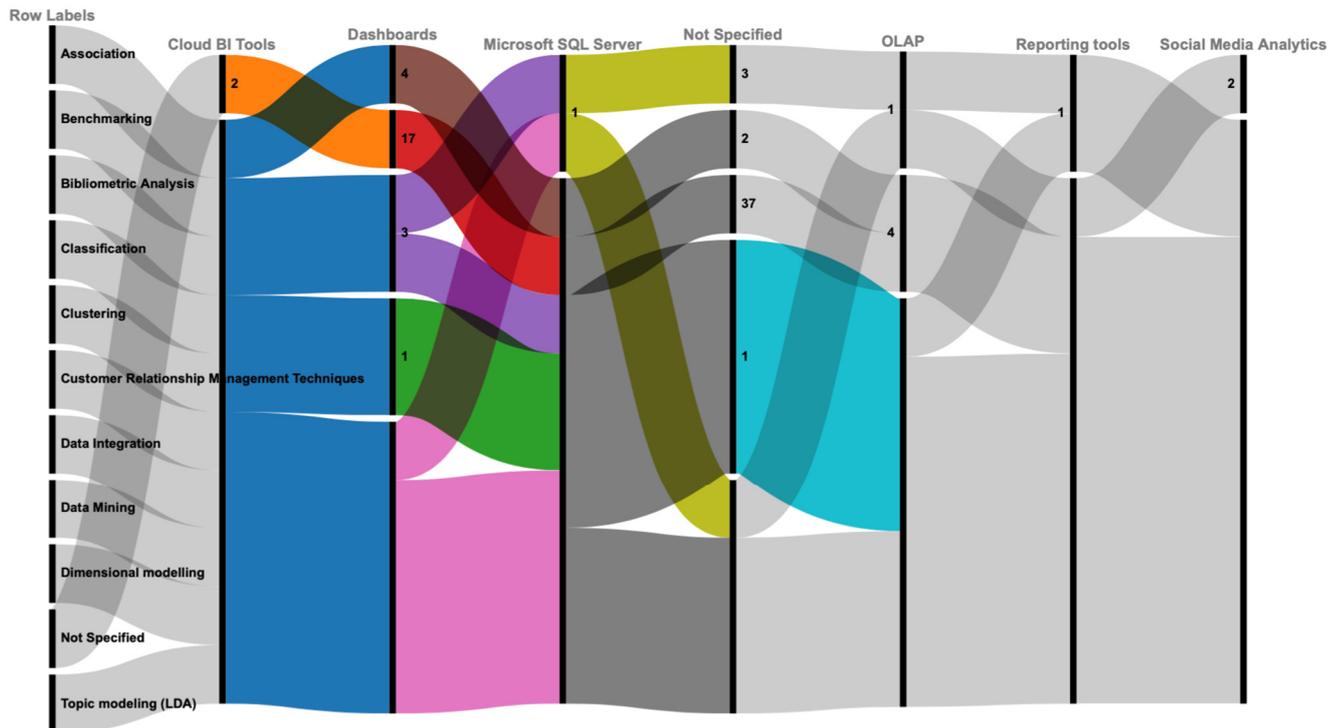


Figure 12. Techniques and tools in data mining and business intelligence.

This lack of comprehensive reporting impacts the comparability of studies and limits the development of standardized best practices. For instance, while dashboards and cloud-based tools are well represented, the underreporting of hybrid models (1.08%) and on-premises solutions (6.45%) restricts our understanding of their strategic implications. Future research must prioritize detailed documentation of the tools and techniques employed in BI models. Such improvements will not only enhance the credibility and utility of research findings but also enable SMEs to make informed decisions about integrating BI technologies tailored to their specific needs. By bridging this gap, future studies can provide a clearer understanding of how BI and data mining tools are utilized to foster competitive advantages and operational efficiency in SMEs, thereby advancing the field's practical and academic contributions.

3.5. Results of Synthesis

This section summarizes the findings of the syntheses conducted across various studies, highlighting the applications and competitive advantages of data mining and business intelligence (BI) in small and medium-sized enterprises (SMEs). Firstly, the analysis of contributing studies reveals a predominant focus on the ICT sector, followed by the manufacturing industry. These findings underscore the pivotal role of BI in enabling SMEs to optimize operations, enhance decision-making, and achieve competitive advantages across diverse industry contexts.

Next, the statistical syntheses emphasize the global interest in BI applications for SMEs, with contributions spanning developed and developing countries. The research incorporates diverse formats, including journal articles, conference papers, dissertations, and book chapters, reflecting a robust and dynamic body of knowledge. Measures of statistical heterogeneity reveal the varying priorities and challenges faced by SMEs in

different economic contexts, with a significant emphasis on developing countries where BI is instrumental in addressing resource constraints and driving growth.

Additionally, the exploration of economic contexts highlights the importance of tailoring BI solutions to the unique needs of SMEs in emerging markets, while sensitivity analyses underscore the growing prevalence of cloud-based technologies. These scalable and adaptable data management solutions reflect current trends and provide SMEs with the tools to enhance operational efficiency and sustain competitive advantages in an increasingly data-driven business environment.

3.5.1. Characteristics and Risk of Bias Among Contributing Studies

The reviewed studies demonstrate a predominant focus on the ICT sector, accounting for 45.16% of the studies, followed by the manufacturing industry at 22.58% (Figure 13). This distribution underscores the critical role of ICT in advancing data mining and business intelligence (BI) adoption, particularly for real-time data analysis, customer relationship management, and cloud-based solutions. The significant representation of the manufacturing sector highlights its growing reliance on data-driven technologies to enhance operational efficiency, optimize production processes, and improve decision-making frameworks.

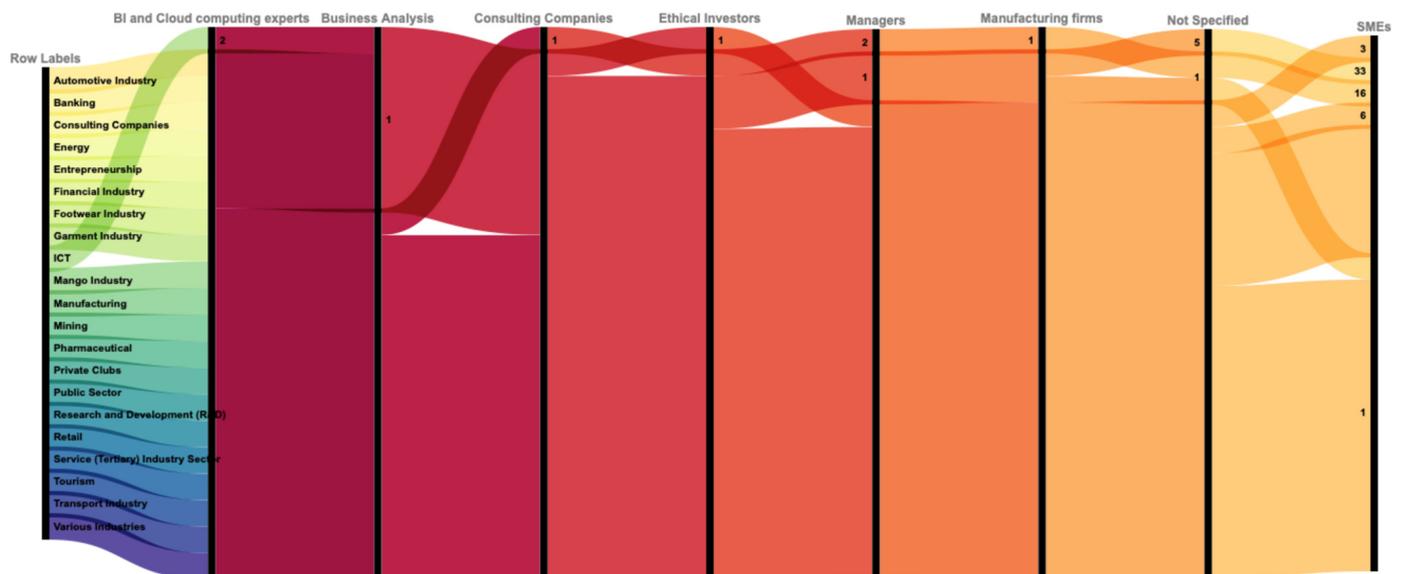


Figure 13. Industry context by study participants.

In the manufacturing industry, clustering emerges as one of the most frequently applied techniques, aiding in identifying production inefficiencies, improving supply chain operations, and optimizing inventory levels. For example, clustering models are used to group products based on sales trends, enabling manufacturers to better forecast demand and align production schedules accordingly. Similarly, dashboards are widely utilized in manufacturing to monitor key performance indicators (KPIs), such as production throughput, equipment downtime, and quality metrics, in real-time. This fosters rapid decision-making, minimizes losses, and ensures operational continuity.

Despite the prominent focus on these industries, underrepresentation in other sectors reveals gaps in the diversity of research. For example, the financial services sector accounts for only 5% of the studies, while the retail industry represents 3% (Figure 13). These findings highlight potential opportunities for expanding research to explore how BI tools can address unique challenges in sectors that rely heavily on customer-centric or transaction-heavy environments. Furthermore, ethical investors (2%) and consulting firms (10%) are

underexplored in the context of BI tool adoption, despite their significant role in shaping strategic decisions in SMEs. This lack of attention suggests a need for future research to investigate how BI tools and data mining techniques can be tailored to industries with distinct objectives, such as sustainability or advisory services.

Additionally, 8% of the studies fall under the “Not Specified” category for industry focus, reflecting a lack of methodological transparency in reporting (Figure 13). This lack of specificity restricts a comprehensive understanding of how BI systems are being applied across diverse business contexts, limiting opportunities for cross-sectoral learning. Addressing these gaps through improved methodological rigor and reporting practices could provide more tailored insights into industry-specific adoption patterns, thereby fostering broader applicability of BI tools across underexplored sectors.

3.5.2. Results of Statistical Syntheses

The geographic and economic context of the reviewed studies in Figure 14 reveal a notable focus on developing countries, which account for 72% of the studies, compared to 28% from developed nations. This distribution emphasizes the significance of data mining and business intelligence (BI) technologies in addressing challenges such as resource constraints, market unpredictability, and scalability needs in emerging markets. Countries like Indonesia, South Africa, and Malaysia represent key contributors to the literature, reflecting a regional focus on leveraging BI tools for economic growth and SME development. In contrast, developed nations like the United States and the United Kingdom show a smaller but impactful contribution, often emphasizing innovation and advanced BI adoption strategies.

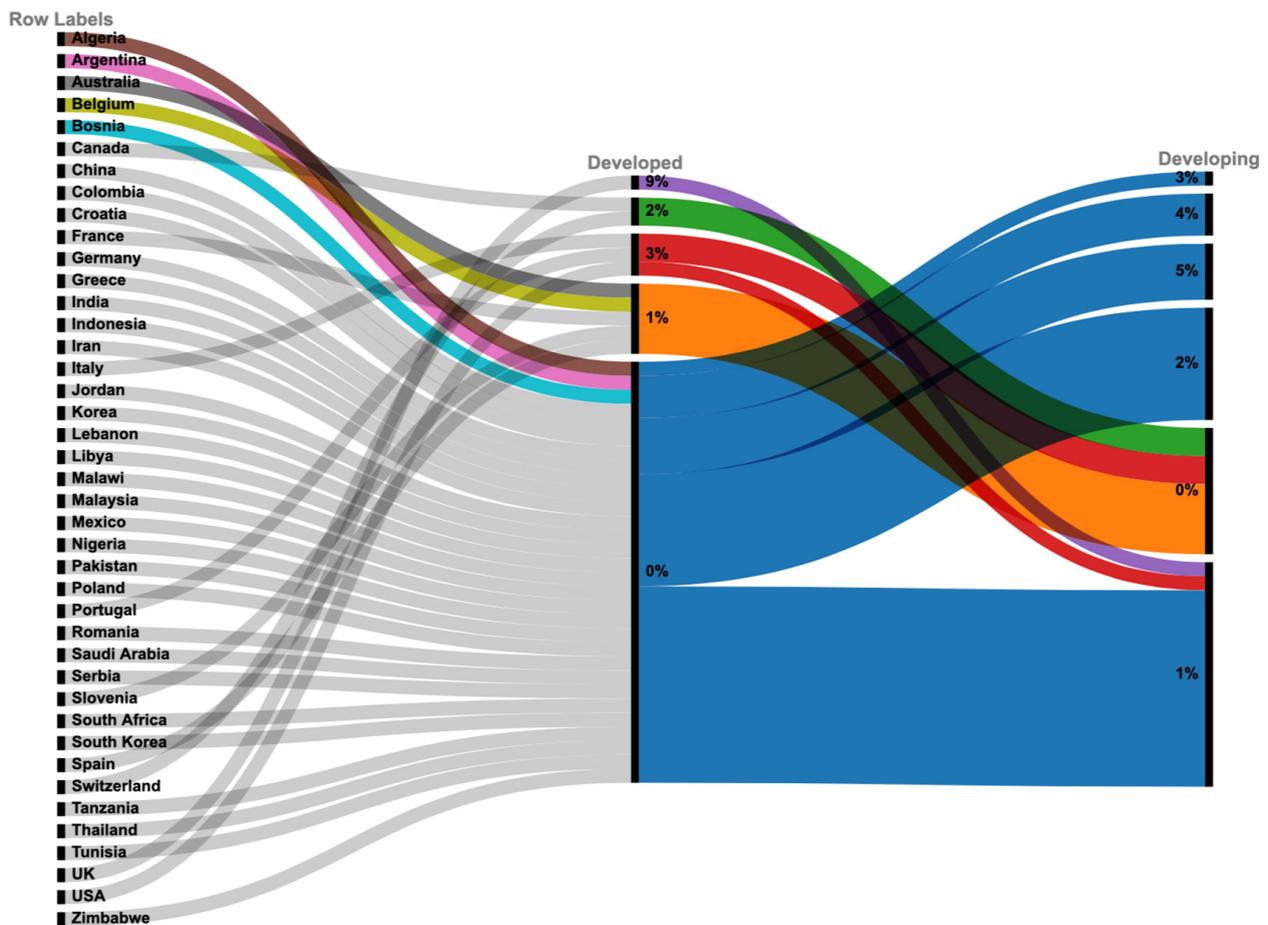


Figure 14. Geographic and economic context of reviewed studies.

The publication types further illustrate the academic landscape, with 68.82% of the studies published as journal articles, 20.43% as conference papers, and smaller contributions from dissertations (6.45%) and book chapters (4.3%). This distribution highlights the diversity of scholarly output, with journal articles providing peer-reviewed, in-depth analyses, while conference papers contribute to ongoing discussions and emerging trends in the field. However, the need for more longitudinal studies to assess long-term BI impacts remains an area for growth.

Among the evaluated performance metrics, data processing speed emerges as the most frequently assessed, appearing in 19.35% of the studies. This focus aligns with the emphasis on real-time decision-making and operational efficiency, particularly in industries like ICT and manufacturing. The frequent evaluation of data processing speed reflects its importance in enhancing the functionality of BI systems, allowing SMEs to respond dynamically to changing market conditions. This connection underscores how geographic and economic contexts shape the priorities of BI implementations, with developing nations often prioritizing cost-effective, real-time solutions to overcome resource constraints.

3.5.3. Investigation of Heterogeneity

The economic context of the studies reveals a clear disparity between developed and developing countries. A total of 67 studies were conducted in developing economies, highlighting the crucial role of data mining and business intelligence (BI) in enhancing the competitiveness and operational efficiency of SMEs within resource-constrained environments. These findings emphasize the importance of technological adoption in addressing fundamental business challenges faced by SMEs in emerging markets. In contrast, 26 studies originate from developed countries, where the focus shifts towards innovation, advanced technological integration, and maintaining competitive advantages through sophisticated BI strategies. This heterogeneity underscores the varying applications and priorities of BI and data mining across economic contexts, shaped by distinct regional challenges and technological maturity levels. Understanding these variations is essential for designing tailored BI solutions that address the unique needs of SMEs in diverse regions.

3.5.4. Sensitivity Analyses Results

Figure 15 highlights the relationship between technology implementation models and their corresponding IT performance metrics in reviewed studies. Cloud-based models dominate, accounting for 32% of the studies, reflecting their growing popularity due to scalability, cost-effectiveness, and real-time data processing capabilities. These models show a significant focus on data processing speed (15%) and competitive advantage (11%), emphasizing their role in enhancing agility and operational efficiency.

On-premises solutions constitute 6% of the studies, catering to industries with stringent security and infrastructure requirements. These studies primarily focus on data quality (4%) and visualization (2%), suggesting their importance in contexts where control over data infrastructure is critical. Hybrid models, representing only 1%, illustrate an emerging approach combining cloud flexibility and on-premises control, but their adoption remains limited. Notably, 61% of the studies did not specify the implementation model, revealing a gap in methodological reporting. This lack of specification limits a comprehensive understanding of the relationship between implementation strategies and IT performance metrics, such as accuracy (1%) and competitive advantage (1%).

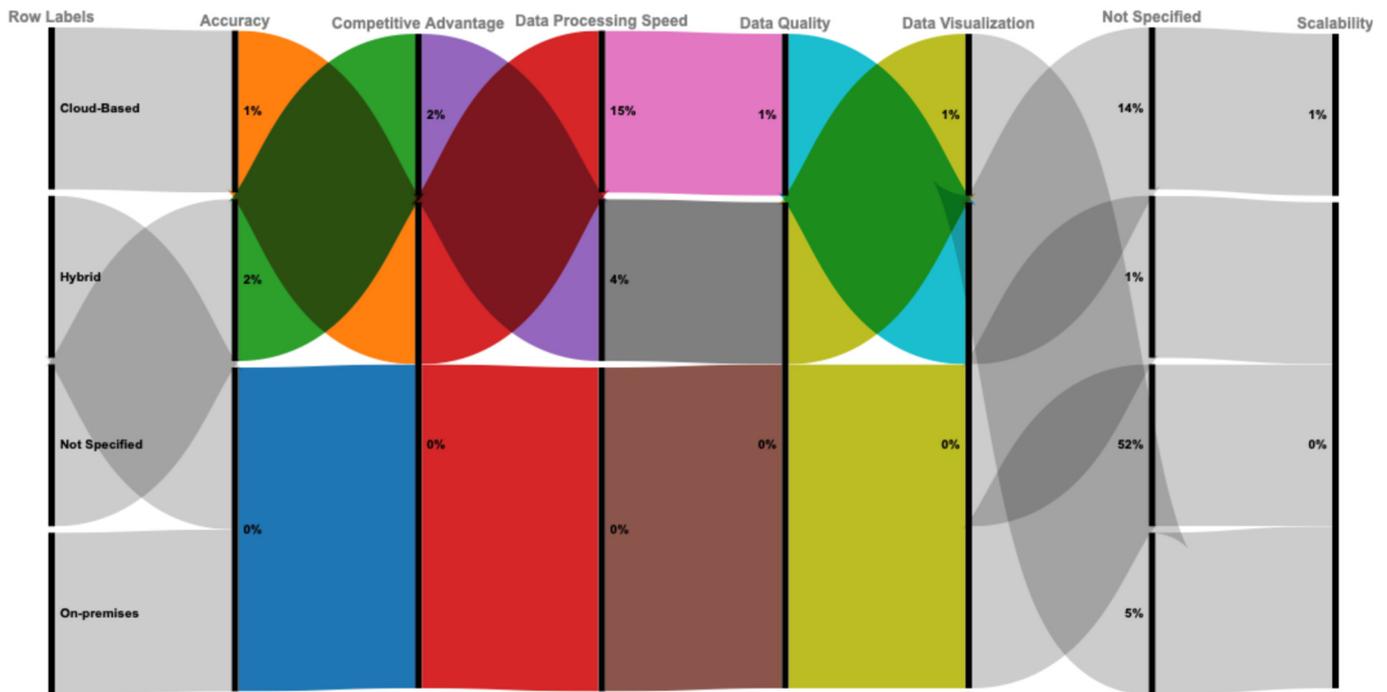


Figure 15. Technology implementation models and related IT performance metrics.

3.6. Reporting Biases

The analysis of sample characteristics across the reviewed studies reveals a strong focus on small and medium-sized enterprises (SMEs), with 75% of the studies (70 out of 93) dedicated to this segment. This focus highlights the central role of data mining and business intelligence (BI) in addressing the unique challenges SMEs face, such as limited resources, scalability constraints, and the need for operational efficiency improvements. SMEs also accounted for the majority of studies that explored the use of cloud-based models, with 32% of these studies emphasizing the benefits of scalability, real-time data access, and cost-effective solutions.

Approximately 25% of the studies focused on other sectors, including consulting firms, manufacturing companies, and business analysts. Within this group, business analysts and consulting firms accounted for a combined 12%, while manufacturing companies represented 8%. Despite the diversity in sample types, these figures reveal a potential reporting bias, as the overrepresentation of SMEs limits the generalizability of findings to larger organizations or sectors that may have different technological and operational needs. The distribution of studies also highlighted discrepancies in the exploration of technology implementation models. While cloud-based solutions were addressed in 32% of studies, hybrid models and on-premises solutions were less frequently discussed, at 1% and 6%, respectively. Notably, 60% of the studies did not specify the implementation model used, pointing to a significant gap in methodological transparency. This lack of specificity restricts a thorough understanding of the adoption trends and their corresponding outcomes. Performance metrics such as data processing speed were evaluated in 19% of the studies, while competitive advantage and business sustainability were explored in 11% and 9% of the studies, respectively. However, critical metrics such as scalability and innovation remained underexplored, each appearing in less than 1% of the studies. These omissions highlight a bias in reporting metrics that prioritize short-term efficiency gains over long-term impacts, such as organizational growth and resilience.

3.7. Certainty of Evidence

Figure 16 showcases the relationship between technology implementation models and their impact on various business performance metrics. Cloud-based solutions dominate, accounting for 32% of the studies. These models are strongly associated with improved decision-making quality (15%) and customer satisfaction (11%), demonstrating their ability to enhance business processes and align strategies with customer needs. On-premises solutions account for 6% of the studies, emphasizing operational efficiency (4%) and financial performance (2%). These models are tailored for industries requiring high control over data and infrastructure, focusing on stability and predictable outcomes. Hybrid models, though representing only 1%, show potential for balancing cloud scalability with on-premises reliability, particularly in enhancing customer satisfaction (1%). However, their adoption remains limited, indicating an emerging trend. A significant portion of the studies (61%) did not specify the implementation model, leaving gaps in understanding how these models influence other critical metrics such as innovation, market adaptability, and resilience. This lack of detail hinders a holistic view of the impact of technology adoption on business performance.

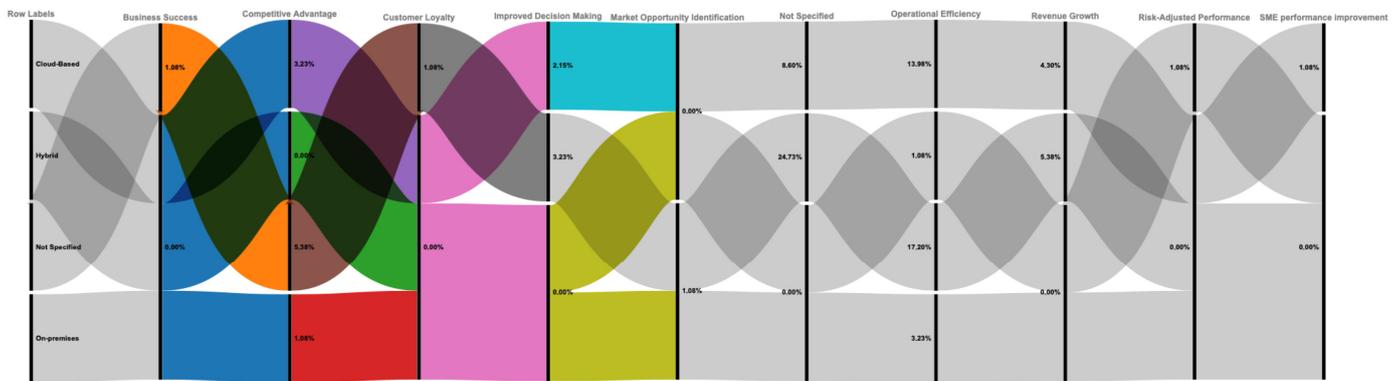


Figure 16. Technology implementation models and business performance.

Figure 17 highlights the relationship between technology implementation models and their impact on diverse organizational outcomes. Cloud-based solutions dominate with 32% of the studies, showcasing their strong association with improved organizational agility (15%), enhanced decision-making capabilities (12%), and competitive advantage (8%). These findings underline the scalability, cost-efficiency, and adaptability of cloud technologies in fostering organizational growth and resilience. Hybrid models account for 1% of the studies and exhibit limited but notable connections to enhanced strategic alignment and innovation capability (1% each). The potential of hybrid models lies in balancing cloud flexibility with on-premises control, yet their adoption remains minimal, signaling an area for future exploration. On-premises solutions, representing 6% of the studies, are linked to improved operational stability (4%) and data security (2%). These models cater to industries with stringent security and compliance requirements, emphasizing controlled infrastructure over agility. A significant portion of the studies (61%) did not specify their implementation model, leaving gaps in comprehensively understanding the diverse outcomes of different approaches. This lack of clarity underscores the need for more detailed reporting on technology strategies to better inform their organizational implications.

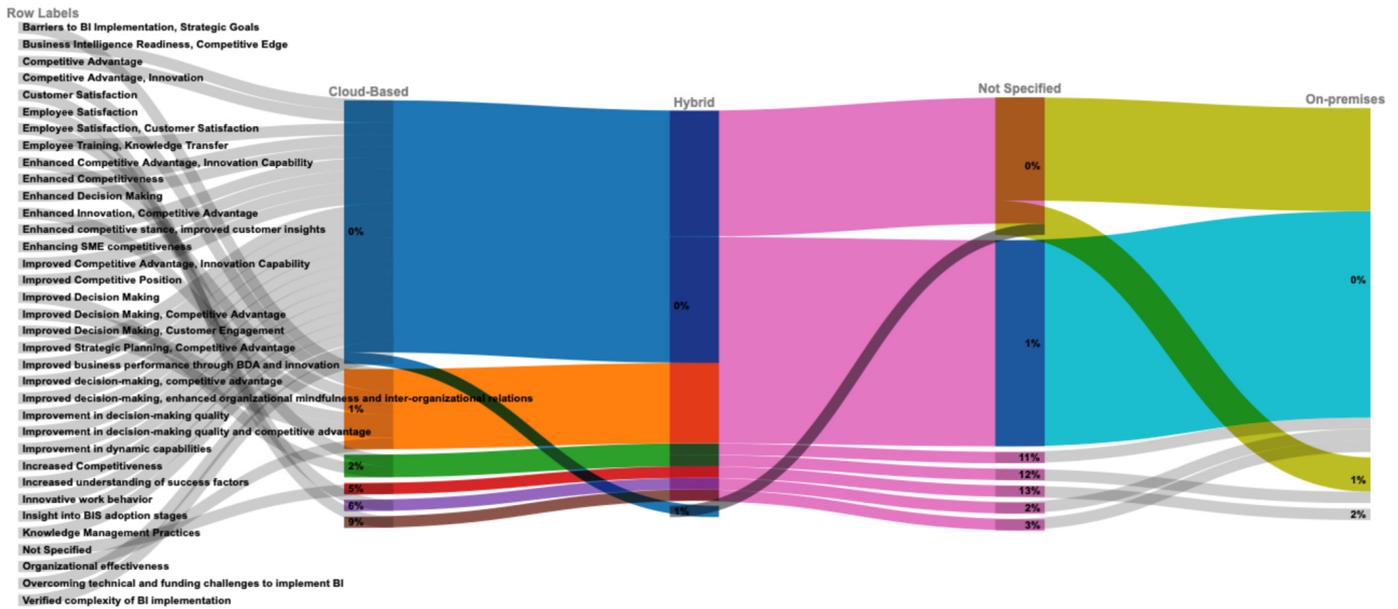


Figure 17. Technology implementation models and organization outcomes.

Figure 18 explores the long-term organizational impacts of various technology implementation models. Cloud-based models are associated with significant benefits, including competitive advantage (11%), business sustainability (4%), and improved long-term business growth (8%). These findings reinforce the role of cloud technologies in supporting scalable and sustainable growth strategies for organizations. Hybrid models, though used in 1% of the studies, show notable associations with improved market strategy formulation and enhanced business competitiveness, reflecting their potential to integrate diverse technological capabilities for strategic objectives. On-premises solutions, utilized in 5% of the studies, emphasize business sustainability and competitive stability, indicating their relevance for industries requiring controlled environments and secure data management. A large proportion of studies (61%) remain unspecified regarding the implementation models, representing a gap in the literature that limits detailed analysis of long-term organizational impacts.

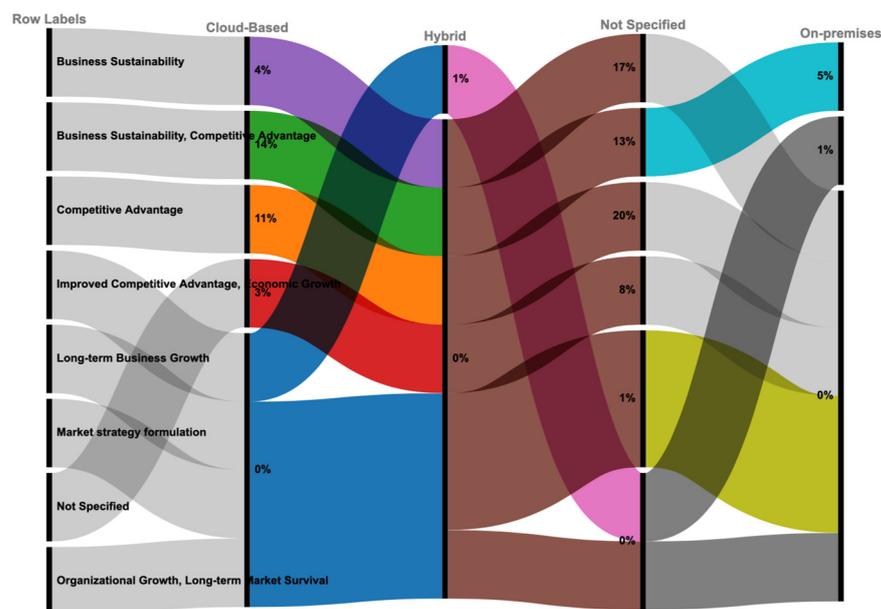


Figure 18. Technology implementation models and long-term impact.

4. Discussion

The insights from the systematic review, guided by the PRISMA framework, illuminate the findings across the research questions, ensuring alignment with the study's core themes of methodological transparency, the dominance of clustering techniques, and broader challenges in data mining and business intelligence (BI) systems for SMEs. Below is a discussion contextualized to these findings and the research questions:

What factors contribute to the underreporting of data mining techniques in business intelligence research, and how can methodological transparency be improved to enhance the field's applicability to SMEs?

The review highlights significant underreporting in the documentation of data mining techniques across the reviewed studies, with 66.67% of papers failing to specify the methods used. This gap can be attributed to several factors, including inconsistent methodological frameworks, the lack of standardized reporting practices, and an emphasis on application outcomes over detailed processes. Such omissions hinder the replicability of findings, limit cross-contextual comparisons, and reduce the ability of researchers and practitioners to understand the nuances of applied techniques. Improving methodological transparency requires the adoption of standardized reporting guidelines, which emphasize not only the outcomes but also the processes and tools utilized in data mining. For instance, specifying whether clustering, association, or predictive modeling was employed, and detailing its configuration and objectives, could provide clearer insights for future research and implementation. Such efforts would bridge the knowledge gap and enhance the applicability of BI systems to SMEs.

Why is clustering the most reported data mining technique in the context of business intelligence for SMEs, and what implications does this have for understanding other underutilized techniques like association or dimensional modeling?

Clustering, reported in 10.75% of studies, emerges as the most utilized data mining technique due to its versatility in grouping data points based on similarity without requiring predefined labels. This technique is particularly advantageous for SMEs operating in dynamic environments, as it allows them to identify customer segments, market trends, and operational inefficiencies. However, the overrepresentation of clustering indicates an imbalance in exploring alternative techniques, such as association (2.15%) and dimensional modeling (1.08%). These underutilized methods could provide complementary insights, such as uncovering product affinities or optimizing database structures, that are equally critical for business intelligence applications. The narrow focus on clustering limits the breadth of knowledge regarding the full spectrum of data mining capabilities and emphasizes the need for a diversified approach in future studies.

How can organizations leverage clustering, the most frequently reported technique, to optimize business intelligence systems and drive operational efficiency in resource-constrained environments?

Clustering enables SMEs to derive actionable insights by segmenting customers, products, or markets based on shared attributes. For example, SMEs in resource-constrained environments can use clustering to allocate resources more efficiently by targeting high-priority customer groups or identifying underperforming market segments. Furthermore, clustering supports inventory optimization by predicting demand patterns, thus minimizing waste and reducing costs. To maximize its potential, SMEs should integrate clustering with other BI tools, such as dashboards, to visualize clustered data and facilitate decision-making. Training staff to interpret and act upon clustering outputs can further enhance operational efficiency and adaptability in competitive markets.

What is the role of cloud-based business intelligence models in facilitating the integration of underreported data mining techniques, such as sentiment analysis or association, to improve SME performance?

Cloud-based BI models, adopted in 32.26% of the studies, provide a scalable and cost-effective platform for implementing diverse data mining techniques, including those underreported like sentiment analysis and association. These platforms offer the computational power and storage capabilities needed to process unstructured data, such as customer feedback, enabling SMEs to gain insights into consumer behavior and preferences. For instance, leveraging sentiment analysis through cloud-based tools allows SMEs to monitor customer sentiment in real time, which is essential for reputation management and personalized marketing. Similarly, association techniques can identify product affinities to optimize cross-selling and bundling strategies. By enabling the integration of such techniques, cloud-based models can help SMEs overcome the technical and financial barriers often associated with traditional on-premises systems.

Given the dominance of clustering and dashboards, how can researchers ensure the representation of other equally valuable techniques and tools to provide a more comprehensive view of BI's capabilities for SMEs?

The dominance of clustering and dashboards, reported in 10.75% and 31.18% of studies, respectively, underscores their central role in BI systems. However, this emphasis risks overshadowing other techniques, such as predictive modeling, dimensional modeling, and association, which offer unique benefits for SMEs. Researchers can address this imbalance by adopting a more exploratory approach that evaluates the comparative effectiveness of diverse techniques in different contexts. Incorporating case studies and experimental designs can help highlight the strengths and limitations of underrepresented methods, fostering a more comprehensive understanding of BI capabilities. Additionally, interdisciplinary collaboration between data scientists, business analysts, and SME stakeholders can identify practical applications for these techniques, ensuring their relevance and representation in future research.

How can methodological frameworks and reporting standards be refined to better capture the diversity of data mining techniques and tools utilized in business intelligence systems for SMEs?

To better capture the diversity of data mining techniques, it is essential to refine methodological frameworks and reporting standards that guide BI research. Existing frameworks should incorporate specific requirements for detailing the tools, techniques, and parameters used in data analysis. For example, frameworks can mandate the inclusion of information about the type of data processed, the rationale for selecting particular techniques, and the outcomes achieved. Reporting standards should also encourage the use of supplementary materials, such as detailed methodologies and code repositories, to enhance transparency and reproducibility. These refinements would not only improve the quality of research but also provide SMEs with actionable insights to tailor BI systems to their unique needs and constraints.

5. Conclusions

This systematic review underscores the pivotal role of data mining and business intelligence (BI) tools in enhancing the performance of small and medium-sized enterprises (SMEs). Key findings reveal that dashboards were the most utilized BI tools, featured in 31.18% of studies, followed by clustering techniques at 10.75%, highlighting their significance in improving operational efficiency and decision-making. However, 66.67% of studies did not specify the BI tools or data mining techniques employed, reflecting a lack

of methodological transparency. Geographically, 72% of studies originated from developing countries, underscoring the critical focus on leveraging BI to overcome resource constraints and enhance competitiveness, while 28% came from developed economies, where the emphasis was on advanced technological integration. Cloud-based models dominated implementation strategies, appearing in 32% of studies, primarily linked to improved decision-making (15%) and competitive advantage (11%), whereas on-premises and hybrid solutions were significantly underexplored at 6% and 1%, respectively. Despite these advancements, essential metrics such as scalability, innovation, and long-term organizational resilience were underreported, appearing in less than 1% of studies. To address these gaps, future research should focus on hybrid implementation models that balance cloud flexibility with on-premises control, enhancing methodological transparency through standardized reporting frameworks, and conducting longitudinal studies to examine the long-term impacts of BI on innovation and market adaptability. Additionally, comparative studies on BI adoption in developed versus developing economies are essential to understand the influence of economic and technological contexts. Cross-disciplinary approaches should also be explored to develop user-friendly and cost-effective BI solutions tailored to SMEs. Addressing these gaps will bridge existing limitations, promote more actionable insights, and ensure BI and data mining systems play a transformative role in SME performance globally.

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Appendix A

Table A1. Comprehensive overview of data mining and business intelligence in SMEs performance.

Ref.	Research Focus	Methodology	Key Outcomes	Challenges Identified	Recommendations
Mikalef et al. (2018)	BI systems in SMEs	Literature review, case studies	Strategic alignment, cloud BI benefits	BI complexity, cost, skills gap.	Simplify BI tools, enhance training, adopt cloud BI
Gomwe et al. (2023)	Role of BI in SMEs	Bibliometric analysis	BI improves decision-making, competitive edge	Complexity, cost concerns	Develop BI and TOE framework integration
Mian and Ghabban (2022)	Data mining's impact in Saudi SMEs	Quantitative survey, SEM	Enhances competitive advantage via training	Personnel selection complexity	Advance data mining techniques, improve training

Table A1. Cont.

Ref.	Research Focus	Methodology	Key Outcomes	Challenges Identified	Recommendations
Chawinga and Chipeta (2017)	Marketing intelligence impact on SMEs	Surveys	Boosts competitive advantage	Limited tool awareness, data privacy	Increase marketing intelligence tool training
Chawinga and Chipeta (2017)	KM and CI in Malawian SMEs	Surveys	Improves decision-making, efficiency	Information protection, knowledge tacitness	Formalize KM and CI processes, technology adoption
Topalović and Azzini (2020)	Data mining applications in Italian SMEs	Case studies, interviews, surveys	Improved decision-making, operational efficiency.	Resource limitations, change resistance	Promote data mining benefits, facilitate adoption
Saeed (2020)	Economic impact of data mining in SMEs	Literature review.	Potential for improved operations	Resource-intensive nature, data security	Start with basic tools, gradually adopt advanced BI
Mohd Selamat et al. (2020)	Barriers in BDA adoption by SMEs	Surveys	BDA improves decision-making, competitive edge	Skilled personnel shortage, BDA tool complexity	Develop cost-effective BDA solutions for SMEs
Khan et al. (2014)	Web support system for BI in SMEs.	Proposed and tested a web-based BI framework.	Cost-effective, user-friendly, improves decision-making.	High costs and complexity of traditional BI tools.	Develop simple, mobile-friendly BI systems.
Pei and Jia (2014)	Data warehouse and mining in steel enterprises.	Three-tier architecture using SQL Server.	Enhanced data integration and decision-making.	Data integration and system scalability.	Use SQL Server, apply predictive algorithms, ensure flexibility.
Antoniadis et al. (2015)	BI for SMEs	Literature review and case study	Improved decision-making and competitiveness	High costs, integration issues	Use affordable, tailored BI solutions and train users
Abbas et al. (2016)	Adoption of Business Intelligence (BI) in SMEs	Literature review and survey of SMEs	BI enhances decision-making and operational efficiency in SMEs	Lack of awareness, high costs, and technical complexity	Increase training, reduce costs, and simplify BI tools for SMEs
Antoniadis et al. (2015)	BI adoption in SMEs	Case study	Improved decision-making, efficiency	Technical skill gaps, high costs	Use affordable BI tools, seek funding
Gheorghe and Țoniș (bucea-Manea) (2015)	BI solutions for Romanian SMEs in network settings.	Literature review and case study with QlikView.	Improved decision-making, productivity, and cost reduction.	Data volume and integration issues	Use BI tools like QlikView; leverage network resources
English and Hoffmann (2018)	Role of data mining in SMEs.	Surveys and data analysis.	Improved decision-making.	Skill gaps in data handling	Train staff, simplify tools.

Table A1. Cont.

Ref.	Research Focus	Methodology	Key Outcomes	Challenges Identified	Recommendations
Elango and Thiagarajan (2016)	Application of business analytics in SMEs	Case study and literature review	Enhanced decision-making and operational efficiency	High costs and complexity of implementation for SMEs	Focus on cost-effective, scalable solutions
Antoniadis et al. (2015)	Adoption of ERP systems by SMEs during crisis	Survey of 37 SMEs in Western Macedonia using structured questionnaires	Identified key advantages like data integration and decision support	High costs of setup and training; underutilization of BI features	Enhance training and BI feature utilization; focus on cost reduction
Ali et al. (2017)	Adoption of Business Intelligence (BI) in SMEs in Zimbabwe	Descriptive research through documentary analysis of existing literature.	BI as a strategic asset can significantly enhance decision-making and competitiveness in SMEs.	Lack of IT infrastructure, high costs, and low awareness among SMEs	SMEs should adopt BI incrementally, align BI with business strategy, and invest in staff training.
Olszak (2014)	Implementation of BI for SMEs	Model-driven approach	Enhanced BI solutions for SMEs	High costs and complexity	Simplify DW implementation with automation to cut costs.
Olszak (2014)	Business Intelligence and Analytics in Organizations	Literature review and survey of 20 organizations	BI improves decision-making, efficiency, and competitiveness	Limited use of BI due to lack of skills and awareness	Enhance BI training, align BI with business goals, and improve data quality
Antoniadis et al. (2015)	BI adoption in Lebanese SMEs	Quantitative survey from 56 SMEs	Quality BI and positive attitudes are crucial.	Resistance from management	Improve culture and train management
Shabbir and Gardezi (2020)	BI in organizations for decision-making and competitiveness.	Literature review, interviews with 20 organizations.	Improved decisions, processes, performance.	Limited BI use in small firms	Increase BI training, define BI strategies, boost leadership support.
Leite et al. (2019)	Implementation of BI in SMEs	Case study using Pentaho BI platform	Demonstrated feasibility of implementing Pentaho in SMEs	Complexity in setup; need for technical knowledge	Use open-source BI; ensure technical support, internal or external
Adeyelure et al. (2018b)	Business Intelligence (BI) adoption in SMEs	Case study on SMEs using BI tools	Improved decision-making and competitiveness	Limited resources and technical expertise in SMEs	Enhance training and support for SMEs on BI tools
Adewusi et al. (2024)	BDA adoption by SMEs	Surveys; SEM analysis	BDA boosts performance	Resource limits, security issues	Enhance training, management support

Table A1. Cont.

Ref.	Research Focus	Methodology	Key Outcomes	Challenges Identified	Recommendations
Kautsaf et al. (2023)	Big Data Analytics in SMEs	PLS-SEM on survey data from 242 SMEs	BDAC boosts performance via business models; COVID-19 amplifies impact	Limited BDAC understanding; poor alignment	Align BDAC with business models; adapt in crises
Ragazou et al. (2023)	BI adoption in SMEs for competitive advantage	Conceptual framework using DOI and ANT theories	Developed a holistic framework for BI adoption in SMEs	Low BI adoption, especially in developing countries	Promote equal importance of all actors in BI adoption
Mupaikwa (2024)	BI adoption in SMEs as a competitive strategy	Guided by Porter's Five Forces Model	Competitive edge through informed decisions	Lack of funding, managerial support, and expertise	Invest in BI, training, further research
Lateef and Keikhosrokiani (2022)	Identify success factors for BI in SMEs	PLS-SEM on survey data from 165 SMEs in Lagos	Key factors: knowledge management, tech orientation, market intelligence	Lack of management support, planning, and resources	Boost management support, invest in tech, focus on key success factors
Gomwe et al. (2023)	BI for competitive advantage in SMMEs	Qualitative study with 12 respondents from 5 areas, analyzed with Atlas.ti.	BI enhances decision-making and competitiveness	Lack of support, funding, training, and commitment	Boost support, funding, skills, and training for BI adoption
Kazemi et al. (2024)	Factors for competitive advantage	Content analysis, F-TOPSIS	Ranked 5 criteria: CRM, marketing, organization, product image	Prioritizing key sub-criteria	Improve customer interaction, feedback, and support
Tarmidi and Taruna (2023)	Success factors for BDA in SMEs	Literature review of existing studies on BDA in SMEs	Key factors: tech capability, support, data quality	Resource limits, lack of skills, privacy issues	Train staff, gain management support, invest in tech
Wu et al. (2022)	Role of competitive intelligence in SMEs	Survey of 150 SMEs, SEM analysis	Social media boosts all competitive intelligence stages	Low use of social media analytics in SMEs	Promote social media analytics adoption
Hassani and Mosconi (2022)	Using social media analytics to boost competitive intelligence in SMEs.	Survey of 140 SMEs, structural equation modeling.	Positive impact on competitive intelligence.	Limited use of analytics in SMEs	Promote analytics adoption in SMEs

Table A1. Cont.

Ref.	Research Focus	Methodology	Key Outcomes	Challenges Identified	Recommendations
Kasasbeh et al. (2021)	Impact of BIS on competitive advantage in Jordanian banks, moderated by EM.	Survey of 300 respondents, PLS-SEM analysis.	BIS boosts competitive advantage; EM enhances this effect.	Complex BIS data; limited research in banking context.	Focus on EM to maximize BIS benefits.
Abiola et al. (2024)	Business analytics for competitive advantage	Literature review, content analysis	Enhances decision-making and efficiency	Data issues, skills gap	Improve data skills, privacy measures
Dereli (2023)	Exploring the use of BI in organizations	Literature review and analysis of BI maturity	BI enhances decision-making and business performance	Limited use of advanced BI models; internal focus	Improve BI adoption with leadership support and training
Tatić et al. (2018)	Business Intelligence in SMEs	Survey with 101 filled questionnaires	SMEs acknowledge BI's benefits but lack implementation, use basic systems like ERP, CRM	Financial limits, lack of BI knowledge, undefined KPIs.	Implement tailored BI systems to enhance decision-making and strategic planning.
Papachristodoulou et al. (2017)	BI System Efficiency in SMEs	Quantitative survey analysis	Environmental factors key to BI efficiency. SMEs underuse BI.	Lack of resources, expertise, and strategic planning.	Focus on environmental factors and expert insights to improve BI use.
Qushem et al. (2017)	Impact of BIS on SME performance	Survey, 181 SMEs; PLS-SEM analysis	Positive BIS influence on performance, especially in marketing, sales, and management.	Lack of data on BIS impact in procurement.	Enhance BIS use in key business areas to boost performance.
Gomwe et al. (2023)	BI Acceptance by SMEs in Tshwane	Survey, 161 SMEs; multinomial logistic regression	Technological, organizational, environmental factors drive BI acceptance.	Resource and knowledge limitations.	Improve resource allocation and training for BI adoption.
Boonsiritomachai et al. (2016)	Big Data in SME Management	Participatory action research, 2014–2017	Big Data reshaped strategy, improved products and CRM.	Limited financial and technical resources.	Integrate Big Data into strategic planning and tools.
Arsawan et al. (2022)	Benefits of Big Data for SMEs	Mixed methods, surveys, and interviews	Enhances decision-making, efficiency, and competitiveness.	Cost, complexity, skills shortage.	Adopt affordable Big Data tools, increase training.

Table A1. Cont.

Ref.	Research Focus	Methodology	Key Outcomes	Challenges Identified	Recommendations
Stjepić et al. (2019)	BIS Adoption in SMEs	Case study in a medium-sized Croatian company	BIS improves efficiency and decision-making, integrates with ERP.	Resistance to new technology.	Foster ongoing education and management support.
Dubravac and Bevanda (2015)	Big Data Implementation for Thai SMEs	Observations and interviews with 40 SMEs	Enhances decision-making and competitive edge.	Technical, financial, and cultural barriers.	Start with basic IT systems; evolve to Big Data applications.
Makhele (2018)	Adoption of Cloud BI in SMEs	Survey of 203 SMEs, PLS-SEM analysis	Significant influences: relative advantage, complexity, management support.	High complexity, lack of management support.	Focus on simplifying BI, boosting management support.
Hamad and Bakar (2018)	Big Data in Organizational Performance	Surveys, 210 SMEs, regression	Big data analytics, via knowledge management, boosts performance.	Cross-sectional limits insight.	Enhance knowledge management to leverage big data fully.
Jackson and Butler (2024)	Predictive BI for Inventory	Data mining, BI semantic model	Effective predictions for inventory management.	Inadequacy of traditional methods.	Use advanced BI tools for inventory decisions.
Choi et al. (2017)	Role of BI in Consulting	Inductive research, cost-benefit analysis	Optimal BI processes for consulting scenarios.	New models needed for BI in quality management.	Implement revised BI processes for better management.
Boonsiritomachai et al. (2016)	BI Maturity in Thai SMEs	Survey with logistic regression	Most Thai SMEs at low BI maturity; key influencers include advantage, complexity, resources.	Limited resources and complexity hinder BI adoption.	Enhance strategies for BI adoption in SMEs by government and IT vendors.
González-Varona et al. (2020)	Data Mining in KM for Colombian SMEs	Exploratory analysis, proprietary software	Improved KM skills and ICT usage via data mining.	Not specified.	Advance data mining integration in KM practices.
Tarek et al. (2016)	CI Model in North African SMEs	Empirical analysis, 180 companies	BI influences competitiveness via innovation and information protection.	Not specified.	Enhance CI with BI, innovation, and asset protection strategies.

Table A1. Cont.

Ref.	Research Focus	Methodology	Key Outcomes	Challenges Identified	Recommendations
Te and Cvijikj (2017)	SME Growth Prediction via Web Mining	Web mining on SME data	Effective growth prediction model from web data.	Data quality and system integration issues	Enhance data collection and system integration.
Alsibhawi et al. (2023)	BI Framework for SMEs	Design science, empirical	Developed BI framework improves decision-making.	Lack of BI expertise and adoption in SMEs.	Enhance BI training, provide clear business cases.
Coleman (2016)	Data-Mining for SMEs with Official Statistics	Case studies, statistical methods	SMEs benefit from integrating open and internal data for better business decisions.	SME data engagement limited by skill gaps.	Promote data integration to enhance SME decision-making.
Tarek and Adel (2016)	BI vs. ECI in North African SMEs	Survey of 300 SMEs, statistical analysis	ECI boosts export intensity more than BI.	Empirical evidence on CI effects scant.	Adopt ECI with internal audits for better competitiveness.
Metaxas et al. (2016)	MBI Framework for Developing SMEs	Textual analysis, PCA, CFA, SEM	Validated MBI framework through statistical tests.	SMEs lack tailored MBI frameworks	Develop localized MBI tools for SMEs.
Willetts and Atkins (2024)	SME Big Data Tool Evaluation	Focus group, case studies	Tool boosts SME competitiveness via better analytics.	Low adoption linked to awareness and expertise gaps.	Enhance engagement, customize tool for easier use.
Kasasbeh et al. (2021)	MBI Framework for South African SMEs	Case study, quantitative and qualitative analysis	MBI framework improves data access and decision-making.	Technical and data management challenges.	Enhance infrastructure and training for MBI use.
Mohd Selamat et al. (2020)	MBI for Developing SMEs	Mixed methods analysis	Validated MBI framework improves SME decision-making.	Technical limitations and poor data management.	Enhance SME training and infrastructure for MBI.
Ragazou et al. (2023)	Big Data in SME Management	Literature review	Enhances decision-making via improved BI.	Resource and expertise shortages.	Implement cloud solutions and open-source tools.
Naznen and Lim (2023)	BI Adoption in Libyan SMEs	Conceptual framework analysis	Factors like change management crucial for BI adoption.	Lacks industry-specific considerations.	Improve SME BI training and resource support.
Mohd Selamat et al. (2020)	MBI Framework for Developing SMEs	Mixed research methods	Developed robust MBI framework for SMEs.	Resource and technical constraints.	Enhance MBI support and infrastructure.

Table A1. Cont.

Ref.	Research Focus	Methodology	Key Outcomes	Challenges Identified	Recommendations
Sjarif et al. (2021)	Knowledge Sharing in SMEs	Quantitative analysis, 259 respondents in Bali	Enhances innovation and competitive advantage.	Limits in design and data bias.	Focus on promoting knowledge sharing for better performance.
Leite et al. (2019)	BI Solutions in Romanian SMEs	Survey of 37 SMEs	BI underused; improves competitiveness and performance.	Cost, user perception, investor support issues.	Boost BI training and support to increase adoption.
Adewusi et al. (2024)	Data Analytics for SME Competitiveness	Literature review, case studies	Enhances SME decision-making and efficiency.	Resource limits hinder advanced analytics.	Adopt analytics tools gradually, focus on training and partnerships.
Adewusi et al. (2024)	Data Analytics in SMEs	Literature review, qualitative analysis	Enhances SME decision-making and efficiency.	Resource limits hinder advanced analytics.	Adopt analytics tools gradually, focus on training and partnerships.
Gauzelin and Bentz (2017)	BI Systems in France	Interviews	BI improves decision-making, efficiency, and satisfaction.	Limited information on BI's impact on SMEs.	Expand BI research and use in SMEs.
Choi et al. (2017)	Impact of Knowledge Services	Data mining, regression	Model assesses knowledge service impact on performance.	Variable correlation and cost issues.	Enhance practical delivery of knowledge services to SMEs.
Dam et al. (2019)	BDA and SME Internationalization	Survey of 266 SMEs	BDA enhances international growth.	BDA governance doesn't boost growth.	Focus on developing BDA capabilities.
Olaifa and Francis (2020)	BIS Implementation in Lagos SMEs	Survey of 387 SME managers	BIS improves decision-making and efficiency.	Cost, expertise, and awareness issues.	Boost BIS training, awareness, and funding.
Jun et al. (2020)	Performance of PPINs	Data analytics, machine learning	PPINs boost R&D but not business performance.	Data linking and model complexity.	Enhance PPINs with better data integration and analytics.
Shabbir and Gardezi (2020)	Big Data in HRM for SMEs	Bibliometric analysis, survey	Enhances HR service and innovation.	Skepticism about big data.	Promote skill development and change management.
Maroufkhani et al. (2020)	BDA Adoption in SMEs	Survey, 171 Iranian SMEs	Boosts financial and market performance.	Complexity and security concerns.	Focus on managerial support and readiness.

Table A1. Cont.

Ref.	Research Focus	Methodology	Key Outcomes	Challenges Identified	Recommendations
Drelichowski et al. (2016)	BI-ERP Integration in SMEs	Case study review	Enhances SME decision-making and data analysis.	Cost and complexity of integration.	Adopt BI-ERP for better operational efficiency.
Lyu et al. (2023)	Ambidextrous Learning in SMEs	Survey of 289 SMEs in Nanjing, China	Boosts competitive advantage via dual learning.	Resource limits impact learning strategies.	Emphasize dual learning strategies in SMEs.
Djiu et al. (2024)	SME Export Performance	Path analysis of 138 SMEs	Tech capabilities boost exports; social media contributes via competitive advantage.	Hard to link social media to export gains.	Utilize tech and social media strategically to enhance exports.
Yoshikuni et al. (2023)	Ambidextrous Learning in SMEs	Quantitative survey of 289 SMEs	Boosts competitiveness and innovation.	Resource and adaptability limits.	Encourage ambidextrous learning for growth.
Mezhoud (2024)	BI and BA Integration in SMEs	Case study with free tools	Free tools boost BI and BA in SMEs.	Cost misperception limits tool adoption.	Use free tools to improve decision-making.
Gottfried et al. (2021)	Mining OGD for BI via Data Visualization	Two-industry case study, LDA topic modeling, pyLDAVis	OGD aids BI in spotting market opportunities.	Limited use of OGD in private sector due to unawareness of benefits.	Promote OGD use in private sector for BI innovations.
Choi et al. (2017)	Intellectual Capital in Jordan	Survey, 569 participants, SEM analysis	Intellectual capital boosts competitive advantage via BI and innovation.	Complexity of relationships and resource constraints.	Enhance training on intellectual capital use.
Almeida and Bernardino (2016)	Open Source Data Mining Tools for SMEs	Comparative analysis of various open-source tools	Open-source tools provide cost-effective, flexible solutions for SMEs' data analysis needs.	Technical complexity and varying levels of user support.	SMEs should choose tools based on specific needs and available technical support.
Dubravac and Bevanda (2015)	Mobile BI Adoption in Croatian SMEs	Empirical survey, literature comparison	Low adoption due to unrecognized benefits and resource constraints.	Lack of funds and knowledge among executives.	Promote awareness and benefits of mobile BI for decision-making.
Kapourani et al. (2015)	LinDA Workbench in Pharmaceutical BI	Case study analysis	LinDA enhances data processing efficiency, reducing operational times significantly.	Complex data linking and analysis processes.	Promote LinDA's integration within SME workflows for enhanced BI capabilities.

Table A1. Cont.

Ref.	Research Focus	Methodology	Key Outcomes	Challenges Identified	Recommendations
Mezhoud (2024)	BI Adoption in Algerian SMEs	Field study, empirical research	SMEs need BI to enhance competitiveness and efficiency.	High costs, lack of knowledge among executives.	Increase awareness and support for BI adoption in SMEs.
Mian and Ghabban (2022)	BI System Adoption in Algerian SMEs	Field survey, descriptive-correlational	BI systems crucial for improving SME efficiency.	Financial constraints, lack of executive knowledge.	Provide educational programs on BI benefits and implementation.
Igboanusi (2023)	BI and Organizational Effectiveness in Nigerian Oil & Gas SMEs	Quantitative survey, online platform	Positive impact of BI on SME effectiveness.	Lack of BI expertise and resources in SMEs.	Enhance training and resources for BI implementation.
Arsawan et al. (2022)	Intellectual Capital in SMEs, South Africa	Literature review, conceptual framework	Intellectual capital significantly enhances SME competitiveness through innovation.	Lack of innovative skills and intellectual capital resources.	SMEs should invest in building intellectual capital and adopt innovative practices
Qushem et al. (2017)	Determinants of BIS Adoption in SMEs	Survey of 181 SMEs, PLS-SEM analysis	Technological, organizational, and environmental factors significantly impact BIS adoption stages.	Complex interplay of factors affecting adoption stages.	Enhance understanding and support for BIS adoption in SMEs.
Puklavec et al. (2018)	BI Maturity in IT SMEs	Literature review, assessment of 14 key factors	Enhanced analytical capabilities in IT SMEs, with varying strengths in construction, deployment, and data management.	Complex data integration and lack of resources.	SMEs should integrate comprehensive BI systems to streamline data analysis and improve decision-making.
Cohen Tzedec et al. (2022)	Impact of BI on SME Innovation and Work Behavior	Theoretical framework, literature review	BI enhances SME innovation and innovative work behavior via knowledge sharing.	Resource limitations and integration complexity.	Encourage SMEs to adopt BI to improve innovation and work practices.

Table A1. Cont.

Ref.	Research Focus	Methodology	Key Outcomes	Challenges Identified	Recommendations
Tatić et al. (2018)	Cloud BI for Iranian SMEs during COVID-19	Mixed methods, including fuzzy Delphi and ISM	Effective model for SMEs, integrating critical factors like SME characteristics and critical success factors.	Financial and knowledge barriers among executives.	Promote cloud BI benefits and provide managerial training in its use.
Topalović and Azzini (2020)	Data Mining in Italian SMEs	SEM-ANN approach, survey	Data mining positively impacts business performance through improved technological, organizational, and environmental factors.	Complexity in integrating and adapting new technologies.	Emphasize training and resource allocation for successful data mining adoption.

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